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Respectfully,

Alexandru TĂBUȘCĂ, PhD

JISOM Editor-in-Chief

JOURNAL OF INFORMATION SYSTEMS & OPERATIONS MANAGEMENT

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THE ACCOUNTING SERVICES QUALITY MANAGEMENT IN THE CONTEXT OF ACCELERATED DIGITALIZATION

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Abstract

In the field of accounting, the concept of "quality" refers to the extent to which the services provided comply with professional standards, legal regulations, customer expectations and organizational requirements. We have identified a series of particular dimensions of accounting service quality that we have developed in this article. Quality management in this context is not limited to compliance with technical norms, but also includes factors such as customer satisfaction, process efficiency and adaptability to external changes. Quality in accounting services plays an essential role, having a direct impact on the financial credibility of an organization and its relations with tax authorities and stakeholders. Accounting is a practical activity carried out by professionals, which has the role of providing useful information for decision-making at the level of economic entities. Every user of accounting information wants to have information that reflects reality, that is, true information.

Keywords: quality of accounting services, dimensions of quality, quality management, quality principles

JEL Classification: L15, M29, M41

1. Introduction

In the field of accounting, the concept of "quality" refers to the extent to which the services provided comply with professional standards, legal regulations, customer expectations and organizational requirements. Quality management in this context is not limited to compliance with technical norms, but also includes factors such as customer satisfaction, process efficiency and adaptability to external changes. Quality in accounting services plays

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a crucial role, having a direct impact on the financial credibility of an organization and its relations with tax authorities and stakeholders.

Considering the concept of specialist J. M. Juran [1], according to which quality management has three pillars: planning, control and improvement, we can notice a series of their particularities regarding accounting services.

■ Quality planning is the activity of developing the processes necessary to satisfy customer needs. The stages of quality planning consist of establishing the following elements: setting quality objectives; identifying customer characteristics; determining customer needs; designing the characteristics of works/processes that meet customer needs; designing/using technological tools that produce the requested characteristics; establishing control methods for the performance process.

■ Quality control establishes the infrastructure necessary for assessing real quality and the possibility of comparing it with the quality objectives of the process by acting on the differences between real and achieved quality.

■ Quality improvement is the process of improving performance by identifying projects and ensuring the necessary infrastructure for diagnosing causes and finding remedies and establishing the resources necessary for quality improvement.

Outlining the characteristics of services is an important aspect, which allows their individualization from other elements that are the object of exchanges within the market. The opinions of specialists differ regarding the characteristics of services, considered an important issue both from a conceptual and practical point of view. The following general aspects are mainly taken into account [2]: intangibility, inseparability, variability, perishability.

Intangibility makes it very difficult for the provider to convince the client to use the respective services. In practice, the beneficiary may have some reservations about the capacity of the respective services to satisfy their organizational needs.

Inseparability highlights the fact that services cannot be separated from their provider either spatially or temporally. In practice, we are talking about the simultaneity of production/performance and consumption.

Variability highlights the fact that the quality of services depends on the provider, when, how and where they provide them, which makes a service differ from one performance to another. A service can almost never be repeated in an identical way. Often, customers negatively assess the differences between the services they receive, because discrepancies appear between the quality promised, delivered, and received.

Perishability basically shows that services are not storable.

2. The dimensions of the quality of accounting services

Starting from these general characteristics, we can identify a number of specific dimensions of the quality of accounting services.

Correctness

It is essential that accounting services are correct, complying with the accounting and tax regulations in force. This aspect includes carefully checking financial documents and ensuring that all calculations and reports are carried out correctly.

Accuracy

Accuracy is fundamental to maintaining the trust of clients and tax authorities, as accounting errors can lead to financial penalties.

Clarity

Accounting services must be clear and transparent, allowing clients to easily understand financial reports, balance sheets and other documents.

Confidentiality

Accounting services must ensure that information is protected from unauthorized access and is managed in accordance with data protection regulations.

Communication

Quality in accounting services also involves effective communication with clients. This involves speed and clarity, accurate information, providing regular updates and being available to address client issues.

Professionalism

Professionalism in accounting services involves adhering to a strict code of ethics, as well as maintaining appropriate behavior towards clients, colleagues and tax authorities. This also includes behaviors related to integrity, transparency and accountability. Ethical and professional behavior is crucial for maintaining reputation and trust.

Process efficiency

Accounting services must be efficient in terms of resource use (time, people, technology) and minimize costs, while maintaining a high level of quality. The efficiency of accounting processes contributes to reducing errors, saving time and improving client satisfaction.

Adaptability

Quality accounting services are able to adapt to frequent changes that may be legislative, economic or technological. Adaptability allows an accounting firm to remain competitive in the market, and innovation can improve services and reduce costs.

3. The fundamental principles of the Quality Management

According to the ISO 9001:2015 standard on quality management systems, there are 7 fundamental principles that form the basis for the implementation and continuous improvement of a quality management system. These principles are [5]:

A. Customer focus

B. Leadership

C. Engagement of people

D. Process approach

E. Improvement

F. Evidence-based decision-making

G. Relationship management

3.1 Customer Focus

Organizations must understand and meet customer requirements and expectations. Customer satisfaction is essential to the success of the organization, and continuous improvement of customer satisfaction must be a priority. Thus, quality management must be focused on meeting customer needs and requirements. In the field of accounting, this means that services must be tailored to the specifics of each client and meet their expectations, while ensuring transparency, accuracy and clarity. Clients are the main source of income for accounting firms. Therefore, client satisfaction is a key indicator of service quality. A customer-oriented approach will contribute to increasing customer loyalty and a positive reputation for the firm. Conducting periodic assessments of customer satisfaction, integrating their feedback into the service improvement process and personalizing accounting services according to the client's needs.

3.2 Leadership

Leaders must set the purpose and direction of the organization. They must create a favorable internal environment for employees to be involved in achieving the organization's goals. Leadership refers to the ability to guide, inspire, and influence a group of people to achieve common goals. An effective leader not only makes important decisions, but also motivates, supports, and develops teams to perform at the highest level. Leadership also involves accountability, integrity, and vision. In the field of accounting, leadership manifests itself in several ways:

■ Managing Accounting Teams:

Accounting leaders must coordinate teams, assign tasks, and ensure that all members are effective and understand the importance of their work. They are responsible for developing and implementing accounting strategies.

■ Strategic Decisions:

An accounting leader must make decisions that ensure not only the organization's financial compliance but also its long-term financial health. This may include tax planning, assessing financial risks, or adopting accounting best practices.

■ Promoting an ethical and compliant environment:

A leader in the field must be an example of integrity, respecting professional standards and tax and financial regulations. He must ensure that the team complies with accounting regulations, avoiding any form of fraud or unethical practices.

■ Innovation and adaptability:

In a constantly changing field such as accounting, a leader must be able to identify new technologies and methodologies that can improve the efficiency of accounting teams and respond quickly to legislative or economic changes.

■ Training and professional development:

Leadership in the accounting field also includes supporting the professional development of teams. Leaders must encourage continuous training, provide constructive feedback, and help team members improve their skills and competencies.

3.3 Engagement of people

The involvement of all employees is essential for the success of the organization. People must be involved and motivated to actively contribute to achieving the organization's objectives, and their skills must be constantly developed. Quality management should not be the exclusive responsibility of a department or a group of employees, but must involve the entire organization. Each employee, regardless of their hierarchical level, must contribute to maintaining quality standards within the organization.

In an accounting firm, all employees, from accountants to managers, must understand and apply the principles of quality management. The involvement of all ensures team cohesion and alignment to the same objectives. Creating a work environment that encourages the active participation of all employees in quality improvement activities, their continuous training and encouraging open and constructive feedback.

3.4 Process Approach

Organizing activities and resources in a systematic and efficient manner is important for achieving consistent and predictable results. The process approach ensures better management of risks and opportunities.

In accounting, this involves analyzing and optimizing workflows and procedures to ensure that all activities are carried out efficiently and correctly. A process-based approach allows for more efficient management of accounting activities, helping to reduce errors and processing time, as well as improving transparency and consistency. Identifying and optimizing key processes in accounting (for example, the process of recording financial transactions, preparing financial reports, managing payments and collecting taxes and automating them), where possible and aligning them with internal quality standards.

3.5 Improvement

Improvement is a permanent goal of the organization. A constant focus on processes and performance helps to identify and implement continuous improvement measures, which leads to better efficiency and effectiveness. In the field of accounting, this involves constantly evaluating the efficiency and effectiveness of accounting processes and identifying ways to optimize them.

The accounting market is dynamic and subject to frequent legislative and economic changes, and improvement ensures the company's adaptability to these changes and maintaining a quality service in the face of external challenges.

This principle is applicable through the implementation of improvement cycles based on the Plan-Do-Check-Act (PDCA) model, periodic evaluation of internal processes and the adoption of innovative solutions, such as the automation and digitalization of accounting activities.

3.6 Evidence-Based Decisions Making

Quality management is based on data-based decision-making and systematic performance analysis. Decisions should be made based on objective analysis and evidence. The proper organization and use of data helps to make informed decisions and optimize processes.

In accounting, this principle is applied by using financial and statistical data to evaluate the efficiency and accuracy of accounting processes. Informed decisions lead to more efficient and accurate solutions, and in the accounting field, this can reduce errors and risks, thus improving the quality of services.

This principle is applicable by using advanced accounting software, implementing a performance management system (e.g., KPIs – key performance indicators), and collecting relevant data to evaluate internal processes and performance.

3.7 Relationship Management

In the context of quality management, this principle refers to the creation and maintenance of strong and trusting relationships between all stakeholders – employees, customers, suppliers and tax authorities. In the accounting field, close collaboration with tax authorities, customers and other external parties is essential to ensure a quality service. Collaboration with them can lead to increased performance and mutual satisfaction.

Partnership relationships allow for better coordination and communication between the parties involved and ensure that all parties work towards a common goal: improving service quality and customer satisfaction.

This principle is applicable by building trusting relationships with customers and tax authorities through transparency and compliance with commitments, collaborating with technology providers to improve IT infrastructure and ensuring clear and effective communication with all stakeholders.

4. Challenges in implementing quality management in accounting

Implementing a quality management system in accounting services can be a complex process, requiring significant obstacles to overcome [4]. These challenges are related both to the specific nature of the accounting field and to external factors, such as constantly changing regulations and customer requirements. The main challenges encountered in implementing quality management in this sector are presented below.

● Complexity of regulations and frequent legislative changes

The accounting field is regulated by norms and standards that change frequently, which can make it difficult to maintain a consistent quality practice. It should also be borne in mind that the tax code also undergoes changes, additions and additions annually. Therefore, accounting firms must always be aware of these changes in order to comply with current regulations. This can lead to difficulties in ensuring consistent quality, especially in the context where the team needs constant training in the context of frequent changes.

● Lack of process standardization

In many accounting firms, processes are not always standardized, which is why the services provided can vary significantly from one client to another. Also, many accounting activities rely on the individual experience of accountants, which can lead to inconsistencies in the application of procedures. Without process standardization, it is difficult to maintain a consistent level of quality. Accounting firms can experience difficulties in providing consistent and predictable services, which affects both efficiency and client satisfaction.

● Resistance to change and adaptation to new technologies

Implementing quality management often involves changes in internal processes, adopting new technologies and working methods. Many accounting professionals can be reluctant to change, which can delay the implementation of a quality management system and make it difficult to integrate new technologies, such as advanced accounting software, automated audit systems or blockchain technologies.

● Limited resources of small firms

Many accounting firms, especially medium and small ones, have limited financial and human resources to invest in implementing a complete quality management system.

The lack of resources can make it difficult to implement effective quality processes, from training staff to purchasing modern technologies to support service quality.

● Complexity of human resource management

Continuous training of staff and maintaining a high level of competence can be a challenge. Staff turnover can affect the continuity of quality processes. Also, differences in experience and training among team members can lead to variations in the quality of services provided.

● Measuring and evaluating service quality

Measuring quality in accounting is more complex than in other service areas, as the success of an accounting service cannot always be assessed directly and immediately. Establishing performance indicators that reflect the quality of accounting services and can be measured objectively is a challenge. For example, client satisfaction or performance before tax authorities are factors that can vary greatly depending on the context.

● Confidentiality and information security

Accounting services involve the management of a large number of sensitive client data, and their protection is an absolute priority. Failure to comply with confidentiality regulations can seriously damage reputation and lead to legal sanctions. In implementing a quality management system, accounting firms must ensure that financial information is properly managed and protected, which may involve significant investments in IT security systems and staff training.

● Adapting to diverse client requirements

Each client has different needs and varying expectations regarding accounting services. This can sometimes lead to difficulties in delivering a uniform and consistent quality service. Managing these diverse requirements can lead to difficulties in establishing unified internal procedures, which can affect the efficiency and consistency of the services provided.

5. Conclusions

Quality in accounting services is not limited to the technical accuracy of financial documents, but involves a holistic approach that includes transparency, client satisfaction, professionalism and process effectiveness. In a constantly changing economic environment with complex regulations, accounting firms must implement quality management methods that respond to both external requirements and client needs to ensure long-term success.

The principles of quality management in accounting are fundamental to creating an efficient work environment and providing high-quality accounting services. By implementing client-oriented management, continuous improvement, involving the entire organization and using data for decision-making, accounting firms can optimize processes, increase client satisfaction and comply with legal regulations. These principles constitute a solid framework for ensuring a constant level of performance and adapting to the constantly changing requirements of the market.

Thus, a number of solutions can be considered: implementing a continuous training system for employees (training sessions and workshops, as well as demonstrations of their benefits for improving the quality and efficiency of accounting processes); adopting standardized internal procedures or implementing an ERP (Enterprise Resource Planning) system; small companies can opt for more accessible solutions, such as cloud accounting software, which can automate many processes, or for the gradual implementation of a quality management system, focusing on the most critical aspects; implementing regular feedback systems from customers, assessments of their satisfaction and measurements of the efficiency of accounting processes, such as response time and error rate in reports; adopting advanced technological data security solutions (e.g. data encryption) and ensuring a clear internal policy on the protection of confidential information; creating customer segments and offering personalized service packages that meet specific needs, but which also comply with the company's internal quality standards.

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BUILDING A SUSTAINABLE FUTURE BY DEVELOPING THE CONCEPT OF DOUBLE DIAMOND IN TRIPLE DIAMOND, A NEW CONCEPT IN CREATING A NUDGE TOWARDS PRO-ELECTRIFICATION BEHAVIOR IN URBAN FREIGHT TRANSPORT

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Alexandra PERJU-MITRAN[2]

Augustin SEMENESCU[3]

Abstract

In the present economic setting, road freight transportation accounts for 77% of the total products moved by land inside the European Union. However, it is undeniable that, from a certain perspective Historically, vehicles were detrimental to the environment. The freight transport sector accounts for one-fourth of greenhouse gas emissions from road transport and roughly 6% of overall greenhouse gas emissions in Europe. Consequently, the vehicle electrical industry is poised for growth in Europe in the future.

Electrification is a growing trend driven by the necessity to reduce carbon emissions, enhance air quality, and ensure compliance. Regulations governing urban emissions are stringent.

These policies are contextualized within the European Union's target of achieving "a reduction of at least 55% of greenhouse gas emissions by 2030 and climate neutrality by 2050," as outlined in the European Green Deal.

The Truck E-mobility concept in urban agglomerations pertains to the use of electric vehicles, both high and small tonnage, for freight transportation in urban settings. This movement is driven by the necessity to mitigate pollution, enhance logistical efficiency, and comply with stringent regulations in densely populated urban areas.

To promote sustainable development, we propose the saddle transformer within the framework of a novel Diamond idea based on the Double Diamond model. The first offers a strategic design framework applicable to innovation processes and issue-solving. The

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Triple Diamond is a novel idea that effectively provides a strategic framework for implementing solutions in problem resolution.

Keywords: Sustainable Transport, Green Economy, Truck E-mobility, Double Diamond, Triple Diamond, Nudging

JEL Classification: Q50, Q55, Q56

1. Introduction

The concept of a green economy, first introduced in 1989 in a report for the United Kingdom government by a group of environmental economists titled "Blueprint for a Green Economy" [1], fundamentally underpinned the implementation of an inclusive green savings strategy at the United Nations Conference on Sustainable Development in 2012 (Rio+20) [2].

The definition provided by UNEP (2011) [3] is one of the most recognized internationally and widely utilized, stating that a "Green Economy" is an economy that enhances the welfare of populations and promotes social equity, while simultaneously significantly reducing environmental risks and constraints. It is an economy characterized by minimal carbon emissions, resource efficiency, and social inclusivity.

The notion of a green economy has garnered substantial international attention in recent years, both as a mechanism for resolving the financial crisis of 2008 and as one of the two themes for the United Nations Conference on Sustainable Development since 2012 (Rio+20). Consequently, this contributed to the growth of the concept through expanding literature and rising international practices. It is essential to acknowledge that when the notion was initially embraced as a theme for Rio+20, there was also ambiguity in EAEC. What is the link between a green economy and internationally accepted objectives, such as sustainable development and poverty eradication, as well as the lack of knowledge in the EAEC? What are the possible problems, risks, costs, and rewards associated with the adoption of a green savings policy?

The primary aim of the EAEC The envisioned economy is one that fosters a sustainable future characterized by low carbon dioxide (CO_2) emissions, achieved through a transition to ecological production and consumption models that prioritize resource efficiency. This work may be accomplished through the utilization of renewable energy, the adoption of energy-efficient technology, and the implementation of circular economic models that prioritize waste reduction and resource efficiency.

The shift to a green economy also has enormous hurdles, including the necessity for substantial investment in technology and infrastructure, as well as the need to balance economic, social, and environmental factors.

Road freight transportation accounts for 77% of the total products moved by land inside the European Union and produces a commercial surplus of billions of euros yearly for the EU. They are a significant and integral element of the economy. The freight transport sector accounts for one-quarter of greenhouse gas emissions from road transport and roughly 6% of overall greenhouse gas emissions in Europe. Consequently, the vehicle electrical market will expand in Europe in the future.

Considering the present setting in which commodities are predominantly carried via road, a mode responsible for 72% of total CO2 emissions from the transport sector, global efforts are being made to promote electric freight transport. These policies are contextualized within the EU's target of lowering greenhouse gas emissions by at least 55% by 2030 and achieving climate neutrality by 2050, as outlined in the "European Green Deal." Governments, corporations, and individuals must collaborate to address these challenges and expedite the transition to electrified urban freight transport.

Electric mobility for trucks (truck e-mobility) plays a vital part in the transition to more sustainable and environmentally sound transportation in urban environments.

Truck E-mobility [4] in urban agglomerations pertains to the utilization of electric vehicles, both big and small tonnage, for freight transportation inside urban environments. This movement is propelled by the necessity to diminish pollution, enhance logistical efficiency, and comply with stringent regulations in densely populated urban areas.

What is the significance of implementing electrification of vehicles in urban areas?

- Air pollution reduction: electric trucks eliminate greenhouse gas emissions (CO_2) and atmospheric pollutants (NOx, fine particulate matter).
- Strict regulations about emissions: several European cities, including London and Paris, are instituting Low Emission Zones (LEZ), which restrict diesel cars, while also mandating a shift to zero-emission vehicles.
- Reduction of urban noise: electric trucks are considerably quieter than their diesel counterparts. What factors help to the reduction of pollutant phonics?
- Delivery request Rapid and sustainable: rise in e-commerce and anticipations client for delivery. The advent of rapid transit has resulted in a heightened influx of automobiles in urban areas; thus, electric trucks are a viable answer for more sustainable transportation.

Electric Mobility for Trucks Urban challenges:

• Autonomy of batteries: electric trucks and vehicles possess a limited range, making them more ideal for short-distance transportation or local delivery rather than intercity transit.

• Charging infrastructure: the scarcity of charging outlets in urban areas and logistics warehouses is a significant hurdle.

Initial expenditures for electric trucks are greater than those for diesel vehicles, however their operational costs are comparatively lower.

• Pregnancy is advantageous: batteries are bulky and heavy, reducing vehicle load capacity.

Integration with electric networks: the rising number of electric cars may need increased energy requirements for networks, which must be equipped to manage rapid loading well.

Emerging solutions and trends in Truck E-mobility:

• Dedicated charging infrastructure: ultra-fast charging stations for trucks, strategically located in urban areas and near logistics depots; logistics hubs equipped with renewable energy sources (e.g., solar panels) for charging purposes.

• Advanced battery technology: high-density batteries provide more power capacity, potentially increasing autonomy and reducing charging times.

• Pilot projects in major cities: firms such as Amazon, DHL, and IKEA are testing electric truck fleets for urban delivery, while manufacturers like Tesla Semi, Volvo FL Electric, and Mercedes eActros are introducing electric trucks for urban transportation.

• Innovations in logistics: last-mile deliveries facilitated by drones or tiny electric vehicles (cargo bikes) and the exchange of data between enterprises for route optimization and a decrease in the number of cars on the streets.

• Governmental subsidies and policies: governments provide incentives. Funding for the procurement of vehicle electrical systems and the construction of charging infrastructure.

Examples of effective practices with the adoption of Truck E-mobility:

• London: Ultra-Low Emission Zones (ULEZ) [5] promote the transition to electric cars for cargo delivery and electric truck fleets utilized by maritime merchants.

• Amsterdam: "Zero Emission Zones" Plan [6] (until 2025) which restricts entry for diesel cars in some areas of the city and establishes Micro-Logistics Hubs for efficient deliveries using electric vehicles.

• Copenhagen: Utilize electric cars for all government supplies and increase the network of charging stations.

Long-term benefits of Truck E-mobility in urban areas:

• Operational cost reduction: Electric energy expenses are lower than those for fossil fuels, and maintenance is very straightforward.

• Sustainability and positive image: Companies that employ electric vehicles may enhance their reputation, appealing to environmentally conscious clients.

• Growth Efficiency: Electric cars may be combined with autonomous driving technology, significantly enhancing logistics efficiency.

Truck E-mobility is essential for addressing contemporary urban difficulties; yet, its success relies on collaboration among manufacturers, governments, and logistics operators. Infrastructure adaptation and cost-reduction technologies will expedite the transition to electric transportation in densely populated cities.

Truck E-mobility is a crucial aspect of the transition towards sustainable development and a sustainable future, linked with global aims to combat climate change and mitigate the negative environmental impacts of transportation. Electric mobility in the vehicle sector provides answers for many economic, social, and environmental concerns, significantly contributing to progress. Sustainable electric mobility for trucks (truck e-mobility) plays a vital part in the transition to more sustainable and ecological transportation.

Consequently, while sustainability and sustainable development are interconnected ideas, they possess unique meanings.

Sustainability denotes the capacity of a system or process to be sustained at a specific level across time. In a background setting, it signifies the necessity of generating current meetings without jeopardizing future capacity production while fulfilling one's own requirements. Sustainable development is a comprehensive term that encompasses not only environmental sustainability but also economic and social sustainability.

The most recognized definition of sustainable development is provided by the World Commission on Environment and Development (WCED) in the Brundtland Report: "Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs." [7]

2. Nudging

Nudging is a concept from behavioral sciences, economics, and psychology that focuses on subtly influencing individuals' actions without constraining their choices or significantly altering economic incentives. It is a method to influence behavior towards a desired outcome by modifying underlying decision-making processes.

The notion of nudge encompasses several strategies employed to assist individuals in making superior decisions without imposing certain outcomes on anybody.

Nudging was introduced in 2008 by Richard Thaler and Cass Sunstein and is described as "any aspect of the choice architecture that modifies individuals' behavior in a predictable manner, without prohibiting any options or significantly altering economic incentives." [8]

For an intervention to qualify as a simple motivation, it must be easily avoidable and inexpensive.

The word was popularized by economists Richard Thaler and Cass Sunstein in their book "Nudge: Improving Decisions About Health, Wealth, and Happiness." [9] In the context of time, "architecture of choice," as defined, pertains to "the environment" in which humans make decisions. [10]

The strategist begins with the premise that sustainable development offers a conceptual framework that, when embraced by citizens, will facilitate the establishment of a fair enterprise characterized by balance and solidarity, enabling adaptation to changes induced by global, regional, and national challenges, including demographic decline.

Skepticism and criticism are common reactions in the rest of the world about "nudges," due to the fact that their objective is to alter an individual's behavior. Some authors regard nudging as both protective and patronizing.

Attributes of nudging:

• Subtlety: Does not enforce rules or prohibitions, but facilitates the decision-making process to promote outcomes that are more beneficial for the person or society.

• Freedom of choice: Does not restrict available options.

• Influence of context: Decisions are affected by the mode in which options are presented. Advantages: Assists individuals in making judgments that may be more advantageous or prudent in the long run; Costs are minimal compared to established laws.

Criticism may be perceived as manipulative, particularly if goals lack transparency; its effectiveness is contingent upon cultural context and the manner of application.

Nudging is a strategy of persuasion that maintains individual individuality while subtly encouraging desirable behaviors, particularly in the context of enhancing urban freight transit in Romania alongside European Union obligations.

Punctuality in the context of assimilating electrification in urban freight transport arises when involved parties encounter challenging and unique scenarios that complicate rational decision-making. In such instances, ISI proposes a well-structured nudge or incentive:

Instances of nudging in the integration of Truck E-mobility inside urban freight transport in Romania (source, author):

• Online environment: Brand awareness through viral video content produced by an influencer on platforms such as Facebook and Instagram, focusing on user engagement; Social messaging: Collantare Trucking's electric vehicles promoting "pro-electrification/pro-neutrality" messages regarding climate and CO_2 reduction, aimed at raising awareness among all interested parties.

3. Double diamond

The Double Diamond is a design process concept popularized by the British Design Council in 2005. [11] The technique was modified following the divergence-convergence model introduced in 1996 by the Hungarian - American linguist Béla H. Bánáthy. [12] [13]. It is prominent in user-centric design because it gives a clear direction for an approach confronts complexity in a systematic and innovative manner.

The Double Diamond framework encompasses two diamonds that integrate four design phases, showing a comprehensive overview of the design process.

1. Discoverr • Purpose: Comprehending context, identifying user needs, and recognizing difficulties. • Methods: User interviews; Observation; Secondary research (data analysis, existing studies) Outcome: A definitive understanding of the actual situation and a compilation of insights.

2. Define • Purpose: Concentrate on the primary issue to be addressed, encapsulating the insights gathered during the Discovery phase. • Methods: Formulation of issue statements; development of empathy maps; mapping of customer journeys • Outcome: A clearly articulated and well-defined design challenge.

3. Development • Objective: To generate and evaluate potential solutions for the identified problem. • Methods: Brainstorming; Prototyping; Rapid Testing (User Testing) Outcome: A collection of prototypes or concepts that address the issue.

4. Delivery • Purpose: Execute the completed solution and initiate its deployment. • Methods: Completion Design; Implementation Solution; Measurement Impact • Outcome: A functioning solution, prepared for implementation.

The visual representation (Figure No. 1) of the "Double Diamond" idea delineates two divergent processes (exploring several choices) and two convergent processes (focused on potentially viable solutions):

1. The initial diamond (problem): Divergence for exploratory issues and convergence for their definitions; 2. The subsequent diamond (solution): Divergence for exploring solutions and convergence for the implementation of optimal solutions.

Benefits of Double Diamond framework:

• Clarity and Structure: Offers a systematic approach to resolving complicated challenges.
• User-centric: Place people and their needs at the core of the process.

• Flexibility: Applicable across many domains, including product design, services, and governmental policies.

• Collaboration and Creativity: Promotes the engagement of interdisciplinary teams and rapid experimentation.

Critique and constraint:

• May be regarded as linear, while the process is, in reality, iterative.

• Requires time and resources for efficient implementation. Success is contingent upon the quality of research and user engagement.

3.1. Practical Applications of Double Diamond Product Design: Development of solutions that directly address consumer demands. • Public Policies: Enhanced and more efficient policy execution. • Digital Services: User-centric application development and platform services.

The Double Diamond framework assists teams systematically addressing difficult challenges while keeping the user at the center of the process.

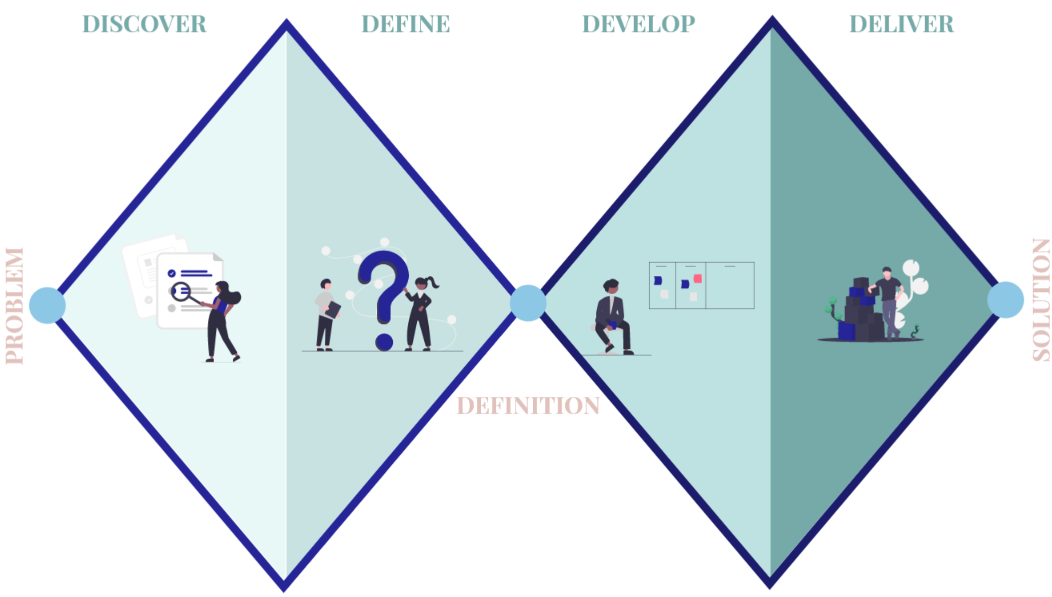

Figure 1. Double Diamond / Design Council of the United Kingdom in year 2019

Source: https://projekter.aau.dk/projekter/files/415128891/

4. The connection between Nudging and Double Diamond

Nudging and the Double Diamond are complimentary ideas applicable in user-centric solution design, particularly in service design, public policy, and consumer behavior. Despite originating from disparate contexts, they can be interrelated to inform the development of successful treatments that impact human behavior. What examines the architectural modeling choices about the use of electricity in urban freight transport and promotes carriers' selection of sustainable options.

Nudging may be included in the Double Diamond approach to provide solutions that subtly impact habits while preserving user autonomy.

1. Discover:

• Identify behavioral streams and the elements that drive them.

• Investigate users to comprehend the rationale behind my decisions (cognitive biases, habits, obstacles).

Examples: Observing decisions made by carriers to comprehend my continued preference for fossil fuel trucks over electric ones.

2. Define:

• Formulating the problem: "How can we devise a solution that promotes desired behavior?"

• Problem statements may encompass: “What strategies may be employed to enhance the electrification rate among carriers?" How can we motivate carriers to conserve energy through saddle SAVE?

• Conduct data analysis to determine the locations and methods for implementing a nudge for A.

3. Formulate:

• Formulating innovative solutions grounded in the principles of nudging, including:

• Default settings: Implicitly configuring certain preferred options (e.g., automatic enrollment in savings programs).

• Social Messages: Communication FACT that "countries such as Germany, France, and the Netherlands have integrated electrification in urban freight transport" to promote adherence.

• Redesign of environmental decision-making: Mandate by legislation.

• Prototyping and evaluating solutions through simulation or pilot studies.

4. Delivery:

• Execution of solutions and assessment of impact.

Examples: Organizing pilot truck "drive test" sessions for electric vehicles by manufacturing for carriers in major metropolitan agglomerations.

• Modify energy bills for A to emphasize consumption in comparison to other nations that have already included electric trucks into urban transport.

In what ways does nudging facilitate the Double Diamond process?

• Validating insights: Researching behavior particular to nudging (observing decisions, testing reactions) might enhance the Discovery phase.

• Prototypes are expedited and iterative: During the development phase, nudging provides straightforward and efficient solutions that can be rapidly evaluated.

• Measurement of success: Nudging relies on minor, quantifiable modifications, facilitating an easier evaluation of impact during the delivery phase.

Advantages of integrating Nudging with the Double Diamond framework:

• Resolutions User-centric: The Double Diamond framework directs the creative process, while nudging guarantees that the solutions are pragmatic and effective.

• Scalability: Nudging facilitates widespread deployment while minimizing expenses.

Quantifiable impact: The integration of user research (Double Diamond) and behavioral testing (nudging) enhances the likelihood of success.

In summary, Double Diamond provides a framework for problem-solving, whereas Nudging introduces a behavioral dimension that enhances the offered solutions. This combination is highly beneficial in formulating effective and lasting solutions.

5. Outcomes

To achieve sustainable development in Romania in alignment with European Union commitments, we must formulate a strategy centered on citizens and future generations concerning the implementation of global trends in "Truck E-mobility" through complementary concepts: NUDGING and DOUBLE DIAMOND.

Specifically, in the context of AUTHOR development, the transformation of the Double Diamond model into a Triple Diamond framework, once embraced by all stakeholders in Truck E-mobility, will facilitate the establishment of a company characterized by equity and solidarity, capable of addressing the challenges posed by global, regional, and national changes.

In contrast to the Double Diamond, which offers a strategic design framework applicable to innovation processes and issue-solving, the Triple Diamond effectively provides a strategic framework for the execution of solutions in problem resolution.

examined the "Double Diamond" idea inside EAEC. The applicability of electrification in urban freight transport is examined by the author, who notes that the two components—Discovery/Definition and Development/Delivery—are intricately connected. However, they must be addressed in a manner that facilitates both a visual representation of standard design phases (problem/solution) and an overview of the implementation/testing process.

This article necessitates the development of three diamonds, envisioned as the "Triple Diamond."

Third diamond visible The author possesses the subsequent phases:

- Training Driver (divergence) / Test Drive (convergence), denoting the procedures designed to apply and evaluate the solution derived from information acquired through observation of the necessity to facilitate the adoption of electric vehicles in urban freight transport.

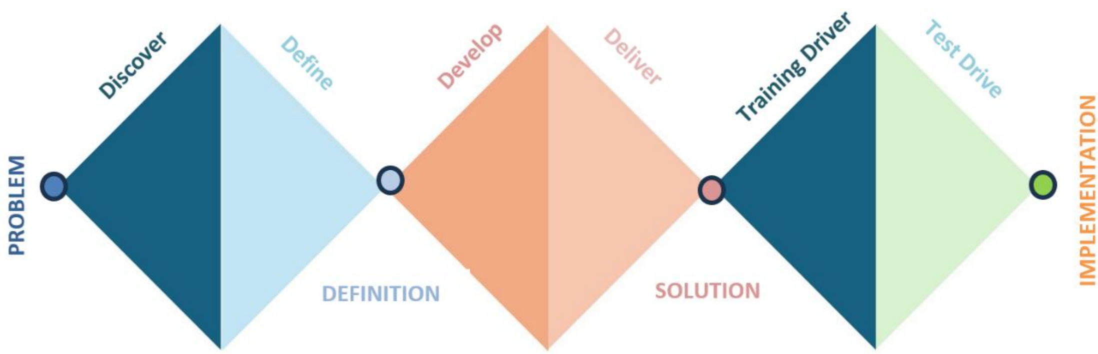

Figure 2. Triple Diamond: Representation visual modified Double Diamond model encapsulates the design process How and implementation

Source: author / contributions PERSONAL

In the Triple Diamond model, the author illustrates that the three diamonds symbolize a process of researching challenges, which may be extensive or profound (divergent thinking), executing targeted actions (convergent thinking), and then implementing solutions. Therefore, the design process has six processes, exceeding the two additional phases typically illustrated in literature according to the Double Diamond design process model, which was popularized by the British Design Council in 2005, specifically:

Discover: comprehend the situation rather than make assumptions about what it is. This step involves engaging in discussions and socializing with individuals impacted by issues.

Define: with the information gathered from the discovery phase, define CHALLENGE in a different way. The concept of challenge utilizing the insights acquired during the discovery phase.

Develop: provide answers different to the problem definition clearly, looking for inspiration from elsewhere part and co -designing with several people different.

Delivery: offer different solutions at scale small.

Training drivers: offer dedicated training sessions for different truck models electric vehicles intended for urban use.

Test Drive: evaluate several electric truck models designed for urban applications for a duration ranging from 2 to 7 days or a minimum distance of 100 km driven, referred to as "Truck E-mobility".

The two additional stages facilitate the monitoring of views and attitudes toward the organization, its goods and services, as well as customer satisfaction and perceptions of mark, and are likely to provide challenges. Including analysis, the candidate is gathering feedback on the company's exploitation by conducting test drives over distances not exceeding 100 km, assessing performance and reception in comparison to rivals.

Through the analysis of this data by the marketing and sales departments, along with other project team members, market gaps can be identified, as well as opportunities for enhancement and innovation in the assimilation and implementation of the "Truck E-mobility" concept from regulatory objectives to practical application.

6. Conclusion

Under the circumstances of "Truck E-mobility," cities face several challenges across various sectors, including the economics, energy, transportation, infrastructure, water supply, environmental protection, and essential services.

To achieve the objectives set by the European Union to reduce greenhouse gas emissions by at least 55% by 2030 and attain climate neutrality by 2050, as outlined in the "European Green Deal," Romania must now devise solutions for the assimilation and implementation of "Truck E-mobility," thereby transforming into one of the future's intelligent cities.

The research indicated that exploring and comprehending fundamental components from specialized literature concerning the brain's organizational modules and their differential responses to events is essential for creating a "nudge" to facilitate the assimilation and implementation of the phenomenon of "Truck E-mobility."

The literature on Nudging and the Double Diamond framework has influenced our research in the creation of the Triple Diamond idea, which centers on the end user of the electric vehicle and may be applied to saddle design. Offer results good outcomes essential for the decarbonization of urban freight transport and line with EU targets (years 2030/2050).

Addressing the mentioned problem in a sustainable manner may involve the adoption of electric truck growth, as evidenced by considerable literature study. We provided a comprehensive analysis of the variables affecting the delayed adoption of electric cars and the constraints that we, as service designers, must consider. When Cream resolves our conceptual issues.

By examining and evaluating recommendations from the specialist literature to develop an effective nudge, the author proposes utilizing these insights in conjunction with our service design tools and the methodologies at our disposal. A research question may be worded as follows: "How can service design be utilized to address the needs of individuals based on sustainable lifestyles?" This research topic will lead us in designing actual, relevant solutions through a case study.

We recognized some notable strengths while also emphasizing areas for future enhancement across a variety of literature, including foundational books on the green economy and sustainable development, as well as specific frameworks such as nudging and the Double Diamond model. This scope provides a robust theoretical framework and contextualizes the importance of truck e-mobility within the broader framework of urban sustainability. The author adeptly integrates design strategy with execution by extending the Double Diamond concept into a Triple Diamond framework.

This conceptual development redefines the design process and underscores the practical challenges of executing sustainable transportation solutions. Our research sought to address the urgent need to reduce emissions in urban transportation while adhering to EU policy goals. The focus on truck electrification due to environmental and regulatory requirements is entirely justified. The discussion on nudging presents an intriguing behavioral dimension to the findings. The essay outlines a sophisticated approach to accelerating the slow adoption of electric vehicles by analyzing how small interventions might affect decision-making. While the theoretical framework is robust, our study heavily depends on existing literature without including significant empirical data or case studies.

Future research may benefit from pilot studies or field trials that validate the proposed Triple Diamond structure in real-world settings.

An additional limitation of our current research is that the transition from the established Double Diamond to the proposed Triple Diamond may be articulated with better precision. Detailed explanations of each phase, especially the "Training Driver" and "Test Drive" components, would improve readers' comprehension of the framework's implementation. Despite the conceptual model's novelty, there is inadequate discussion of the practical challenges and limitations (e.g., infrastructure, financial implications, stakeholder participation) that may affect its adoption. A thorough evaluation of these challenges would improve the analysis. Moreover, using quantitative metrics (such as performance statistics, cost-benefit analyses, or impact assessments) might provide a more balanced view between theory and practice. Future initiatives may include pilot projects or case studies employing the Triple Diamond framework in actual urban transportation settings. This would not only validate the model but also highlight any necessary improvements for different circumstances. Furthermore, given the multidisciplinary nature of the issue, a thorough stakeholder analysis might provide insights into how diverse organizations (governments, logistics companies, urban planners) can collaborate to resolve implementation challenges. Investigating the lasting impacts of nudging strategies on behavior and the effectiveness of electric vehicles in urban logistics would yield valuable insights into the sustainability and scalability of this method.

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RETHINKING HR MANAGEMENT FOR THE DIGITAL WORKPLACE

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George CARUTASU [2]

Abstract

Building on recent theoretical advances, including digital human capital theory, organizational adaptability, strategic alignment, and technology adoption, this study examines how digital HR tools improve organizational agility, personalization, and decision making while maintaining a focus on people-centric strategies. A two-tiered evaluation framework was proposed to assess both organizational outcomes and employee perceptions, enabling a balanced analysis of hybrid HRM practices. This framework supports evidence-based decision-making by combining quantitative performance indicators with qualitative feedback mechanisms. Supported by industry examples and benchmarking data, this study highlights the benefits of aligning digital solutions with strategic HR objectives, while acknowledging implementation challenges related to data security, organizational readiness, and employee adaptation. Additionally, this study highlights the role of predictive analytics and continuous learning in optimizing HR interventions. The findings reinforce the need for gradual, evidence-based adoption of HR technologies and provide practical guidance for designing agile, inclusive, and sustainable HRM systems that are ready for the complexities of the digital age.

Keywords: Human resource management, Digital transformation, Strategic alignment, Employee engagement, Performance appraisal, Predictive analytics, Hybrid HR strategies

JEL Classification: M12; M53; D24

1. Introduction

Human resource management is of great importance in organizations, as it deals with the recruitment, selection, training, development, appraisal, evaluation, and reward of employees. The main aim is to provide the human resources needed by the organization to

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achieve its strategic objectives. Human resource management aims to optimize the performance of human resources by creating a favorable and beneficial work climate and developing employees. A well-trained, motivated, and performing team can differentiate between the success and failure of an organization.

A central theme emerging from contemporary research is the concept of digital human capital, which expands the traditional understanding of human capital by including digital skills and adaptability. According to digital human capital theory [1], organizations need to invest not only in attracting talent with digital capabilities but also in nurturing and retaining talent through continuous learning opportunities and a culture of innovation. In the context of a competitive digital labor market, the ability to build and sustain digital competencies internally becomes a strategic advantage.

Adaptability is another pressing challenge for organizations. As external environments evolve rapidly, there is a growing need for employees to continually update their skills and respond effectively to organizational changes. The theory of organizational adaptability [13], posits that employees who cultivate adaptability skills are better equipped to integrate new technologies and workflows. HRM strategies that support continuous learning, flexibility, and psychological safety create conditions for such adaptability.

The strategic alignment between employee needs and corporate goals remains an enduring concern in HRM. The theory of strategic alignment in HRM [7], emphasizes the need to synchronize HR initiatives with the overall goals of the organization. When performance management, career development, and reward systems are aligned with both strategic priorities and individual aspirations, organizations benefit from increased employee engagement and more consistent performance outcomes.

In addition, promoting diversity and inclusion is increasingly being recognized as both a social and a performance driver. Organizational inclusion theory [15], emphasizes the value of creating work environments in which diverse employees feel respected, represented, and empowered. Inclusive human resource management practices such as bias-aware recruitment, promotion equity, and inclusion training contribute to greater innovation, collaboration, and employee well-being.

High staff turnover, another major challenge, is often linked to poor work-life balance. The work-life balance theory [6], argues that employee satisfaction and retention improve when individuals are supported in managing their professional and personal roles. HRM policies that include flexible work schedules, remote work options, and personal development support have been shown to significantly reduce attrition and improve organizational commitment.

Leadership development also plays a critical role in organizational success. The transformational leadership theory [2], asserts that leaders who inspire and empower their teams promote high levels of engagement and innovation. HRM interventions that focus on cultivating transformational leadership competencies through training, coaching, and feedback can have far-reaching effects on team dynamics and organizational outcomes.

Finally, the successful adoption of HR technologies is essential for increasing the efficiency and transparency of processes. The theory of technology adoption in HRM [9], explores how digital platforms can improve various HR processes from recruitment and onboarding to performance appraisal and career planning. However, adoption depends on both the technological readiness of the organization and the perceived usefulness of the tools by employees and managers. Human resource management strategies must therefore address not only system implementation but also change management, communication, and digital literacy. Together, these theories provide a sound conceptual basis for designing HRM systems that are strategic, responsive, and human-centered. In the digital age, efficient human resource management is not only about automation, but also aims to create a flexible, inclusive and technology-supported environment in which employees can evolve and perform to their full potential.

2. The role of human resources management (HRM)

HRM is essential to the smooth functioning of an organization, with the main purpose of ensuring a climate conducive to employee development and performance to achieve organizational objectives. Human resource management focuses on overseeing human capital by balancing organizational goals with employee rights and motivations.

Human Resource Management (HRM) holds a crucial position in influencing an organization's ability to reach its long-term strategic objectives. HRM contributes significantly to improving performance, ensuring employee engagement, and maintaining legal and ethical compliance through a combination of structural, developmental, and relational functions. The following analysis presents the main strategic role of HRM and its practical impact on modern organizations.

Recruitment and selection are core responsibilities of HRM. This function ensures that the organization attracts and identifies candidates whose skills and competencies align with specific job requirements and organizational values. For example, Google has partnered with leading universities to access emerging talent through its internships. By identifying and onboarding high-potential candidates before graduation, the company cultivates a culture of innovation and alignment. This approach is underpinned by the human capital theory, which emphasizes that investing in human resource education and development yields significant long-term organizational benefits. The results of such strategies in Google include sustained capacity for innovation and an agile talent pipeline.

Another key dimension of HRM is employee training and professional development (PD). Ensuring access to continuous learning opportunities improves both individual competencies and overall organizational adaptability. Toyota exemplifies the best practices in this area through its on-the-job training programs, whereby new employees acquire skills directly in production environments alongside experienced mentors. This model mirrors Kolb's experiential learning theory, which argues that learning is most effective when it occurs through a direct experience. Consequently, Toyota was able to cultivate not only technical competence but also a strong sense of team integration and loyalty.

Human resource management (HRM) plays a critical role in maintaining employee motivation. Motivational strategies aim to sustain a positive organizational climate and encourage long-term employee engagement. Spotify provides a compelling example of adopting a flexible working model that allows employees to structure their own schedules, including the option of remote working. These practices are rooted in the self-determination theory, which suggests that autonomy enhances intrinsic motivation. The empirical results at Spotify include higher levels of employee satisfaction and reduced absenteeism and turnover rates, reinforcing the strategic value of flexibility.

Performance management is another strategic HRM function that involves monitoring and evaluating employees' contributions against predefined objectives. General Electric (GE) has implemented a 360-degree feedback system, allowing for multidimensional evaluation from supervisors, peers, subordinates, and, in some cases, customers. This comprehensive approach is consistent with the multiple-source feedback theory, which posits that diverse perspectives produce more balanced and objective performance evaluations. The practical impacts of the GE system include improved diagnostic accuracy, more targeted development plans, and improved performance alignment.

HRM also plays a key role in managing labor relations, including maintaining constructive communication channels and resolving workplace conflicts. In Google, an internal mediation mechanism facilitates early conflict resolution through confidential and non-punitive processes conducted by specialized staff. This system aligns with the conflict management theory, which emphasizes the value of structured dialogue in promoting collaboration and maintaining a positive work environment. The introduction of such mechanisms has contributed to a measurable reduction in workplace tensions and has supported the development of cooperative organizational cultures.

Another fundamental responsibility of HRM is ensuring legal compliance. This involves upholding labor standards, protecting employee rights, and adhering to evolving legislative frameworks. Accenture provides an example of best practice through its dedicated HR and legal units tasked with monitoring regulatory changes and implementing the necessary adjustments. This commitment reflects legal compliance theory, which emphasizes the strategic importance of regulatory adherence in minimizing legal risks and protecting organizational legitimacy. The Accenture's strict compliance protocols have enabled it to avoid litigation and maintain an environment of high trust among its workforce.

Together, these roles highlight the multidimensional nature of HRM as both an operational and strategic function. By aligning recruitment, development, motivation, performance management, conflict resolution, compliance with organizational goals, and theoretical underpinnings, HRM serves as a central driver of sustainable performance and organizational resilience in the digital age.

3. Functions of Human Resource Management

The responsibilities of Human Resource Management involve the set of actions carried out by this department to support and fulfill the organization's established goals. The primary functions of HRM (presented in Table 1).

Human Resource Management (HRM) has a central role in organizations' strategic and operational success. Core HRM functions serve not only administrative goals but also strategic transformation and long-term performance. Below, we explore the key HRM functions by integrating relevant theories, practical examples, and observed results.

One of the fundamental functions of HRM is recruitment and selection, which aim to attract and identify the most suitable candidates for organizational roles. For example, Google's collaboration with top universities to find top talent through internship programs illustrates a strategic recruitment approach. This aligns with human capital theory [1], which posits that investment in skilled human capital generates long-term organizational benefits. As a result, Google promotes an innovation-driven culture anchored in talent and aligned with the company's vision.

Another key area is training and development, which ensure that employees continuously evolve with the needs of the organization. Toyota provides an exemplary model through hands-on training on the production line, allowing employees to learn by doing so. This practice reflects Kolb's (1984) experiential learning theory, which emphasizes learning-by-experience. This results in a skilled, engaged workforce with a deep sense of ownership and connection to the company. The synthetic process is presented in Table 1.

HRM Function	Description	Practical example	Relevant theory	Results
Recruitment and selection	Attracting the right	Google: University partnerships for	Human Capital Theory	Innovative culture, aligned with talents.

	candidates for open positions.	the early search for talent.	(Agarwal et al., 2020)	
Training and development	Professional development improve employee skills.	Toyota: On-the-job training at the workplace model.	Experiential Learning Theory (Kolb, 1984)	Technical growth and team membership.
Performance evaluation	Continuous and objective performance monitoring.	GE: 360-degree evaluation system.	Feedback theory from multiple sources (DeNisi & Williams, 2020)	Holistic assessment and improvement.
Motivation and rewards	Maintaining satisfaction and loyalty.	Spotify: Flexible working model.	The Theory of Self-Determination (Ryan & So, 2000)	Increased satisfaction and retention.
Labor Relations Management	Creating a harmonious working environment.	Google: Internal mediation system.	Conflict Management Theory (Rahim, 2002)	Reduced internal conflicts.
Strategic HR Planning	Long-term planning aligned with strategy.	IBM: Digital transformation and reskilling.	Strategic Human Capital Planning (Lawler & Boudreau, 2021)	Technology-based workforce adaptation.
Legal Compliance	Compliance with labor laws and data regulations.	Google: GDPR compliance and employee training.	Data Protection Theory (Jarrahi, 2020)	Legal risk mitigation and trust.

Table 1 Principal functions of human resource management (HRM)

Performance evaluation plays a key role in the overall HR strategy. GE's use of 360-degree feedback ensures a comprehensive review of each employee by peers, subordinates, and managers. This approach is based on multi-source feedback theory [4], which promotes objectivity and well-rounded evaluations. GE has improved individual performance by providing balanced and actionable feedback tailored to individual developmental needs.

Motivation and reward systems significantly influence employee engagement. Spotify's implementation of a flexible working model supports autonomy and work-life balance, which are the basic tenets of self-determination theory [3]. This policy has led to increased employee satisfaction and a notable decrease in turnover, proving that motivational strategies directly affect employee retention.

Labor relations management is also vital for maintaining a positive organizational climate. Google's internal conflict-mediation system exemplifies proactive relationship management. Based on the conflict management theory [6], this approach emphasizes addressing issues proactively and finding common ground, which helps foster better teamwork and minimizes workplace friction.

Another strategic component of human resource management is human resource planning, which forecasts future talent needs in line with business strategy. IBM exemplifies this through reskilling initiatives as part of its digital transformation [10].

Google's GDPR compliance underscores the importance of data protection and regulatory compliance. This is supported by the data protection theory [9], which emphasizes the role of privacy and trust in HR operations. By training employees and enforcing strict privacy protocols, Google mitigates legal risk and maintains stakeholder trust.

In short, effective HRM functions are based on a balance between theory-driven practices, technology integration, and people-centered strategies. The synergy of these elements improves organizational agility, innovation, and long-term performance.

4. Evolution of HRM methods: from classical approaches to digital solutions

Human resource management (HRM) has undergone a profound transformation, evolving from traditional manual practices to digitally supported strategies designed to improve efficiency, objectivity, and accessibility. This section compares the classic methods historically used in HRM with contemporary digital approaches, highlighting the key differences in recruitment, training, and performance appraisal.

4.1. Classical methods in human resource management

Classical HRM methods are predominantly manual, time consuming, and often limited in scope. These approaches were prevalent before the widespread adoption of digital tools, and relied mainly on face-to-face interactions and paper documentation. In the field of recruitment and selection, classic methods rely on advertising vacancies in newspapers, attending job fairs, and using personal recommendations. The assessment of candidates usually consisted of face-to-face interviews and handwritten assessments conducted without the support of standardized instruments or data analysis. This approach, while offering a degree of personalization, is resource intensive and often prone to subjectivity.

Training and development in the classical context involves face-to-face workshops and mentoring sessions conducted on-site or in external training facilities. While these programs facilitated personal interaction and the acquisition of practical skills, they required substantial time and financial investment, limiting access and scalability. Employees had to be physically present, which further restricted their flexibility and inclusion. Traditional methods of performance appraisal typically involve annual appraisals based on written reports and supervisor observations. Feedback is formal, periodic, and often delayed, which reduces its effectiveness as a development tool. The subjective nature of these evaluations raises challenges regarding consistency and fairness. While these methods laid the foundation for professional HR practice, their limitations in scale, speed, and objectivity created the need for more adaptive and data-driven approaches.

4.2. Digital methods in human resources management

With the advent of digital technologies, HRM has shifted to methods that offer improved efficiency, broader reach, and data-driven decision making. Digital solutions have enabled process automation, real-time performance monitoring, and personalization at this scale.

In recruitment and selection, digital platforms such as LinkedIn and (Applicant Tracking Systems) have transformed the way organizations identify and assess talent. Artificial intelligence is now being used to scan resumes, assess compatibility with job descriptions, and support objective filtering. Video interviewing and automated assessments have further accelerated the hiring process and expanded access to a global pool of candidates, thereby reducing the time to hire and increasing diversity.

Employee training has changed, and e-learning platforms and learning management systems (LMS) allow organizations to deliver customized training programs remotely, enabling flexible and cost-effective upskilling. Courses can be tailored to individual needs, and employee progress can be tracked and analyzed. This digital shift has democratized access to high-quality learning resources and supports continuous development at all employee levels.

To assess performance, modern organizations are increasingly using software solutions that enable continuous feedback, track KPIs in real-time, and generate comprehensive analytical reports. These tools provide structured, measurable, and objective information about employee performance, facilitating timely coaching and aligning individual contributions with organizational goals. The continuous feedback culture fostered by these systems increases transparency and supports continuous improvements.

A 2023 study by Undelucram (citation), involving over 5,000 employers and 200,000 employees, highlights the importance of digital HR tools in bridging the gap between organizational offerings and employee expectations. Findings revealed that:

- 76.22% of employees prioritize bonuses and financial benefits;
- 31.85% prefer educational and development benefits;
- 94.24% of employers currently offer free or subsidized training programs;
- 90.65% offer meal vouchers.

These results highlight the discrepancies between the types of benefits offered and those desired by employees, underscoring the need for the digital personalization of HR strategies. By using digital tools, organizations can tailor benefit packages to individual preferences, thereby increasing satisfaction, engagement, and retention.

In conclusion, while classic HRM methods have established essential frameworks for personnel management, their limitations have been increasingly addressed through digital innovation. The integration of digital technologies not only improves operational efficiency but also enhances employee experience, supports strategic decision-making, and aligns HR practices with contemporary organizational dynamics.

4.3. Comparison of classical and digital methods

The digital transformation of human resource management (HRM) has had a significant impact on organizational processes, particularly in terms of operational expenses and processing time. The implementation of digital technologies has enabled organizations to streamline recruitment, training, performance appraisal, and employee data management processes, resulting in substantial cost savings and increased efficiency.

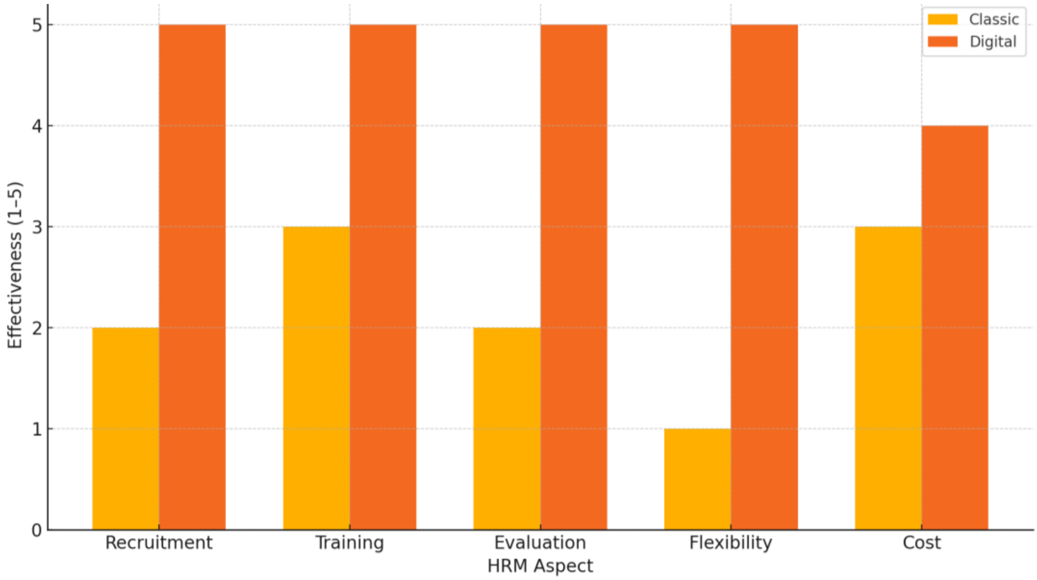

Figure 1 Comparison between classical and digital HRM methods

Aspect	Classic methods	Digital methods
Recruitment	Newspapers, job fairs, recommendations	Online platforms, application management systems (ATS), video interviews
Selection	Traditional interviews, manual tests	Automatic screening, AI for resume analysis
Training	Face-to-face courses, classic courses	E-learning, LMS, interactive online courses
Performance evaluation	Written reports, annual interviews	Continuous feedback, performance appraisal software
Flexibility	Limited	High: access to trainings and assessments anytime

Table 2. Multi-aspect comparison between classic and digital HRM methods

A study conducted by [11], found that 83% of recruiters worldwide believe that recruitment technology saves them significant time during the selection process. According to this study, implementing an applicant tracking system (ATS) can reduce recruitment time by up to 50% compared with traditional manual methods.

In addition, a 2022 report by consulting firm PwC indicates that automated recruitment technologies can reduce the time it takes to go from advertising to hiring a candidate by at least 30%.

5. Methodological framework for evaluating hybrid HRM strategies at organizational and employee level

In the current landscape of accelerated digital transformation and increasingly dynamic labor markets, human resource management (HRM) systems are challenged to evolve beyond traditional frameworks. Contemporary organizations no longer operate on static administrative processes alone but rather require a strategic, agile, and people-centric approach that integrates digital technologies with conventional HR practices. In this context, hybrid HRM models, which combine traditional methods with digital applications, have emerged as an essential response to the increasing complexity and volatility of organizational environments.

A hybrid HRM approach utilizes digital technologies such as applicant tracking systems (ATS), e-learning platforms, performance dashboards, and predictive analytics tools while retaining the relational and contextual richness of face-to-face interviews, coaching sessions, team meetings, and interpersonal communication. This combination improves recruitment efficiency, enables personalized learning trajectories, supports real-time feedback in performance appraisal, and ensures a balanced relationship between employees and the organization. However, the success of such an integration depends to a large extent on the organization's ability to assess both the operational effectiveness and human impact of these practices.

To address this need, we propose a methodological framework based on a two-level evaluation matrix that simultaneously considers organizational performance indicators and employee-level perceptions. This two-dimensional model enables a comprehensive diagnosis of HRM effectiveness and human centeredness by aligning strategic objectives with employee experiences.

For example, in recruiting, digital platforms are key to reducing the time to hire and expand access to a more diverse talent pool, but these operational gains must be assessed in tandem with candidate perceptions of fairness and subsequent alignment between selected employees and organizational culture. Similarly, blended training programs that combine online modules with in-person workshops can increase flexibility and scalability, but their real impact is reflected in employee satisfaction, skill acquisition, and the applicability of learning to everyday work contexts.

Performance management further exemplifies this dualism. While digital performance dashboards provide valuable data on goal tracking and productivity, they must be complemented by human-centered feedback processes to ensure clarity, transparency, and motivational support. Digital communication platforms, such as Slack or Microsoft Teams, facilitate real-time interaction and documentation, but without sustained interpersonal dialog, such as one-on-one meetings or structured team discussions, the risk of alienation or miscommunication increases (Table 3).

HRM Strategy	Organizational KPIs	Employee KPIs	Measurement Method (Org)	Measurement method (employee)	Result indicator and thresholds
Recruitment	Time to hire, cost-effectiveness, diversity of talent	Perceived fairness, fit, and commitment after employment	ATS metrics, recruitment cost reports	Onboarding surveys, feedback for new employees	Employment time < 30 days, diversity ratio > 30%
Training and development	Return on investment in learning, completion rates, improvement indices	Satisfaction, applicability, perception of growth	Training ROI Calculator, LMS Analysis	Post-training assessment, competence self-assessment	ROI > 150%, completion rate > 80%
Performance Management	Goal alignment indicators, feedback cycle efficiency	Transparency, clarity, motivation and assumption of objectives	Dashboard reports, KPI completion rates	360° feedback, pulse surveys	Achievement > 85%, positive feedback > 75%
Labour relations	Speed of resolution, policy	Trust in HR, quality of communicati	HR system logs,	Engagement survey, HR	Problem solving < 3 days,

	compliance, digital adoption	on, emotional climate	compliance audits	satisfaction rating	engageme nt score > 70%
Digital integration	Adoption rate, digital productivity, problem solving	Digital trust, autonomy, learning curve	Adoption dashboards, usage logs	Digital skills self-checks, user experience surveys	Adoption rate > 90%, satisfactio n with tools > 80%
Process automatio n	Reduction of administratio n burdens, time efficiency, error rate	Accessibility, customizatio n, technical stress level	Process logs, HR operations reports	Employee feedback forms, usage ratings	Reduction of working time > 30%, error rate < 2%
Predictive analytics	Forecast accuracy, improved retention, talent utilization	Perception of fairness, trust in data, alignment with aspirations	Predictive accuracy reports, retention statistics	Perception, Trust Index and Fairness Surveys	Prediction accuracy > 85%, wear < 10%

Table 3 Detailed HRM Assessment Matrix

To assess the effectiveness of these strategies in a structured and multidimensional manner, we propose an HRM evaluation matrix that captures both the macro- and micro-level dimensions. On the organizational side, the matrix tracks metrics, such as recruitment cycle time, training ROI, alignment between individual and corporate goals, digital adoption rates, administrative workload reduction, and predictive accuracy. In terms of employees, the model captures perceptions of fairness, engagement, satisfaction, digital competency, learning experience, and overall alignment with personal and professional goals.

This framework provides a strategic tool for HR professionals and decision makers to assess the real-world impact of hybrid HR management strategies. It promotes a balanced perspective, emphasizing that technological progress should not come at the expense of human connections, nor should traditional methods resist innovation for the sake of familiarity. Instead, an adaptive HRM system should continually assess and adjust its components based on data-driven insights and human feedback to ensure resilience, relevance, and sustainability.

In addition, the adoption of digital tools should precede and be supported by targeted training and capacity-building efforts to address potential resistance and digital skills gaps. Organizations, such as Microsoft, have demonstrated the effectiveness of a leadership-first model, in which managers are the first to be trained in the use of new technologies, ensuring smoother transitions and internal advocacy. In parallel, the automation of repetitive HR tasks, such as payroll, scheduling, and documentation, can significantly improve operational efficiency, but only when counterbalanced by the continued presence of HR professionals who provide developmental guidance and psychological support.

Advanced HR analytics, such as those deployed by IBM, allows the prediction of employee disengagement or turnover risk, enabling timely and personalized interventions. However, the use of such tools needs to be governed by ethical principles and transparent communication to foster trust among employees and to avoid perceptions of surveillance or misuse of data.

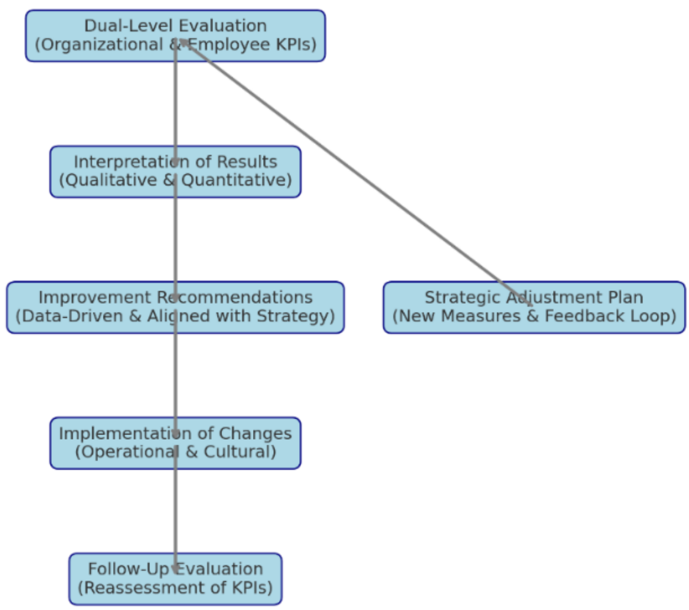

Figure 2 Human resource management assessment framework at organization and employee level

Figure 3 Example of Evaluation of Two-Matrix Evaluation

6. Conclusions

A comparative analysis between traditional and digitally enhanced human resource management (HRM) methods reveals fundamental distinctions in the way organizations approach employee-related processes and operational efficiency. While both models have demonstrated value in different organizational contexts, this study highlights the increasing relevance of integrating digital technologies into HRM frameworks to meet growing demands for scale, speed, personalization, and data security.

Traditional HRM methods tend to be slower, more rigid, and less scalable, although they are based on interpersonal interactions and established routines. Their reliance on manual operations makes them less suitable for large- or medium-sized organizations that require real-time feedback. However, they offer a sense of familiarity and trust, especially in smaller institutions or cultures, where face-to-face communication remains the norm.

By contrast, digital HRM methods offer significant advantages in terms of automation, speed, and adaptability. Tools such as artificial-intelligence-based recruitment software, e-learning platforms, performance analytics, and cloud-based HR systems enable organizations to streamline processes while delivering more personalized and accessible employee experiences. This increased flexibility contributes to greater satisfaction and engagement, particularly in hybrid or remote working environments.

However, digital transformation in HRM is challenging. The initial implementation requires considerable investment in infrastructure, training, and change management. Security and data protection, especially under frameworks such as GDPR, must be proactively addressed. Despite these challenges, properly managed digital systems can provide greater control over sensitive data and improve decision-making accuracy.

A key insight of this study is the complementary nature of these two approaches. Rather than viewing traditional and digital HRM as mutually exclusive, organizations should seek to combine their strengths. For example, while digital tools can optimize recruitment and training, performance reviews can benefit from face-to-face interactions to maintain trust and ensure nuanced communication.

This study also highlights the growing importance of predictive analytics and machine learning in HRM. Organizations, such as Accenture and Microsoft, have already begun to implement models capable of identifying employees at risk of disengagement or having difficulty adopting new technologies. This information enables targeted interventions such as customized training or mentoring programs, thereby promoting retention and adaptability. Predictive models trained on historical data and employee feedback can predict the likelihood of attrition or development gaps, enabling a more strategic and proactive approach to HR.

From a methodological perspective, the proposed two-level assessment framework, focusing simultaneously on organizational performance indicators and employee perceptions, represents a significant contribution to the field. This two-dimensional model enables a nuanced assessment of HRM initiatives, supporting the alignment of strategic outcomes with people-centered values.

Despite its practical relevance, this study has some limitations. First, the assessment is based on secondary data and theoretical models, which may not capture the full complexity of HR dynamics across industries and cultures. Second, the predictive potential of digital tools is limited by the quality and granularity of available data. Third, although examples from companies such as Google, IBM, and Spotify provide valuable benchmarks, generalization to smaller organizations may require additional contextual adaptation.

Future research should prioritize the empirical validation of the proposed framework through longitudinal case studies and sector-specific analyses. In addition, it is important to carefully consider the ethical concerns regarding the use of AI in HRM, particularly regarding transparency, openness, and employee autonomy.

Based on the findings and framework presented, several practical recommendations have emerged. First, organizations are encouraged to pursue the strategic integration of traditional and digital HR methods, tailoring their application to different stages of the employee lifecycle. Second, it is advisable to gradually implement digital tools, allowing ample time for organizational adaptation. Finally, sustained investments in employee training and enhanced digital literacy are vital for fully leveraging HR technology investments and mitigating resistance to change.

In short, hybridizing HRM practices - if guided by robust assessment, ethical technology implementation, and sustained attention to employee experience - can enable organizations to navigate the complexities of the digital age while reinforcing human value at the core of organizational development.

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MEASURING THE PERFORMANCE OF A SMART HOME AUTOMATION SOFTWARE USING DESIGN PATTERNS

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Abstract

In the rapidly evolving landscape of smart home technologies, the efficiency of software systems is paramount in ensuring seamless automation experiences for users. This scientific article proposes an in-depth examination of the performance metrics of a Smart Home Automation System (SHAS) software constructed through the integration of diverse design patterns. The study aims to contribute valuable insights into the impact of design patterns on the efficiency, reliability, and scalability of the SHAS software.

The research employs a rigorous methodology that encompasses the identification, implementation, and analysis of various design patterns within the software architecture. Key performance indicators such as response time, resource utilization, and system scalability will be systematically evaluated to assess the overall effectiveness of the chosen design patterns. Comparative analyses will be conducted to highlight the advantages and potential challenges associated with each pattern.

Through this investigation, we anticipate uncovering optimal design patterns that enhance the SHAS software's performance, ultimately contributing to the advancement of smart home technologies. The findings of this study hold significant implications for developers, researchers, and industries engaged in the design and implementation of intelligent home automation systems.

Keywords: software development, design patterns, Internet of Things

JEL Classification: C61

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1. Introduction

In the contemporary era of smart living, Smart Home Automation Systems (SHAS) have emerged as integral components, reshaping the way we interact with and manage our living spaces. These systems leverage cutting-edge technologies to provide users with unprecedented control over various aspects of their homes, from lighting and climate to security and entertainment. At the heart of these systems lies the software infrastructure, a critical determinant of the overall performance and user experience.

As the demand for smart home solutions burgeons, the imperative to develop efficient and scalable SHAS software becomes increasingly paramount. The efficacy of such software is intricately tied to the underlying architectural decisions, with design patterns playing a pivotal role in shaping the software's structure, modularity, and extensibility. This scientific article embarks on a comprehensive exploration into the performance metrics of a Smart Home Automation System software, specifically designed and implemented with a variety of design patterns.

The motivation for this study stems from the recognition that while design patterns offer proven solutions to recurring architectural challenges, their impact on the performance of SHAS software remains a relatively underexplored domain. By dissecting and evaluating the performance implications of various design patterns, this research aims to provide a nuanced understanding of their role in enhancing or potentially impeding the overall functionality of smart home automation.

Through meticulous analysis and empirical measurements, we seek to shed light on the intricate relationship between design patterns and the performance attributes crucial to SHAS software, including responsiveness, resource utilization, and scalability. This investigation is poised to unravel insights that not only contribute to the academic discourse on software architecture but also offer practical guidance to developers and industry stakeholders engaged in the evolution of intelligent home automation systems.

In essence, this study endeavors to bridge the gap between theoretical design paradigms and real-world performance outcomes, fostering a deeper comprehension of the intricate interplay between design patterns and the efficacy of Smart Home Automation System software.

The landscape of smart home technologies is characterized by an ever-expanding array of devices, protocols, and user preferences. Consequently, the need for SHAS software to seamlessly adapt to this complexity underscores the significance of selecting appropriate design patterns. However, while design patterns are recognized for their ability to enhance software maintainability and flexibility, their influence on performance remains a dynamic field of investigation [1].

This study acknowledges the dynamic nature of smart home environments and the necessity for SHAS software to not only accommodate diverse functionalities but also to execute these operations with optimal efficiency. As the smart home ecosystem evolves, the role of SHAS software becomes increasingly intricate, demanding a meticulous evaluation of the impact of design patterns on its performance characteristics.

Through a structured examination of the chosen design patterns, our research seeks to address fundamental questions surrounding their efficacy in the context of SHAS software. Which design patterns prove most effective in optimizing response times? How do different patterns impact resource utilization, and to what extent do they contribute to or alleviate scalability challenges inherent in smart home environments? These inquiries form the crux of our investigation and aim to elucidate the nuanced relationships between design decisions and the tangible performance outcomes in SHAS software.

In a rapidly advancing technological landscape, the findings of this research are poised to inform not only the development of smart home automation systems but also the broader discourse on the symbiotic relationship between software architecture and performance optimization. By navigating the intricate terrain where design patterns intersect with the demands of modern smart living, this study aspires to furnish valuable insights for architects, developers, and researchers committed to advancing the frontiers of smart home technologies.

The concept of smart home automation systems has evolved over several decades, blending technological advancements with the vision of creating more convenient and efficient living spaces. The history of smart home automation can be traced back to early attempts at automating household tasks and integrating technology into homes [2].

The roots of smart home automation can be found in the 1950s and 1960s, marked by the introduction of basic home automation concepts. At this time, futuristic visions of homes equipped with automated appliances and systems began to emerge. The idea was often portrayed in science fiction literature and films, influencing the public's perception of what the future home might look like.

The 1980s and 1990s witnessed the development of various home automation protocols and systems. X10, one of the earliest home automation protocols, allowed devices to communicate over power lines. This technology laid the foundation for controlling lights, appliances, and other devices remotely.

Despite the innovations, adoption remained limited due to interoperability issues and a lack of standardized communication protocols. Home automation systems during this period were often expensive, complex, and accessible only to enthusiasts or those with substantial financial resources.

The 2000s marked a significant turning point for smart home automation, driven by advancements in connectivity and the proliferation of the internet. The rise of Wi-Fi technology and the development of the Internet of Things (IoT) paved the way for a more interconnected and accessible smart home ecosystem.

Smart home devices and systems began to gain popularity, offering enhanced control and monitoring capabilities. Companies introduced products like smart thermostats, security cameras, and automated lighting systems. The advent of smartphones played a pivotal role, providing users with the ability to control their homes remotely through dedicated apps.

The 2010s witnessed a surge in the adoption of smart home technologies, moving beyond individual devices to integrated ecosystems. Major tech companies introduced comprehensive platforms, such as Apple's HomeKit, Google's Nest, and Amazon's Alexa, aiming to streamline the user experience and enhance interoperability.

Voice-activated assistants became a common feature in smart homes, allowing users to control devices through natural language commands. Integration with third-party services and devices further expanded the capabilities of smart home automation systems.

In the present day, smart home automation has become increasingly ubiquitous, with a wide range of devices and systems available to consumers. The integration of artificial intelligence (AI) and machine learning has enhanced the intelligence and adaptability of smart home systems, enabling them to learn user preferences and anticipate needs.

The future of smart home automation holds the promise of even greater connectivity, interoperability, and energy efficiency. As technology continues to advance, smart homes are likely to evolve into highly adaptive environments that seamlessly integrate with other aspects of daily life, contributing to a more sustainable and comfortable living experience and maybe even integrating robots in the process.

Robots in homes and their integration with smart home automation systems hold great promise for transforming our living spaces. As technology continues to advance, robots are poised to play increasingly integral roles in enhancing convenience, security, and overall home management. Here are some key aspects of the future trajectory for robots in homes and their integration with smart home automation systems: personal assistance and companionship, smart home integration, autonomous cleaning and maintenance, security and surveillance, healthcare assistance, customized environmental control, education and entertainment, and energy efficiency.

While the future of robots in homes and their integration with smart home automation systems presents exciting possibilities, ethical considerations, and privacy concerns will also need to be addressed. Striking a balance between innovation and responsible deployment will be crucial for ensuring the widespread acceptance and success of these technologies in our homes.

2. Related Work

Smart home automation systems rely on a variety of hardware platforms to connect and control various devices. These platforms can be broadly categorized into dedicated smart home hubs, smartphone/tablet apps, and web-based interfaces.

Devoted smart home hubs serve as the central control unit, managing communication with connected devices. They often feature voice assistants, local processing capabilities, and customizable automation rules. Popular examples include Amazon Echo, Google Home, and Samsung SmartThings.

Smartphone and tablet apps provide a convenient way to manage smart home systems remotely. They offer a user-friendly interface for controlling devices, creating automation rules, and accessing real-time sensor data. Examples include the official apps for various smart home hubs and standalone apps for specific devices or functions.

Web-based interfaces offer a platform-independent way to manage smart home systems. They provide access to all the features and capabilities of the system from any web browser. This can be particularly useful for managing devices from a computer or when using multiple devices [3].

The related work in the field of smart home automation systems with a focus on employing design patterns for performance improvement encompasses a range of seminal books, articles, and research papers.

The foundational work of [4] establishes a solid understanding of design patterns that can be applied to enhance the modularity and maintainability of smart home automation software. Additionally, "Building Scalable and High-Performance Java Web Applications Using J2EE Technology" by Greg Barish contributes valuable insights into scalable software design, offering principles applicable to the performance optimization of smart home systems.

Extensions of these principles to enterprise-level applications provide a framework for designing scalable and robust systems that align with the complex requirements often found in smart home environments [5]. Furthermore, [6] addresses the broader context of IoT, providing a foundation for understanding the architectural considerations and protocols relevant to smart home automation.

While technical, [7] provides practical guidance on applying UML and design patterns in software development. The insights are particularly valuable for iterative development processes, aligning with the dynamic and evolving nature of smart home automation systems.

In parallel, works such as [8] offer a user-centric perspective, emphasizing the importance of understanding end-user needs and experiences in the design and implementation of smart home automation software. This user-focused approach complements the technical literature, providing a well-rounded understanding of the challenges and opportunities in the domain.

To stay current with the latest advancements, researchers often turn to the IEEE Xplore Digital Library and the ACM Digital Library, which host a plethora of research papers. Exploring these databases with keywords such as "smart home," "IoT," "design patterns," and "performance" yields a wealth of recent research, offering novel approaches and techniques for optimizing smart home automation software. The collective body of related work provides a comprehensive foundation for the design and evaluation of smart home automation systems leveraging design patterns for enhanced performance.

Continuing in the realm of related work, recent advancements in smart home automation systems and design patterns have been shaped by a dynamic landscape of research and development. The exploration of cutting-edge concepts often involves perusing the latest publications available in scholarly databases and forums.

One notable source of inspiration is the IEEE Xplore Digital Library, where researchers delve into a multitude of papers to stay abreast of evolving methodologies. The integration of design patterns into the development of smart home automation software is often informed by the findings of studies such as [9]. This survey not only provides a historical perspective but also sheds light on the diverse applications of IoT, a critical context for understanding the interconnected nature of smart home ecosystems.

Furthermore, recent research articles [10] explore the integration of edge computing to improve the real-time processing capabilities of smart home automation software. This represents a novel extension to traditional design patterns, considering the distributed nature of computation in modern smart home environments.

In the pursuit of optimizing energy efficiency, [11] introduces green computing principles to the realm of smart homes. This work is particularly relevant for those seeking to design sustainable and eco-friendly smart home automation solutions.

Additionally, researchers interested in the security aspects of smart home automation software can refer to [12]. This survey not only outlines the existing security challenges but also provides insights into incorporating secure design patterns to fortify smart home systems against potential threats.

Collaborative efforts, as demonstrated in [13], offer insights into cooperative security models that leverage design patterns to enhance the resilience of smart home automation systems. The cooperative approach acknowledges the interconnected nature of devices within a smart home and proposes strategies for collaborative threat detection and mitigation.

In conclusion, the related work in the domain of smart home automation software, especially concerning the integration of design patterns for performance enhancement, encompasses a rich and evolving body of literature. The combination of foundational principles from classic texts, insights from recent publications, and emerging paradigms in areas such as edge computing, green computing, and cooperative security contribute to a holistic understanding of the challenges and opportunities in this dynamic field.

3. Proposed Architecture

The proliferation of smart home technologies has ushered in an era where homes are increasingly equipped with a myriad of interconnected devices, ranging from thermostats and lighting systems to security cameras and entertainment units. As the complexity and diversity of smart home environments continue to expand, the demand for intelligent automation systems capable of orchestrating these devices seamlessly has become paramount. To address the challenges inherent in managing such intricate ecosystems, this scientific article introduces a sophisticated architectural framework that leverages well-established design patterns.

Smart home automation systems play a pivotal role in enhancing user comfort, security, and energy efficiency. However, as the number and diversity of devices within these systems grow, so does the complexity of managing and coordinating their interactions. This complexity necessitates innovative approaches to software architecture that can accommodate the dynamic nature of smart home environments while providing a robust foundation for scalability, adaptability, and ease of maintenance.

In response to these challenges, our proposed architectural framework embraces a carefully curated set of design patterns. These design patterns serve as building blocks, each addressing specific concerns critical to the success of a smart home automation system. By integrating the Singleton Pattern, Observer Pattern, Command Pattern, Factory Pattern, and Decorator Pattern, our framework aims to provide a comprehensive solution that addresses fundamental aspects such as configuration management, real-time device monitoring, customizable automation tasks, dynamic device creation, and extensible feature augmentation.

The use of design patterns in software architecture is a well-established practice, and their relevance becomes particularly pronounced in the context of smart home automation. As homes evolve into intelligent ecosystems, the need for a centralized configuration manager (utilizing the Singleton Pattern) becomes evident to ensure consistency across diverse devices. Real-time updates on device states, facilitated by the Observer Pattern, are essential for users to stay informed and maintain control over their smart home environment.

Furthermore, the Command Pattern empowers users with the ability to create and execute commands, providing a user-friendly interface for customization. The Factory Pattern addresses the challenge of accommodating various device types by introducing modularity and adaptability to the system. Finally, the Decorator Pattern facilitates the dynamic augmentation of device functionalities, enabling the smart home automation system to evolve alongside technological advancements and changing user needs.

1. Singleton Pattern: Centralized Configuration Manager

The Singleton Pattern [4] plays a pivotal role in ensuring the consistency and coherence of configuration settings throughout the smart home automation system. By implementing a centralized configuration manager as a singleton, we guarantee that there exists only one instance responsible for managing configuration parameters. This design choice facilitates a unified point of access for configuration settings across the entire application. Whether it's regulating the behavior of individual devices or establishing system-wide preferences, the Singleton Pattern ensures a single, authoritative source for configuration data. This approach simplifies maintenance, reduces the likelihood of conflicting configurations, and enhances the overall reliability of the smart home automation system.

2. Observer Pattern: Real-Time Device Monitoring

In the context of a smart home automation system, real-time updates on the state of devices are crucial for providing users with accurate information and facilitating prompt decision-making. The Observer Pattern [4] is employed to establish a dynamic communication mechanism between smart devices and the user interface. Each smart device serves as a subject, and the user interface acts as the observer. When the state of a device changes, it notifies the observer (user interface) instantly, allowing for real-time updates on the user interface. This ensures that users are well-informed about the status of their smart home devices and can take immediate actions based on the current conditions.

3. Command Pattern: Customizable Automation Tasks

The Command Pattern [4] empowers users with a flexible and intuitive means of customizing automation tasks within the smart home environment. Users can create commands encapsulating specific operations and execute them as needed. This pattern facilitates the decoupling of the sender (user interface or automation controller) from the receiver (smart device), enabling a wide range of customization possibilities. Whether it's scheduling routines, automating sequences of actions, or responding to specific events, the Command Pattern provides a versatile framework for users to tailor the smart home automation system to their preferences.

4. Factory Pattern: Dynamic Device Creation

The Factory Pattern [4] is instrumental in addressing the diverse landscape of smart devices within a modern home. By creating various smart device factories, we establish a modular approach and each factory is responsible for creating a specific type of device, ensuring that the system can seamlessly incorporate new device types without modifying existing code.

This not only simplifies the addition of new devices but also enhances the system's adaptability to emerging technologies. The Factory Pattern contributes to the scalability and maintainability of the smart home automation system by promoting a consistent and structured approach to device creation.

Each factory is responsible for creating a specific type of device, ensuring that the system can seamlessly incorporate new device types without modifying existing code. This not only simplifies the addition of new devices but also enhances the system's adaptability to emerging technologies. The Factory Pattern contributes to the scalability and maintainability of the smart home automation system by promoting a consistent and structured approach to device creation.

4. Deployment Tools

The burgeoning field of smart home automation demands meticulous consideration of deployment tools to orchestrate the seamless integration and optimal functionality of diverse hardware and software components. This part of the research endeavors to scrutinize and assess the preeminent deployment tools prevalent in the smart home automation domain, examining key attributes such as compatibility, user-friendliness, community support, and customization capabilities. As smart homes become increasingly sophisticated, the choice of an appropriate deployment tool plays a pivotal role in ensuring the reliability and efficiency of these systems.

Among the many deployment tools, Home Assistant emerges as a prominent open-source platform renowned for its versatility and expansive device compatibility. With deployment options ranging from the resource-efficient Raspberry Pi to the scalable Docker containers, Home Assistant caters to users with diverse hardware preferences. Its commitment to local control and privacy underscores its appeal, offering users a robust foundation for orchestrating a comprehensive smart home ecosystem.

In the realm of Java-based deployment tools, Open Home Automation Bus (OpenHAB) distinguishes itself by prioritizing protocol compatibility and cross-platform versatility. OpenHAB's capacity to seamlessly operate across Windows, Linux, and macOS positions it as an attractive choice for users seeking a comprehensive solution that accommodates a spectrum of smart home technologies. Its robust framework and active community contribute to its standing as a formidable deployment option.

Built on Node.js, ioBroker offers an open-source automation platform designed to harmonize with diverse hardware environments. Its support for various devices, coupled with cross-platform compatibility, provides users with a flexible and adaptable deployment solution. IoBroker's modular architecture empowers users to integrate and control an array of smart home devices, establishing it as a dynamic player in the smart home automation landscape.

Recognized for its lightweight design and ease of use, Domoticz positions itself as a pragmatic choice for users entering the realm of home automation. Supporting an array of devices and protocols, Domoticz offers deployment options across platforms like Raspberry Pi, Windows, and Linux. Its accessibility and broad compatibility contribute to its appeal as a straightforward yet powerful deployment tool.

For those inclined towards visual programming, Node-RED [14] stands out as a compelling tool tailored for IoT and home automation projects. Its node-based interface simplifies the creation of automation flows, allowing users to design intricate smart home scenarios. Node-RED's deployment across various platforms enhances its accessibility and integration capabilities.

In the paradigm of containerization, Docker [15] emerges as a cornerstone for efficient and portable smart home automation deployment. Docker containers provide a lightweight and standardized environment, facilitating the deployment of software across diverse platforms. Platforms such as Home Assistant and OpenHAB offer official Docker images, underscoring Docker's role in streamlining the deployment process.

This comparative analysis of deployment tools within the smart home automation domain illuminates the diverse landscape of options available to users and developers. Each tool presents a unique set of features and advantages, catering to different preferences and requirements. By considering factors such as device compatibility, deployment flexibility, and community support, stakeholders can make informed decisions when selecting the most suitable deployment tool for their smart home automation endeavors. As the field continues to evolve, ongoing research will be paramount in assessing emerging tools and technologies, ensuring that smart home deployments remain at the forefront of innovation and efficiency.

5. Elements of Comparison

As the landscape of software development continues to evolve, the importance of maintaining code quality remains paramount. Object-oriented programming, a widely adopted paradigm, emphasizes modular design and code reusability. In this context, metrics play a crucial role in assessing various aspects of code quality, as we described in the analysis from Table 1.

Table 1

Free Memory (in KB)

With Design Patterns	Without Design Patterns
248,952	143,154

In the pursuit of advancing our understanding of these metrics and their implications on code quality, this paper presents the outcomes of rigorous experiments conducted on SHAS software. The experiments aim to validate the efficiency of these metrics in assessing the quality of object-oriented code. For example, we obtained a better memory performance when using the design patterns as we see in Table 2. Moreover, the study investigates the relationships between these metrics and their combined impact on the overall maintainability and performance of a codebase.

Table 2

Static Code Analysis (Average Values)

Classes	CBO	LOC	LCOM*	TCC
25	3	62	05875	0.7825

CBO (Coupling between objects): Counts the number of dependencies a class has. The tools check for any type used in the entire class (field declaration, method return types, variable declarations, etc). It ignores dependencies to Java itself (e.g. java.lang.String).

LOC (Lines of code): It counts the lines of code, ignoring empty lines and comments. The number of lines here might be a bit different from the original file, as we use Eclipse JDT (Java Development Tools) internal representation of the source code to calculate it.

LCOM* (Lack of Cohesion of Methods): This metric is a modified version of the current version of LCOM implemented in CK Tool. LCOM* is a normalized metric that computes the lack of cohesion of class within a range of 0 to 1. Then, the closer to 1 the value of LCOM* in a class, the less the cohesion degree of this respective class. The closer the value of LCOM* in a class, the greater the cohesion of this respective class. This implementation follows the third version of LCOM* defined in [16].

TCC (Tight Class Cohesion): Measures the cohesion of a class with a value range from 0 to 1. TCC measures the cohesion of a class via direct connections between visible methods, two methods or their invocation trees access the same class variable.

6. Conclusions and Future Work

In conclusion, this research paper has undertaken a comprehensive investigation into the performance of a Smart Home Automation System Software implemented in Java and designed with the incorporation of various object-oriented design patterns. The findings and analyses presented herein shed light on key aspects that contribute to the effectiveness and efficiency of the software in real-world smart home environments.

Through rigorous performance testing and measurement, we have evaluated critical aspects such as response time, throughput, scalability, resource utilization, and concurrency. These metrics provide a holistic view of how well the system responds to user interactions and handles varying workloads.

The integration of design patterns, such as Singleton, Observer, and Command, has played a pivotal role in enhancing the software's architecture. The application of these patterns has improved modularity, flexibility, and maintainability, contributing to the overall success of the system.

The adherence to object-oriented principles in Java, including encapsulation, inheritance, and polymorphism, has been instrumental in achieving a well-structured and extensible codebase. This has facilitated easier maintenance and future enhancements to the Smart Home Automation System Software.

The research has highlighted the importance of design patterns in managing device compatibility, ensuring that the software seamlessly integrates with diverse smart devices. This interoperability is essential for creating a cohesive and user-friendly smart home ecosystem.

Building on the insights gained from this research, several avenues for future work and improvement have been identified.

Investigate the incorporation of additional design patterns to further optimize specific aspects of the software, addressing any identified performance bottlenecks or enhancing specific functionalities.

Explore the integration of machine learning algorithms to predict user behavior and automate device control based on historical usage patterns. This could contribute to a more intelligent and adaptive smart home system.

Investigate the potential benefits of a distributed architecture, utilizing design patterns suitable for distributed systems. This could enhance scalability and resilience in large-scale smart home deployments.

Implement design patterns to facilitate dynamic device discovery and configuration, allowing the system to seamlessly adapt to changes in the smart home environment without manual intervention.

Research and apply design patterns that promote energy efficiency, considering the growing emphasis on sustainable and eco-friendly smart home solutions.

Conduct real-world deployment studies to validate the software's performance in diverse smart home environments. This includes considering factors such as network conditions, user behaviors, and the presence of various smart devices.

Foster community involvement and collaboration by open-sourcing certain components or providing APIs that encourage third-party developers to contribute to the software's evolution.

Implement continuous performance monitoring mechanisms to detect and address any performance degradation over time. This ensures that the software remains optimized and responsive as it evolves.

By addressing these areas in future work, the Smart Home Automation System Software can evolve into a more sophisticated and adaptive solution, continually meeting the ever-changing demands of the smart home ecosystem. This research lays the foundation for ongoing advancements in the field, contributing to the broader discourse on the intersection of Java, design patterns, and performance in smart home automation systems.

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ONLINE VERSUS IN-PERSON PRODUCTIVITY IN DIFFERENT TEAMWORK CONTEXTS

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Abstract

This article examines the impact of online and physical environments on productivity within different team contexts. We analyze many aspects, such as team meetings, communication methods, and team management, evaluating their influence on collaboration efficiency.

By identifying key elements, we offer a perspective on the factors that shape productivity in both digital and traditional environments, contributing to the understanding of the complexity of current-era collaboration.

Keywords: team productivity, online collaboration, virtual teams, communication methods, team management, meetings.

JEL Classification: C61

1. Introduction

In today's age, teamwork is widely accepted as a smart way to organize the operation of an organization and today's technology allows such managerial and organizational actions to

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be done both physically and digitally. The technological advances of the 90s permitted the emergence and rise of virtual teams.

At the start of the 21st century, virtual teams have been defined as teams that coordinate their activities using primarily technological means. Establishing the foundation of understanding, integration, and trust, putting together the people and the context, involving the leadership for the knowledge management and information sharing, implementing the information technology, and acting regarding processes and development – these were steps that an efficient virtual team needed to cover [1]. Today, these technological means are represented by instant messaging, video calls, online meetings and conferences, etc.

At their emergence, virtual teams had the purpose of destroying the geographical barriers present in the conception of teams to be able to select the best individuals from a now much wider pool of candidates. Virtual teams expand the demographics of the modern workforce and allow the selection of the best candidates and the improvement of personal flexibility [2]. Today virtual teams have risen in popularity due to the limitations imposed by a global pandemic. Therefore, the concept of remote work has settled into the life of the modern employee. The adoption of teleworking in Europe increased after 2005. Results indicate that telework has become routine for over 20 percent of all gainfully employed. Expansion is explained by a working life transition: besides enabling information and communication technologies, factors associated with managers' trust and control; the character of jobs, work tasks, and contracts in knowledge-based industries; and individual and household work-life balance issues. Telework is connected to permanent employment in the advanced services sector, slowly diffusing into other sectors. It is increasingly performed in the home and is becoming more frequent. Individuals with families and children are overrepresented and among the fastest-growing groups. Broadband access at home is an enabler. Larger urban regions strengthen their position in favor of teleworking [3].

Although the concept of virtual teams, described and defined two decades ago, is still relevant, a lot of aspects regarding productivity and communication studied back then are not applicable anymore. Technology that benefits online collaboration has seen rapid advancement in the last years and its efficiency proved to be good enough that some modern online collaboration tools have settled into the physical environment as well. A good example is instant messaging at the workplace, which has long ago replaced, in most cases, moving to the colleague's cubicle or in a meeting room.

This paper will concentrate on how team productivity and efficiency are affected by the choice of conducting one or more collaboration aspects either digitally or physically.

2. Efficiency of meetings

In some professional contexts, successful teamwork is based on organizing team meetings to integrate the individual work of the team members and to make sure that everybody is on the same page moving forward.

Team productivity, in this situation, is represented in two forms: the individual productivity and performance of team members in the period between the meetings and the efficiency of communication between the members at the time of the meeting.

2.1. A thorough research

Teleworking has become even more popular after the spread of COVID-19, supported by rapid technological development. Despite the great convenience, questions about its productivity arise. Yi Li et al. [4] analyzed the productivity of stock analysts in the context of online versus offline work environments. The empirical analysis shows that analysts' forecasts are accurate after offline visits. Additionally, teleworking impacts forecast accuracy based on analyst experience, resources, firm visibility, and transparency. Measured in the quality and quantity of forecasts, analysts' productivity was higher after participating in traditional meetings rather than in online ones. That is believed to be closely related to the amount of information gathered from meetings.

Offline meetings consist of face-to-face communication between analysts and that allows them to engage in a lot more social interaction and build a stronger and closer relationship with their managers. This enables them to gather sufficient information from the meetings. Likewise, offline meetings provide an opportunity to visit the company's headquarters, which helps with a better understanding of the company's environment.

Yi Li et al. also discovered that the negative effect of online meetings on analysts' productivity is more pronounced with analysts with poor ability and limited resources. This suggests that analysts with enough experience and resources do not rely as much on the outcome of the meetings and therefore their productivity is not impacted as much by their quality.

Nonetheless, despite their reduced quality, online activities like annual shareholder meetings and online board meetings have been found to improve management. Also, in the context of not being able to hold offline meetings, the online alternative still offers an information advantage and raises the productivity levels of analysts who have participated in them besides those who did not.

Overall, while online meetings present some benefits like flexibility and convenience, they may also have a negative impact on productivity compared to their offline counterparts.

2.2. Online meetings disadvantages

Meetings are ubiquitous at work. Therefore, understanding what makes meetings effective (or not) is important. Blanchard and McBride [5] have studied the disadvantages of online meetings amidst the start of the pandemic context. They have found that online meetings do not allow the same level of engagement as offline meetings do, leading to decreased motivation and attention of team members. Also, they have discovered that a lack of visual cues and nonverbal communication can have a negative impact on the effectiveness of communication between team members during the meeting. When meeting participants perceive a high enough level of group-ness in their meeting, then they begin to enact the processes to create a successful meeting and experience the outcomes of a successful meeting. The authors propose a model connecting the characteristics of successful face-to-face (FtF) meetings to entitativity and extrapolate this model to online meetings.

We will explain the role that effective communication has in team productivity further in the article. Additionally, online meetings present technological challenges such as glitches, poor Internet connection, and software compatibility problems.

Furthermore, online meetings are also at a disadvantage because of the possibility of experiencing ‘Zoom fatigue’. Fauville et al. [6] have researched Zoom fatigue and found that people who use video conferencing more frequently, for longer, and with fewer breaks have expressed more Zoom fatigue. They have also described the disadvantages of Zoom fatigue: it can lead to exhaustion and burnout among frequent participants, and it can be amplified or produced by mirror anxiety and hyper-gaze, both of which can distract and decrease focus. They provided empirical evidence that Zoom fatigue is influenced by the dynamics of individuals' video-conferencing usage and their psychological experience of the meeting.

Also, maintaining the effort put into giving nonverbal communication cues required on video calls drains the participant and reduces the ability to properly understand the discussion held. On the whole, Fauville et al. have found that Zoom fatigue can harm productivity by causing the disadvantages discovered, taking away cognitive resources from actual work tasks.

2.3. Why meetings matter

Even decade-old research acknowledges the importance of meetings and their effect on productivity. Kauffeld and Lehmann-Willenbrock [7] have found that successful meetings that contained proactive communication and in which the participants contributed ideas and suggestions had a positive impact on team productivity. After having recorded 92 regular team meetings, the study followed the idea that the key to understanding team meeting effectiveness lies in uncovering the microlevel interaction processes throughout the meeting.

It has also been found that participating in meetings where they could contribute ideas and personal goals in an open discussion led to a 10.6% average increase in worker productivity during a field experiment. The brief participatory meetings also increased treatment workers' retention rate and feelings of empowerment such as job satisfaction and a sense of control [8].

While they have the disadvantages presented above, virtual meetings can also lead to increased productivity, based on reduced travel time and increased flexibility in scheduling. During the pandemic, office workers were accustomed to fully remote work or partially remote hybrid work. Many of them did not intend to go back to commute to a workplace full-time, no matter the cost. Research from the ADP Research Institute, covering more than 32,000 workers, fully 64% said they would consider looking for a new job if they were required to return to the office full-time. More than half said they would accept a pay cut of up to 11% if they could guarantee themselves remote or partially remote hybrid work [9].

3. Communication methods

Amidst the labyrinth of collaborative dynamics, the profound impact of effective communication on team productivity unfolds as a pivotal dimension that requires scholarly exploration. This exploration, grounded in the principles of research paper language and concepts, delves into the intricate facets of communication methods, providing critical considerations for the optimization of team functioning.

As teams embark on complex missions and objectives, the nuanced exchanges of information, the articulation of ideas, and the cultivation of mutual understanding emerge as fundamental determinants shaping the trajectory of collective productivity.

Within the academic discourse on team dynamics, a rigorous analysis of communication methods is essential to uncover the subtle nuances influencing the efficacy of team interactions. Scholarly investigations, exemplified by the studies conducted by Li et al. [4], contribute valuable insights into the impact of exclusive reliance on specific communication modalities.

This scholarly scrutiny is essential for teams navigating the contemporary landscape, where the strategic selection of communication methods becomes a decisive factor necessitating a nuanced understanding of associated advantages and disadvantages.

The examination of communication tools, including email, instant messaging, and verbal interactions, forms a focal point in this academic exploration. Li et al.'s research [4], for instance, sheds light on potential delays and varied interpretations resulting from exclusive reliance on email. Moreover, the comparative studies conducted by Li et al. [4] offer an objective lens through which the influences of instant messaging and verbal communication on team productivity can be systematically assessed.

Beyond the instrumental considerations of communication methods, the academic inquiry extends to the profound impact of effective communication among team members on broader organizational outcomes. Sunarsi et al.'s findings [10] exemplify this, revealing a correlation between effective team communication and heightened job satisfaction. This linkage underscores the motivational force embedded within communication quality, fostering employee engagement and, consequently, contributing intrinsically to the overarching productivity metrics of a team.

In the ever-evolving landscape of work, this scholarly discourse serves as a compass, guiding teams toward informed communication strategies aligned with the complex objectives of contemporary organizational contexts. As teams navigate the intricate interplay between communication and productivity, these research-driven insights pave the way for strategic choices that enhance collaborative efficacy and contribute to the enduring success of teams within dynamic work environments.

3.1. Written Communication Challenges

In scrutinizing written communication, email emerges as a robust tool for documentation; however, Li et al.'s [4] caution against exclusive reliance on it reveals potential pitfalls. Relying solely on email can lead to delays and varied interpretations, primarily stemming from the absence of non-verbal cues.

Moreover, the ubiquity of instant messaging, while fostering real-time interactions, introduces challenges. It may create an environment pressuring immediate responses, thereby influencing the overall work pace. A comparative study by Li et al. [4] becomes imperative to unravel the nuanced influences of both instant messaging and verbal communication on team productivity.

3.2. Verbal Communication Dynamics

Verbal communication, whether unfolding in physical meetings or through phone calls, injects a layer of richness into team interactions through non-verbal elements. However, the transition to the online environment reveals potential challenges.

Technical issues may compromise the advantages brought by gestures and vocal tones, introducing sound or connection delays. The emphasis from Kauffeld and Lehmann-Willenbrock's study [11] on proactive communication within meetings underscores the significance of these sessions beyond information exchange. Such meetings serve as catalysts for innovation and the expeditious making of crucial decisions.

3.3. Team Member Communication Impact

The impact of effective communication among team members, as gleaned from Sunarsi et al.'s findings [10], extends beyond operational efficiency. It correlates significantly with higher job satisfaction, fostering motivation and engagement among team members. The pivotal nature of choosing communication methods becomes evident, guided by discernment and a comprehensive understanding of their advantages and disadvantages.

This choice is instrumental in cultivating an environment of effective communication, supported by appropriate methods and practices, ultimately encouraging active participation and contributing significantly to achieving heightened productivity and meeting established goals.

3.4 Connectivity in Distributed Teams

Communication emerges as the lifeblood of team unity and awareness. In distributed teams, maintaining optimal connectivity becomes a prerequisite for efficient collaboration. However, the online environment, while facilitating remote interactions, poses challenges. Saghafian and O'Neill's observations [12] shed light on the heightened efforts exerted by online teams to establish optimal communication channels, underscoring their connectivity concerns compared to teams operating in physical proximity.

Cang et al. [13] further argue that the absence of physical co-presence and non-verbal communication contributes to reduced connectivity in online collaborative work. The delicate balance in connectivity is essential, preventing information overload and maintaining focus on individual tasks, ultimately preserving and enhancing overall team productivity.

4. Team management

4.1. Transformational versus transactional

The way a team is led can be an influencing factor in team productivity. Recently, there have been conducted thorough studies on two leadership styles: transactional and transformational.

The transactional model is characterized by offering rewards such as bonuses for finishing clearly defined tasks and by setting punishments to motivate team members. The transformational model requires a much deeper implication from the team leader in team dynamics to develop the skills of team members and motivate them by being supportive and setting high expectations.

Even though both models present very different characteristics, they both contribute to the growth of job satisfaction. However, the transformational model has been found to have a stronger impact, suggesting that its motivational aspects have a wider influence on bettering job satisfaction [10]. Also, this model has proved to be more efficient in the context of virtual teams because it can be used to strengthen the feeling of trust between team members [14].

Job satisfaction is a key factor for productivity. The effect culture has on employee satisfaction is also important. One of the biggest strengths of the organization is the relationship and communication between the employees and the managers. Research has discovered that workers with a high level of job satisfaction have a higher chance of being motivated and engaged in their work-related tasks, which leads to higher productivity [15].

4.2. Challenges of leading teams in an online environment

In an online environment, leaders face new challenges generated by the transition to a different work setting. Chamakiotis, Panteli, and Davison have found that maintaining subordinated engagement requires more effort from the leaders [14]. They have also identified that leaders are required to find new ways to create a feeling of trust between team members and sustain the work-life balance for both themselves and the team members.

Besides choosing to implement the transformational leadership model, the leader of a former traditional team must be creative and adapt easily to the numerous challenges that arise when transitioning to the management of a virtual or partially virtual team.

4.3. Why effective communication matters for leadership

Effective leadership requires physical interaction because it allows a leader to grow strong interpersonal relationships with team members. Developing strong interpersonal relationships enhances engagement and satisfaction among team members and leaders who prioritize it are more likely to inspire and motivate team members, which leads to increased productivity [16].

As mentioned above, distance takes a toll on effective communication. With the increasing commonness of remote work, managers must face the challenge of effectively communicating with team members, which is heavily impacted by time zone differences [17].

5. Ways of improving productivity

5.1. Using technology to promote effective communication

Yuka, Koyano., et al. [18] claim that one of the main problems of working in an online team is the meetings because it is difficult to read the intentions and thoughts of the other participants and the atmosphere of the place. Conventional online meeting systems are designed on the premise that the participants turn on the camera to show their own faces. To improve productivity, teams can use avatars that directly reflect their facial expressions. The system analyzes the participants' facial expressions and reflects them on a cartoon-like avatar provided.

The program also extends a voting feature that allows participants to vote in speech and chat. The results of the voting are displayed, and the users can check the differences of opinion. The system can also show the negative-positive ratio, and the facial expression ratio of a meeting and generate a word cloud.

5.2. Using the project management method to increase productivity

Turetken et al. [19] identify several ways to increase productivity through Agile project management. These methods include focusing on the customer (this can help increase productivity as teams concentrate on delivering products or services that are valuable to customers); delivering value quickly (helps increase productivity as teams can receive feedback from customers earlier and make adjustments accordingly); working in small and autonomous teams (helps increase productivity as teams can communicate and collaborate more easily); and adapting to changes (helps increase productivity as teams can better cope with unforeseen changes).

Kirkman et al [20] define team virtuality as the extent to which team members use virtual tools to coordinate and execute team processes, the amount of informational value provided by such tools, and the synchronicity of team member virtual interaction. They identified a key factor that can influence the productivity of a team, the size of the virtual team, and the implications of their model for management theory and practice.

The dimension that should be the best depends on three main keys: the task characteristics (the nature of the task can influence how the team uses technology), team characteristics (their experience with virtual work), and organizational characteristics (the organization's policies and procedures). These factors still influence the team’s productivity in the present.

5.3. The power of receiving feedback

To enhance online productivity, Rice et al. propose a model for adapting team processes [21]. 16 teams that worked together for periods ranging from 3 months to 3 years were studied. Team processes that emerged naturally from long-duration teams were formalized and taught to shorter-duration teams. These shorter-duration teams comprised 3 different cohorts, each of which received different levels of training.

This model involves receiving feedback to identify areas that need improvement and addressing issues; designing new processes tailored to specific needs and objectives;

implementing the new processes and monitoring them; evaluating the effectiveness of the new processes and adjusting as needed; and maintaining to ensure continuous improvement.

Geister et al. conducted a study with 52 virtual teams formed by students, divided into two groups: one group received feedback on the tasks they completed, while the other group did not receive feedback [22]. The experiment's results showed that the group that received feedback recorded improvements in motivation, satisfaction, and performance. Because team members were more motivated, they were more satisfied with their team experience and were able to accomplish more tasks in a shorter time.

The authors of the article suggest that feedback on team tasks had a positive effect through the following mechanisms: increasing transparency and accountability as team members better understood how the team functioned and contributed to the development of individual responsibility; improving communication and collaboration; and increasing trust and respect among team members. For feedback to have the greatest impact, it needs to be specific, relevant, timely, and provided by a trustworthy person (e.g., a mentor or team manager).

Although the effects of feedback were noted in two studies two decades ago, its relevance remains unmodified. Feedback is a powerful tool to improve the productivity of teams even nowadays.

6. Discussion

Even though virtual teams were introduced as a revolutionary way to manage a project, that was two decades ago. Time since then has shown us how hard it is to replicate the quality of teamwork using virtual means to collaborate.

We have split our research into three categories: meetings, communication, and leadership. We consider these aspects to be the most important when it comes to the essence of teamwork. Out of these three, communication is the most important because it stands at the root of both meetings and leadership.

When it comes to meetings, choosing to stick to physical ones proves to be highly beneficial due to the use of social interaction. Building strong relationships inside the team is such an important factor that it influences every aspect of teamwork. Online meetings, however, present a multitude of challenges that not only disturb the focus of participants but also do not allow the efficient gathering of information from the other participants.

Leadership is also impacted by the online environment. In comparison to meetings, leadership doesn't come with its own specific hardships, and it's heavily influenced by the quality of communication. That being said, communication quality is lower in online settings, and that is reflected in online-based leadership.

Lack of visual cues and other non-verbal elements block virtual-based communication from reaching the nature of traditional communication. Effortlessly staying connected to teammates is the backbone of collaboration.

Effective communication, motivating leadership, and competent meetings are the fundamental part of productive and effective teamwork and as such we need to make sure all three elements are treated vigorously.

7. Further research

The research does not cover the whole subject of the productivity impact of online and physical environments. While the study provides valuable insight, some aspects remain unexplored. Mainly, traditional and online meetings were examined, but hybrid meetings have become more relevant. Similarly, the study focused on leadership in fully remote and fully in-person meetings, while hybrid leadership contains elements from both styles. The research showed the importance of project management to increase team productivity, however, details of a comparison between online and in-person methods were not primarily focused on and would provide valuable insight.

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FACILITATING ITALIAN LANGUAGE ACQUISITION AMONG ROMANIAN SPEAKERS IN AN ONLINE SETTING: THE ADVANTAGES OF INTEGRATING DIGITAL RESOURCES

Mariana COANCĂ[1]

Abstract

This study examines the integration of digital tools and flipped classroom strategies in the online delivery of an A1-level Italian course for Romanian speakers. Using an online course from a well-known platform, instruction combined multimedia input, Romanian-language scaffolding, and cross-linguistic comparisons to support early language acquisition. Supplementary resources such as collaborative activities and gamified platforms enhanced vocabulary development, grammatical accuracy, and learner engagement. Feedback indicated that flexible preparation, multimodal materials, and immediate corrective support contributed significantly to the learners' progress, with English proficiency aiding access to external resources. The findings highlight the effectiveness of a digitally enriched, learner-centered design for beginner-level Italian language instruction in online education.

Keywords: online course, cross-linguistic comparisons, digital pedagogy, multimedia input, feedback

JEL Classification: I21, I23

1. Introduction

Italian language is widely recognized for its melodic and expressive qualities, characterized by phonetic clarity and rhythmic intonation, making it appealing to a diverse audience, including business professionals, travelers, and language enthusiasts. While Standard Italian is promoted for official and educational purposes, there is a growing movement to preserve regional languages and dialects such as Neapolitan, Sicilian, Venetian, Lombard, and Sardinian, as integral components of Italy's cultural heritage [1]; [2].

Globally, Italian ranks among the top 25 most spoken languages, with approximately 67 million native speakers in the European Union and up to 85 million speakers worldwide [3]; [4]. Although its global reach may not match that of English or Mandarin, Italian has significant value due to its rich artistic, literary, musical, and architectural heritage.

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Proficiency in Italian provides us with direct access to these cultural treasures in their original form.

Beyond cultural attractions, Italian offers strategic advantages in various professional fields. Italy's global influence in fashion, automotive design, gastronomy, and the fine arts enhances the utility of Italian in international markets. Consequently, individuals are often motivated to learn Italian due to personal relationships, such as family ties or romantic partnerships, as well as professional collaborations.

From a cognitive perspective, bilingualism has been associated with enhanced cognitive reserve, potentially delaying the onset of age-related cognitive decline and conditions like dementia [5]; [6]. Linguistically, Italian shares significant structural and lexical similarities with other Romance languages, including French, Spanish, Portuguese, and Romanian. This typological proximity facilitates cross-linguistic transfer, making Italian more approachable for students who already speak another Romance language, as they can utilize familiar grammatical patterns and cognates.

2. The Acquisition of Italian by Romanian Speakers

Third language (L3) acquisition is a well-established domain within the field of multilingualism. It investigates the processes by which individuals who already possess proficiency in two or more languages acquire an additional language and examines how their existing linguistic repertoire influences this learning trajectory. The acquisition of Italian as a third language involves a dynamic interplay of linguistic proximity, cognitive processes, and pedagogical practices. This section draws on research in language transfer, language proximity, cross-linguistic transfer, and the role of technology in facilitating language acquisition.

Romanian and Italian share a high degree of structural, lexical, and phonological similarity, which lowers the learning barrier for native Romanian speakers engaging with Italian as a third language. One of the most prominent features aiding mutual intelligibility is the abundance of cognates (i.e. words that are etymologically related and often retain similar meanings and forms across both languages). Examples such as *mamă* (Romanian) and *mamma* (Italian), or *casă* (Romanian) and *casa* (Italian) facilitate intuitive vocabulary recognition for students. These linguistic parallels often allow Romanian speakers to infer the meanings of unfamiliar Italian words with minimal effort. Furthermore, both languages exhibit similar verb conjugation systems, including regular and irregular patterns, as well as subject-verb-object sentence structure, for example, the Romanian sentence "*Ea vorbește limba italiană*" and its equivalent sentence in Italian "*Lei parla l'Italiano*". While no Italian dialect is directly close to Romanian, there are notable linguistic similarities between Romanian and certain southern and central Italian dialects particularly in vocabulary, grammar, and phonetics due to their shared Latin roots [7]; [8].

Syntactic parallels such as noun-adjective agreement and gendered articles provide students with a familiar grammatical framework. For instance, constructions like *un câine frumos* in Romanian and *un cane bello* in Italian reflect almost identical structural logic, making them easily transferable. However, one important grammatical difference lies in the gender system: while Italian operates with two grammatical genders (masculine and feminine), Romanian maintains three (masculine, feminine, and neuter). This asymmetry may lead to confusion, particularly when Romanian neuter or feminine nouns correspond to masculine nouns in Italian, potentially interfering with article and adjective agreement during production ("libro" in Italian is a masculine noun whereas its Romanian equivalent "carte" is a feminine noun; "giorno" in Italian is a masculine noun whereas its Romanian equivalent "zi" is a feminine noun).

As for the pronunciation of words, Romanian and Italian both maintain five core vowel sounds with relatively stable pronunciations, and their consonant systems and stress patterns follow predictable and comparable rules. This phonetic proximity greatly aids Romanian speakers in acquiring accurate Italian pronunciation and prosody. However, as [9] points out, second language learners often face challenges in phonology, vocabulary, and grammar due to interference from their first language (L1) habits. Consequently, according to [10], the comprehensible input hypothesis posits that language acquisition is most effective when students are exposed to input that is both understandable and slightly beyond their current level of proficiency. A multimodal strategy that incorporates such input across diverse, authentic contexts promotes repeated encounters with key language structures, thereby supporting both understanding and practical use.

[11] provides insights into the dynamics of L3 acquisition by examining the roles of the first language (L1) and second language (L2) in L3 production. His findings reveal that learners often rely on their L2, especially when it shares similarities with the L3. However, when acquiring a third language, Romanian speakers may experience language interference by transferring linguistic elements from their native language to the Italian language. A common example is the phonological interference, such as the pronunciation of the letter *h*. In Italian, *h* is silent, while in Romanian it is clearly articulated. As a result, Romanian speakers at A1 level of Italian proficiency may overpronounce *h* in Italian words like *ho*, *hai*, and *ha* (forms of the verb *essere*), reflecting transfer from their native phonological system.

Other researchers seek to understand the broader conditions under which linguistic transfer occurs. Specifically, in a systematic review they examine what factors determine when, how, and to what extent previous linguistic experience, whether from the first language, second language, or both, affects the initial stages and beyond of adult third language (L3) acquisition [12]. Finally, [13] advocate for linguistically responsive teaching practices in multilingual settings. Their work emphasizes the need for educators to recognize and leverage learners' existing linguistic resources, promoting a more inclusive and effective language learning environment.

Recognizing the role of sociocultural engagement in virtual settings, the integration of digital tools and platforms expands opportunities for meaningful interaction and personalized learning, enhancing both the accessibility and effectiveness of online Italian instruction. Digital platforms have revolutionized language learning by offering flexible, learner-centered approaches. Tools such as Duolingo, and Coursera provide interactive content, immediate feedback, and self-paced progression, which are valid elements that support effective acquisition of Italian. Among freely available tools for Italian language learning, the course "Parliamo in Italiano" on Edulia Treccani – Scuola[2] stands out for its comprehensive and methodologically sound structure. Developed by one of Italy's leading linguistic institutions, Treccani, the course is designed for adult and young adult learners acquiring Italian as a foreign language, and spans four levels aligned with the Common European Framework of Reference for Languages (CEFR), covering A1–A2 and B1–B2 proficiency levels [14].

3. Instructional Design for A1-Level Italian: Integrating Digital Tools in an Online Setting

This section outlines the instructional design and teaching strategies employed in the online delivery (via Microsoft Teams) of an A1-level Italian course for Romanian speakers, with particular attention to the integration of external digital tools to enhance third language acquisition. The course, *Parliamo in Italiano*, was used to teach fifteen Romanian learners whose second language is English. The primary objective was to guide learners toward successfully completing the A1 level of Italian proficiency within three months.

To ensure the successful implementation of online resources, it was crucial to consider a well-prepared instructional design and the digital competence of both the teacher and the learners. For the teacher, digital competence involved not only the technical ability to navigate and use various educational technologies but also the pedagogical knowledge to integrate these tools meaningfully into the learning process. This included selecting appropriate resources, adapting content for online delivery, and providing ongoing support for them in using these tools. For a learner, digital competence meant having the skills to engage with the online course materials, participating in digital activities, troubleshooting common technical issues, and collaborating with peers through online platforms.

The online course supports both guided instruction and independent study, making it suitable for classroom integration as well as autonomous learning [15]. What distinguishes "Parliamo in Italiano" is its integration of multimedia content, interactive exercises, and authentic spoken input. Each thematic unit is centered around communicative situations drawn from everyday life, beginning with a video sequence that features authentic spoken

[2] Source: https://inclasse.edulia.it/resources?type=parliamoitaliano

Italian and is available with or without subtitles [16]. These video inputs are intended to spark learner motivation while activating cognitive and perceptual mechanisms essential to language acquisition [17]. Morphosyntactic, pragmatic, conversational, and lexical features of Italian are contextualized within these scenarios and further explored through a range of focused tasks within each unit [18], as shown below.

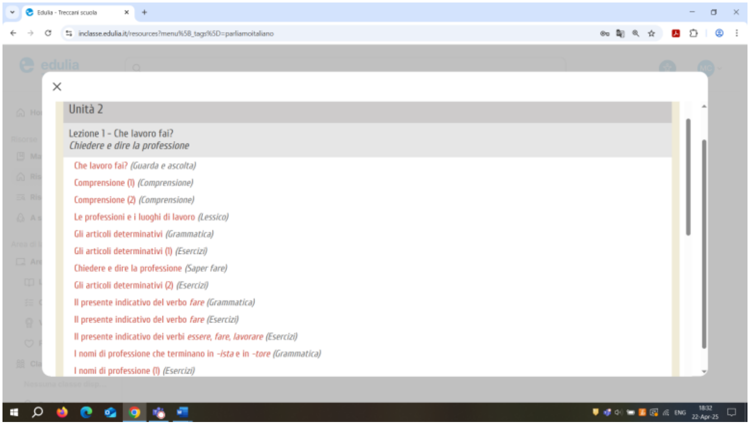

Figure 1: Screenshot of the overview of activities in Unit 2, Lesson 1 from the "Parliamo in Italiano" course, Edulia Treccani - Scuola[3]

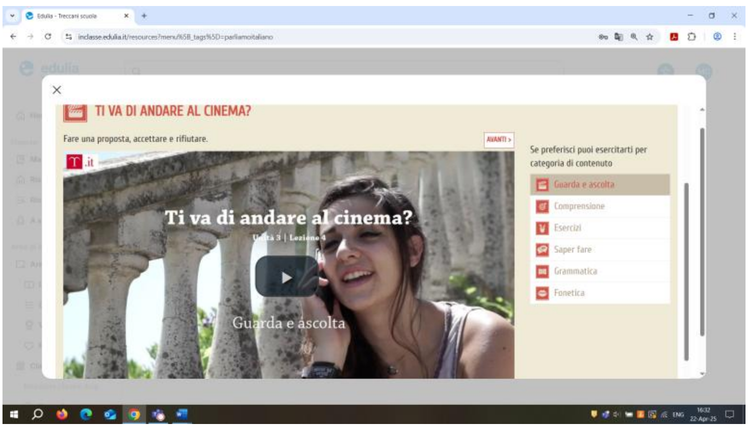

Figure 2: Screenshot of a Lesson Interface from "Parliamo in Italiano" course, Edulia Treccani - Scuola: "Ti va di andare al cinema?"[4]

[3] Source: https://inclasse.edulia.it/resources?menu%5B_tags%5D=parliamoitaliano

[4] Source: https://inclasse.edulia.it/resources?menu%5B_tags%5D=parliamoitaliano

To achieve the objectives of an instructional design, the teacher selected the lesson "Ti va di andare al cinema?" from the "Parliamo in Italiano" course (see Figure 2). This lesson introduces foundational communicative competencies relevant to everyday social interactions, including making and refusing invitations, expressing availability, and employing modal verbs such as "potere", "volere", and "dovere".

The Flipped Classroom Model

In recent years, the flipped classroom model has gained significant attention in language education as a means of enhancing learner engagement, autonomy, and active classroom participation. The flipped model, as defined by [19], enhances adult learners' engagement by shifting initial input and rule discovery to individual preparation, allowing class time to focus on communicative practice and collaborative tasks.

In the context of Italian as a foreign language (IFL), the model has been applied across educational levels, including beginner (A1) courses, with promising results. For example, a foundational study examining the integration of flipped learning in a university-level beginner Italian course, emphasizes that the flipped model, when aligned with the principles of inductive learning and communicative pedagogy, can enhance learner autonomy and in-class collaboration through a cyclical structure of pre-class video content, interactive class practice, and post-class reinforcement [20].

Adding to recent innovations, Carmelo Galati's "Gratis!: A Flipped-Classroom and Active Learning Approach to Italian" offers an open-access flipped classroom resource specifically designed for Italian language instruction [21]. The textbook integrates asynchronous learning materials such as video lectures and digital exercises with active, student-centered classroom activities aimed at developing communicative competence. Expanding the application of technology-enhanced flipped models, Laura Capitani's blended learning course at Maastricht University offers another example of successful integration. As reported by [22], Capitani combines Babbel's online modules with supplementary resources and individualized Skype sessions: students first engage independently with structured Babbel lessons, then reinforce their skills through additional practice activities, before participating in one-to-one tutorials focused on communicative practice. This model not only promotes learner autonomy and flexibility but also personalizes instruction, allowing students to progress at their own pace and receive immediate, targeted feedback [23].

Finally, in their study on the broader adoption of flipped learning in Italian schools, [24] report that educators employ the model to foster student-centered learning environments. Their findings suggest that technology accessibility and teacher training are pivotal factors influencing the model's success. Although their study does not focus solely on Italian language instruction, it reflects the growing institutional support for flipped pedagogies in Italy.

Implementation

Prior to the online session, learners engaged with the video of the lesson and accompanying comprehension activities. At the beginner stage, they are still developing a basic understanding of the new language. To support this process, the teacher initially explained key lesson concepts in Romanian, ensuring that students understood essential vocabulary, grammatical rules, and sentence structures related to making invitations, expressing refusals, and offering alternatives. This approach allowed students to grasp the material more easily, drawing on their familiarity with Romanian linguistic structures. For example, when teaching the conjugation of verbs in the present tense, the teacher highlighted the similarities between the two languages, helping students recognize the shared patterns and structure. Drawing explicit cross-linguistic comparisons during instruction can enhance comprehension, reduce cognitive load, and promote positive transfer from Romanian to Italian in the early stages of communicative language use. A comparison between the two languages reveals important similarities that can facilitate the acquisition of these competencies. Both Italian and Romanian, as Romance languages, use specific verbs to express ability (*potere* / *a putea*), necessity (*dovere* / *a trebui*), and desire (*volere* / *a vrea*). However, while Italian typically combines these modal verbs directly with an infinitive (e.g., *Posso leggere il tuo nome* – "I can read your name"), Romanian often introduces an additional particle (*să*) before the infinitive (e.g., *Trebuie să citesc mesajul – "I must read the message"*). Understanding these structural differences can help them transfer existing knowledge while adapting to the syntactic patterns of Italian.

While the course provides structured and comprehensible content, its implementation in an online environment could be significantly enhanced by incorporating supplementary digital tools and platforms. For instance, the video of the lesson was replayed during class with strategic pauses to facilitate clarification and pronunciation drills. Learners were also introduced to supplementary resources, such as "The Beginner Podcast series" from "News in Slow Italian"[5], which is specifically designed for A1 level of proficiency. This podcast delivers news content at a slower pace, using simplified language to support language acquisition [25]. To reinforce their understanding of modal verbs such as *dovere*, *potere*, and *volere*, the teacher incorporated an interactive digital grammar quiz focused on practicing these modal verbs, which are essential for expressing intentions and managing invitations. In this exercise (see Figure 3), they completed sentences by selecting the correct conjugated verb form based on context such as *Perché Francesco non ___ venire alla festa?* (potere) or *Noi ___ vedere quel bosco* (volere)[6].

These structured yet contextually rich exercises provided immediate, scaffolded practice with high-frequency verbs crucial for A1-level communicative competence. The visually clear interface and focused input helped support the development of grammatical accuracy

[5] Source: https://www.newsinslowitalian.com/

[6] Source: https://www.newsinslowitalian.com/series/grammar/27/186/quiz/2

while maintaining learner engagement. Although the platforms support a limited selection of languages, excluding Romanian, they were able to successfully engage with the tasks thanks to their intermediate English proficiency (ranging from B1 to B2), minimizing potential language barriers. They are increasingly accustomed to navigating various digital platforms for diverse purposes and their familiarity with online environments likely facilitated their engagement with the tasks and enabled them to manage the technological aspects of the learning process with greater ease.

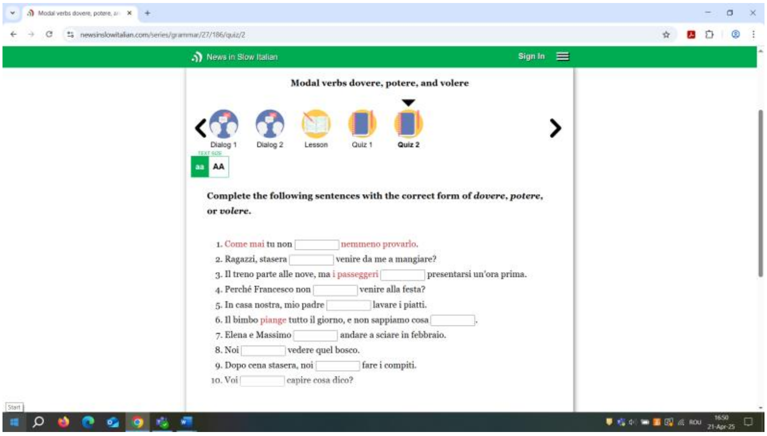

Figure 3**:** Screenshot of a grammar activity from *"News in Slow Italian"*, The Beginner Podcast series, practicing modal verbs[7]

Social Interaction

To enhance social interaction, the teacher adopted an innovative approach using Microsoft Teams. Learners were paired in breakout rooms to role-play invitations and refusals in real-time. One illustrative A1-level breakout activity, titled "Inviting a Friend Out", focused on the use of functional expressions like *Ti va di...?; Che ne dici di...?* together with the modal verbs (*potere, volere, dovere*). To model the task, the teacher performed a brief sample dialogue with a student: *Che ne dici di andare al cinema sabato? / Mi dispiace, non posso. Vado a trovare mia madre. / Allora, facciamo domenica? / Va bene, volentieri!*. Key expressions were shared via screen or chat to support comprehension. Students, working in pairs, were then instructed to co-construct a short dialogue including one invitation, one polite refusal with a reason, and one accepted alternative, using at least three of the target structures. The activity followed a structured timing breakdown: 2 minutes to enter breakout rooms, 3 minutes to review instructions, 8 minutes to write and rehearse the dialogue, 5 minutes to perform and self-correct, and 2 minutes to return to the main room. This

[7] Source: https://www.newsinslowitalian.com/series/grammar/27/186/quiz/2

scaffolded role-play not only reinforced functional language use but also promoted peer collaboration and real-time negotiation of meaning in a communicative context. In alignment with the sociocultural theory and the Interaction Hypothesis, these dialogic exchanges played a crucial role in facilitating the internalization of syntactic structures and pragmatic norms, particularly among adult learners capable of metalinguistic reflection [26]; [27].

As part of a personalization-oriented technique, students were tasked with writing customized dialogues in which they invited peers to events of personal interest (e.g., concerts, dinners, sports, etc.). These dialogues were composed and shared collaboratively via the Files section of Microsoft Teams. For instance, one pair created a conversation in which a student invited a classmate to a live concert using the expression "*Ti va di venire al concerto sabato sera?*", followed by a polite refusal and an alternative proposal. Peers were encouraged to view, comment on, and suggest edits directly within the shared document, fostering a sense of co-authorship and reflective learning.

In parallel, the teacher provided targeted written feedback through the document's comment feature, praising accurate usage of expressions (e.g., *Benissimo! Ottimo uso di "Ti va di...")* and gently correcting errors related to syntax or verb conjugation. In some instances, teachers added reformulations or guiding questions (e.g., *Potresti aggiungere un'alternativa più specifica?*) to promote revision and metalinguistic awareness. This scaffolded feedback loop enhanced the pedagogical value of the activity by supporting both accuracy and learner autonomy. [28] emphasizes that learners engage more deeply with materials that connect to their social identities and experiences. In this context, the opportunity for personalization combined with collaborative authorship and timely feedback, made the language practice both meaningful and memorable.

Finally, to reinforce vocabulary acquisition and grammatical structures introduced during instruction, as well as to sustain learner motivation in the online environment, the teacher the teacher developed interactive exercises to review the introduced vocabulary and structures. For example, they were tasked with matching expressions to appropriate responses (e.g., *Ti va di uscire? → Mi dispiace, non posso*), completing sentence gaps using modal verbs (e.g., *Voglio andare al cinema, ma non posso, devo studiare*), and selecting context-appropriate invitations from multiple-choice options, such as:

Ce înseamnă "Ti va di andare al cinema?"
A) Vrei să mergi la cinema?
B) Mergi la cinema?
C) Poți să mergi la cinema?
D) Nu vreau să merg la cinema.

Care este răspunsul corect la invitația "Ti va di mangiare fuori stasera?" dacă nu poți merge?
A) Mi dispiace, non posso.

B) Va bene, ci vediamo alle 7.
C) Non voglio.
D) Sì, mi piace mangiare fuori.

Care dintre următoarele este un refuz politicos la o invitație?
A) Sì, con piacere!
B) Mi dispiace, non posso.
C) Andiamo!
D) Mi piace molto l’idea.

These questions helped them connect vocabulary and expressions to their real-world equivalents in Romanian, reinforcing comprehension and recall.

4. Insights and Perspectives

Requesting feedback allows instructors to ensure that their teaching aligns with learners’ needs and to adjust accordingly. In this study, the teacher determined that the most practical moment to collect feedback was at the end of the lesson, using the Microsoft Teams chat function. At this point, all had already engaged with the content and were better positioned to reflect on the effectiveness of the session. The teacher prepared questions to allow them to reflect on different aspects of their learning experience, from content preparation to engagement and interaction. Key questions included: *How effective did you find the online resources in helping you prepare for the lesson?; How did the online format impact your participation?; What part of the lesson did you find most engaging or useful? Why?; Were the multimedia resources helpful in reinforcing the lesson content? If yes, how?* and *What would you recommend for progressing to the next level of Italian proficiency?*

They actively shared their insights, and the teacher observed that, in an online environment, they tended to provide feedback more readily than students participating in face-to-face settings. To illustrate this, they emphasized that access to pre-class video materials and multimedia resources enabled them to prepare at their own pace, fostering a sense of autonomy and boosting their confidence during live sessions. This flexible preparatory phase supported deeper engagement with the content and promoted mental readiness for interactive classroom activities.

Moreover, they found the combination of visual and auditory input particularly beneficial for vocabulary retention and comprehension, as it allowed for more effective internalization of new structures. In-class pauses during video playback were especially appreciated as they offered moments to reflect on the language, identify grammatical patterns, and consolidate their understanding of modal verbs and functional expressions through guided scaffolding.

Finally, the integration of external resources that give access to grammar tutorials and contextualized video examples was also perceived as highly supportive. Most of these tools were accessed in English, due to the limited availability of Romanian-language materials on mainstream platforms. Collaborative in-class activities, including role-plays, dialogue construction, and peer interaction in breakout rooms (via Microsoft Teams), were considered meaningful opportunities for communicative practice and personalization of the language. The use of collaborative digital tools further encouraged creative expression and enabled them to receive written feedback, which they regarded as particularly useful for developing grammatical accuracy and reflective learning strategies. Gamified platforms were also highlighted as effective tools for enhancing engagement. These tools encouraged active recall in a low-pressure environment, and the immediacy of feedback they provided was especially valued for allowing timely self-correction and reinforcement of vocabulary and grammar.

Although the course was delivered online and entirely in Italian, posing occasional challenges, they felt that the availability of support materials in English effectively compensated for the absence of Romanian-language resources. Their ability to draw on English-language explanations and examples was identified as a key factor in their progress. They also observed that their mother tongue, Romanian, positively influenced their acquisition of Italian, particularly in the development of speaking skills. They identified structural and lexical similarities between the two Romance languages, which facilitated pronunciation, the intuitive use of cognates, and the construction of basic sentence patterns. However, several learners expressed a preference for a blended learning approach, suggesting that a combination of online and in-person instruction could enhance the learning experience. Such a format would foster stronger social connections and encourage more spontaneous spoken interaction.

5. Conclusion

The Italian language has both cultural significance and professional value, particularly in globally influential sectors such as tourism, fashion, design, and gastronomy. For Romanian speakers, Italian acquisition is notably facilitated by the structural, lexical, and phonological similarities between the two Romance languages, which support accelerated comprehension and production through the recognition of cognates and comparable grammatical patterns.

The design and delivery of the A1 lesson, conducted online, via Microsoft Teams, demonstrated the pedagogical effectiveness of digitally mediated instruction. The integration of external digital resources, such as "News in Slow Italian" and gamified learning platforms, further enriched the multimodal, learner-centered environment, promoting scaffolded development and fostering autonomy. Learners consistently emphasized the benefits of combining visual, auditory, and interactive content, which contributed to improved vocabulary retention, grammatical understanding, and pronunciation accuracy. Although the absence of Romanian-language support materials

presented some challenges, participants successfully utilized their English proficiency as a mediating tool in their third language (L3) acquisition.
Future adaptations of the course could benefit from a blended learning model, combining online flexibility with in-person sessions to enhance interpersonal communication, strengthen group cohesion, and boost learner motivation through spontaneous interaction.
In conclusion, the instructional model employed in this study offers a flexible and effective framework for beginner-level Italian learning in online contexts, leveraging digital tools and learner-centered strategies to support communicative competence in third language acquisition.

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EXPLORING THE LINK BETWEEN INNOVATION AND ICT READINESS. A COMPARATIVE ANALYSIS OF ESTONIA AND ROMANIA

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Justina Lavinia STĂNICĂ[2]

Abstract

This paper examines the relationship between the Summary Innovation Index (SII) and certain ICT readiness indicators, including the Network Readiness Index (NRI) and the Human Resources in Science and Technology (HRST) Index, across the EU-27 countries. The objective is to gain a deeper understanding of how digital infrastructure and human capital contribute to innovation performance within the region. The results obtained confirm the previous research of the authors of this paper regarding the close connection between innovation and ICT.

In the second part of the paper, we conducted a case study in which we analyzed the innovation and ICT readiness landscapes in Estonia and Romania, two countries that present a clear contrast.

Keywords: ICT, innovation performance, correlation, Summary Innovation Index (SII), Network Readiness Index (NRI), Human Resources Science and Technology (HRST) Index

JEL Classification: M15

1. Introduction

The European Union has long recognized that fostering innovation is key to driving economic growth, enhancing global competitiveness, and addressing societal challenges. Therefore, at the EU level, innovation-driven growth has become a key priority, focusing on directing resources to foster research and development. Investments in research, development, education, and skills are crucial policy areas for the EU, as they play a vital role in driving economic growth and establishing a knowledge-based economy.

This paper examines the relationship between different indicators of innovation and ICT readiness. Recent studies have highlighted the importance of aligning innovation strategies

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with ICT readiness frameworks across European nations [1]. Also, the role of digital transformation in enhancing innovation performance is analyzed in [2]. In addition, previous research conducted by the authors shown a strong linkage between innovation and ICT, considering various indicators, such are: the Summary Innovation Index (SII) and the the Global Innovation Index (GII), for the innovation, and, respectively the Networked Readiness Index (NRI), the ICT Development Index (IDI), and various EUROSTAT indicators, for ICT [3][4]. Therefore, by analyzing the models provided, we aim to better understand the demand for and supply of highly qualified individuals in science and technology, alongside the essential need for continued investments in R&D.

Materials and methods

For the materials and methodology, all charts and graphics included in this paper were created by the authors using Microsoft Excel (including ANOVA analysis), with data sourced from the European Innovation Scoreboard (EIS) 2024, the Global Information Technology Report 2024, and Eurostat. The HRST indicator values were updated on 13 December 2024.

The Summary Innovation Index (SII)

The **European Innovation Scoreboard (EIS)** is an initiative launched by the European Commission to provide a comparative analysis of innovation performance across European countries, both at national and regional levels. EIS is published annually, and it measures and ranks countries based on their innovation capabilities and outcomes, helping to identify trends and gaps in innovation across Europe.

The purpose of the EIS is to assess different aspects of innovation, through a variety of indicators:

1. **Human Resources** – the availability of skilled individuals in science and technology.
2. **Research Systems** – the performance of research institutions and public research expenditure.
3. **Innovation-Related Investments** – private sector investments in innovation and R&D.
4. **Enterprise and Innovation Activities** – the presence and performance of innovative companies and startups.
5. **Intellectual Assets** – indicators like patents, trademarks, and designs.
6. **Market and Economic Impact** – the contribution of innovation to economic performance, including productivity and job creation.

The initiative came to life in 2001, but over time, it has undergone changes. At the beginning, the report was published under the name "Innovation Union initiative". The current name of EIS was acquired in 2015. In addition, the indicators in the early versions of the EIS focused on more traditional aspects of innovation, such as R&D investment, patents, and scientific publications. Their structure has changed over, in order to reflect more accurately the changes of the economies. One of the most recent, important updates of EIS happen in 2021, they were meant to better reflect evolving trends in innovation. Some of the key changes introduced in 2021 include: (1) Expanding Indicators on Digital Transformation, (2) Introduction of the "Green Innovation" Dimension, (3) New Methodology for Composite Indicator.

In recent editions, the methodological framework of the scoreboard is based on a total of 32 indicators, divided into four main categories and 12 dimensions, to assess the innovation performance of the EU, its Member States and selected third countries (EIS, 2024). Based on these indicators, a composite index, **Summary Innovation Index (SII)** is calculated yearly for every country:

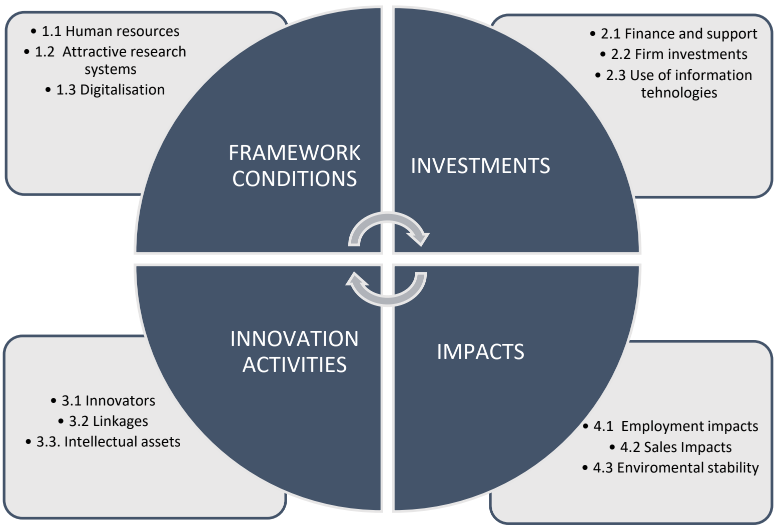


Figure 1. The structure of the Summary Innovation Index (SII) in 2024
(chart made with Ms. Excel, by authors)

Based on their SII index values, the 27 Member States are categorized into four performance groups (Figure 2):

- **Innovation leaders** (Denmark, Sweden, Finland, and the Netherlands) – perform in innovation well above the EU average (above 125% than EU average);
- **Strong Innovators** (Belgium, Austria, Ireland, Luxembourg, Germany, Cyprus, Estonia, and France) – innovate below the leaders, but above the EU average;
- **Moderate innovators** (Slovenia, Spain, Czechia, Italy, Malta, Lithuania, Portugal, Greece and Hungary) – perform in innovation below or equal to the EU average (at least 70% of EU average);
- **Emerging innovators** (Croatia, Poland, Slovakia, Latvia, Bulgaria and Romania) – innovate well below the EU average.

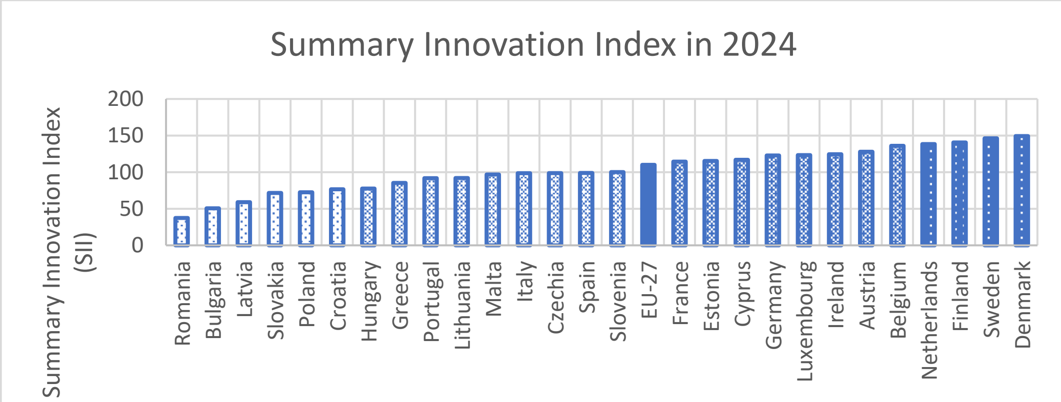


Figure 2: The four groups of EU-27 countries by their innovation performance (SII) relative to EU scores, in 2024

(chart made with Ms. Excel, by authors)

We note that, according to EIS 2024: "All performance scores described in this report are relative to that of the EU in 2017 to facilitate the tracking of progress and trends that enable policymakers to identify specific areas requiring attention through strategies and programmes at national level." [5, pg. 9].

Measuring the ICT readiness

In order to assess the ICT readiness of a country, we have used two indicators:

1. **HRST Index** measures **the availability and quality of human capital** in science, technology, engineering, and mathematics (STEM) fields.
2. **NRI** assesses a country's **overall readiness to leverage information and communication technologies (ICT)** for economic and social development.

The **Human Resources in Science and Technology (HRST) Index** is a key measure used by Eurostat to assess the availability of skilled labour in science and technology fields across European countries. It includes people with higher education qualifications in science and technology fields, such as those with degrees in engineering, life sciences, physical sciences, and information technology [6].

In our analysis, we have used the HRST indicator with the following dimensions:

- Unit of measure: Percentage of population in the labour force (PC_ACT)
- Category: Persons with tertiary education (ISCED) and/or employed in science and technology (HRST)
- Age class: From 15 to 24 years and 65 to 74 years (Y15-24_Y65-74)

Using the HRST Index, we can rank the 27 Member States as follows:

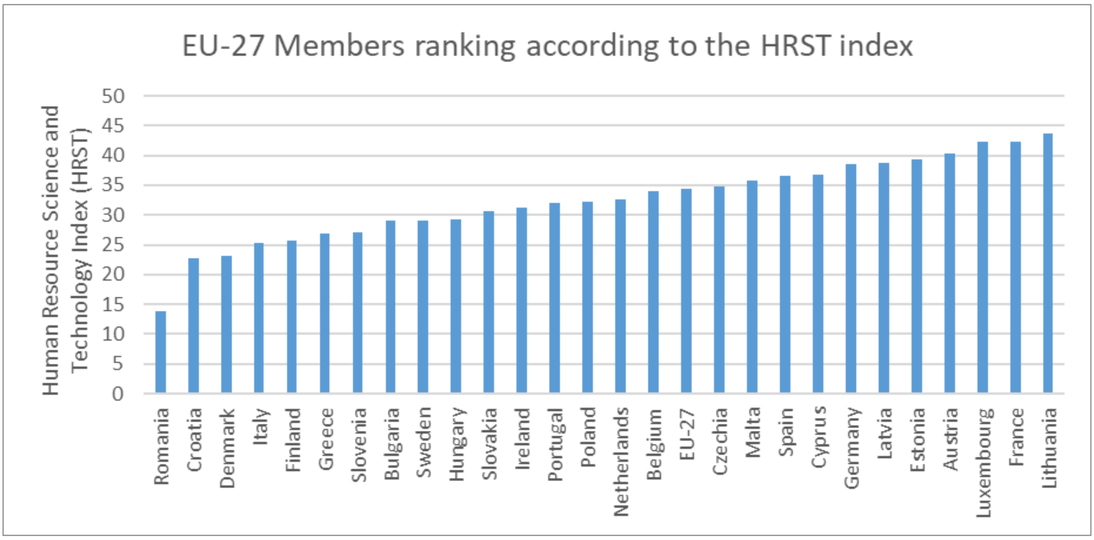


Figure 3: The EU-27 countries ranked by their S&T performance (HRST Index 2023) (chart made with Ms. Excel, by authors)

The **Network Readiness Index (NRI)** is also a composite index meant to offer a description of the digital economy of a country. It is published as part of the Global Information Technology Report [7], as a result of collaboration between various partners, including the World Economic Forum (WEF) and INSEAD. The 2024 version was published under the motto "Building a Digital Tomorrow: Public-Private Investments and Global Collaboration for Digital Readiness", by the Portulans Institute in collaboration with Saïd Business School, University of Oxford.

The NRI is built around four main pillars, each of which is broken down into sub-pillars and indicators:

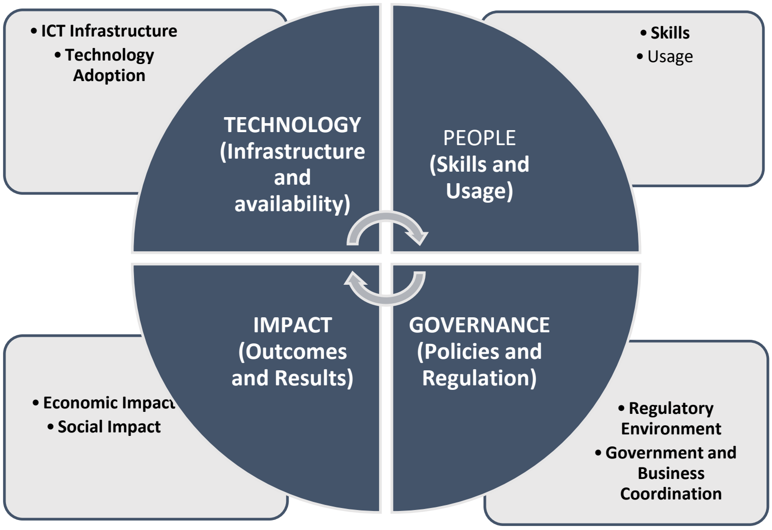


Figure 4. The structure of the Network Readiness Index (NRI) in 2024
(chart made with Ms. Excel, by authors)

In the next graphic the ranking of the 27 EU members, according to their NRI values. The four pillars Technology, People, Governance and Impact are also represented:

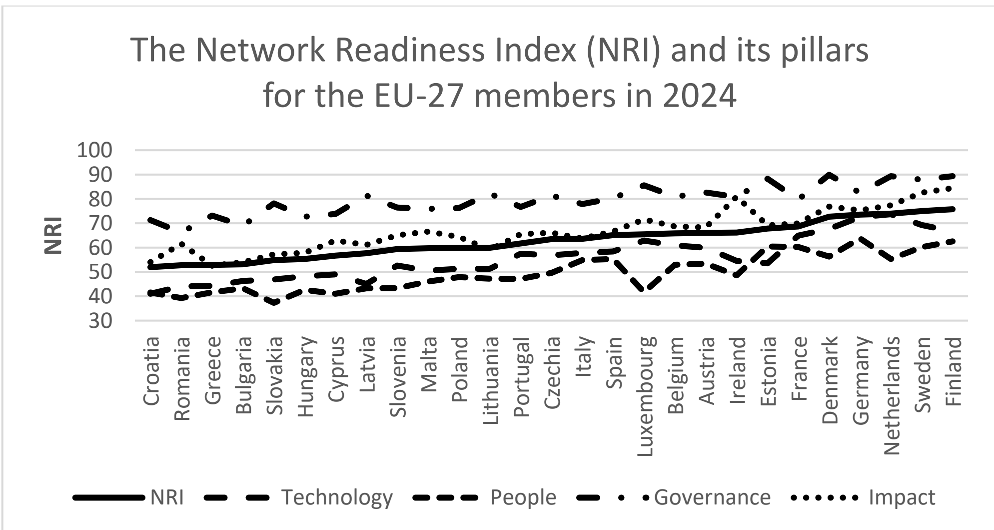


Figure 5. The Network Readiness Index (NRI) and its pillars for the EU-27 members in 2024
(chart made with Ms. Excel, by authors)

2. Correlations between innovation and ICT for the EU-27 Member States

In this section, we aim to examine the correlation between the SII and ICT readiness indicators, such as the NRI and HRST Index, for the EU countries in order to better understand how digital infrastructure and human capital influence innovation performance across the region.

2.1 Summary Innovation Index (SII) vs Network Readiness Index (NRI)

The next diagram illustrates the Summary Innovation Index (SII) and Network Readiness Index (NRI) indexes for the 27 EU Member States in 2024 suggesting that a linkage exists between them. This visual representation indicates that countries with higher NRI scores tend to have stronger innovation performance, as reflected by their SII:

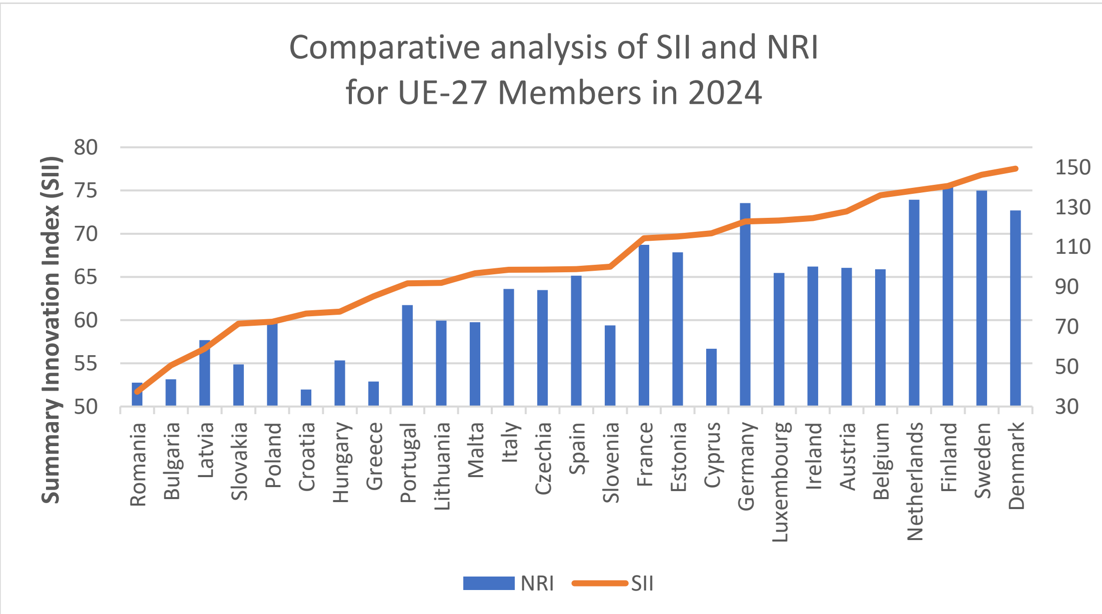


Figure 6. Comparative analysis of SII and NRI for UE-27 Members in 2024
(chart made with Ms. Excel, by authors)

Our next step was to describe this relationship using a linear model. The figure below shows that the two composite indexes for 2024 are linearly correlated:

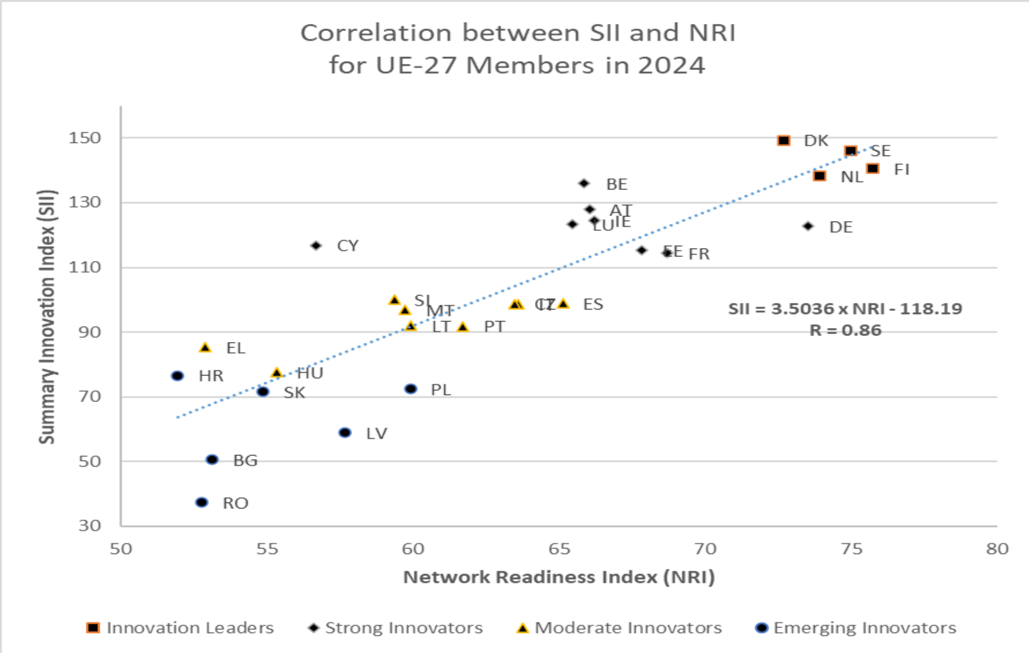


Figure 7. Correlation between SII and NRI for UE-27 Members in 2024
(chart made with Ms. Excel, by authors)

The equation of the linear regression is provided:

$$SII = 3.50 \times NRI - 118.19$$
$$R = 0.86$$

further demonstrating the strength of this correlation and offering a quantitative basis for understanding the connection between human capital in science and technology and innovation performance across EU Member States.

2.1 Summary Innovation Index (SII) vs. the Human Resources in Science and Technology (HRST) Index

Our next investigation referred to the relationship between the Summary Innovation Index (SII) and the Human Resources in Science and Technology (HRST) Index for the EU-27, at the global level, for the period 2017 to 2024:

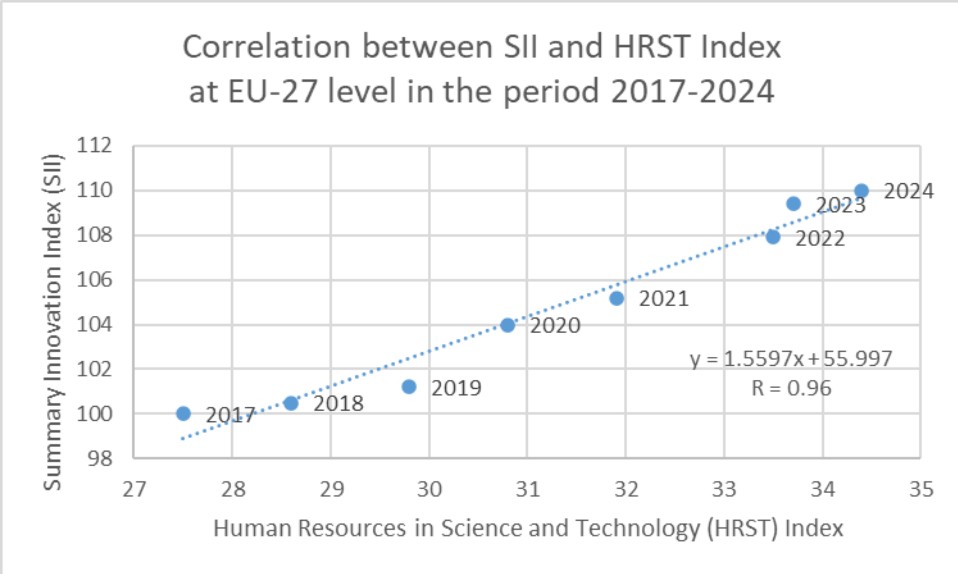


Figure 8. Correlation between SII and HRST Index at EU-27 level in 2024
(chart made with Ms. Excel, by authors)

As expected, they are also strongly correlated because both indicators reflect key drivers of innovation. The HRST Index measures the availability of a skilled workforce in science and technology, which is essential for fostering research, development, and technological advancements.

3. Comparative analysis between Romania and Estonia in terms of innovation and ITC readiness

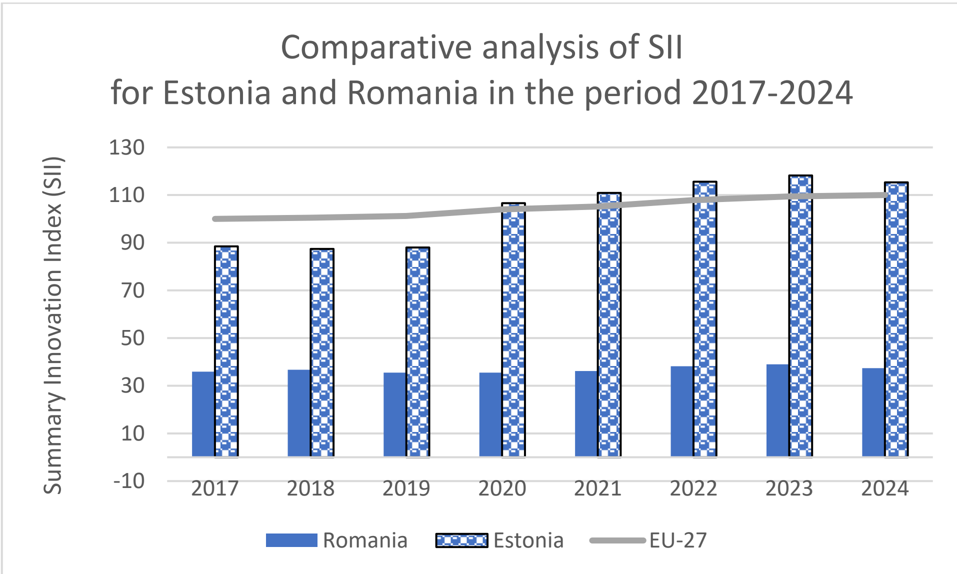
Romania faces significant challenges in terms of innovation, which have hindered its progress in the global digital economy. Despite having a relatively young and educated workforce, the country struggles with inadequate infrastructure and limited access to high-speed internet, particularly in rural areas. This digital divide hampers the widespread adoption of new technologies and stifles the growth of digital businesses. Moreover, while the country has made strides in some sectors, the public and private sectors are often slow to embrace digital transformation, with outdated governance structures and regulatory frameworks that do not fully support innovation.

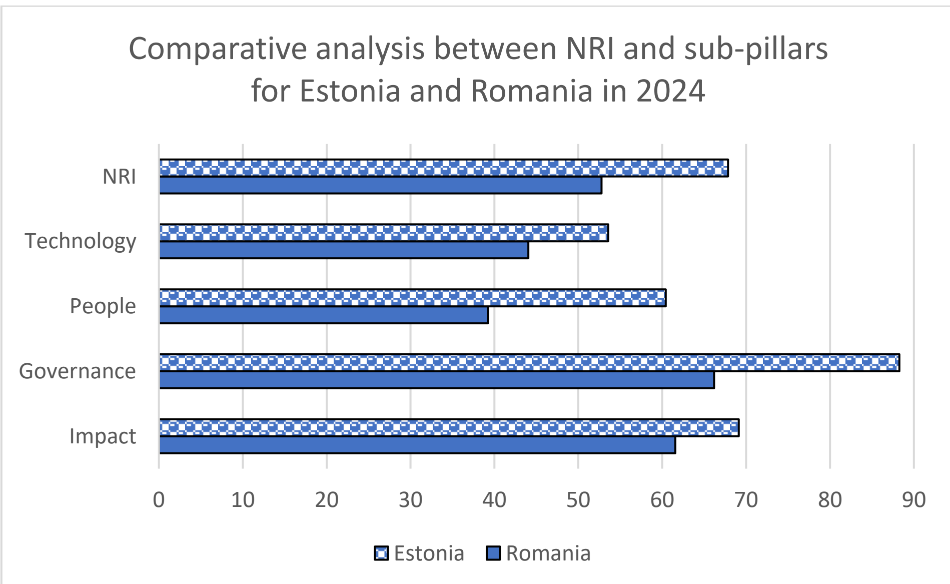
Additionally, Romania's education system, though improving, still falls short in providing the necessary digital skills to equip the workforce for the demands of the modern economy. As a result, Romania's innovation ecosystem remains underdeveloped, with limited investment in research and development, low rates of collaboration between businesses and academia, and insufficient support for startups and digital entrepreneurship.

These factors contribute to Romania's relatively low ranking in global innovation indices, hindering its competitiveness in an increasingly digital world.

In contrast, Estonia stands out as a leader in innovation. Estonia's regulatory frameworks are designed to encourage investment in research and development, collaboration between businesses and academic institutions, and the growth of digital entrepreneurship.

As a result, Estonia consistently ranks among the top performers in global innovation and ICT readiness indices, contrasting sharply with Romania's situation:





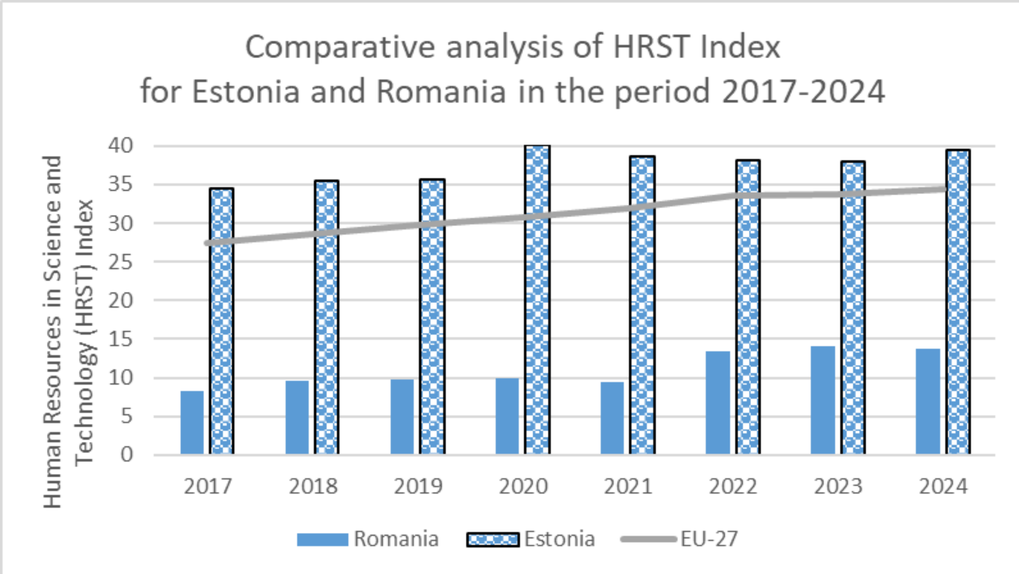
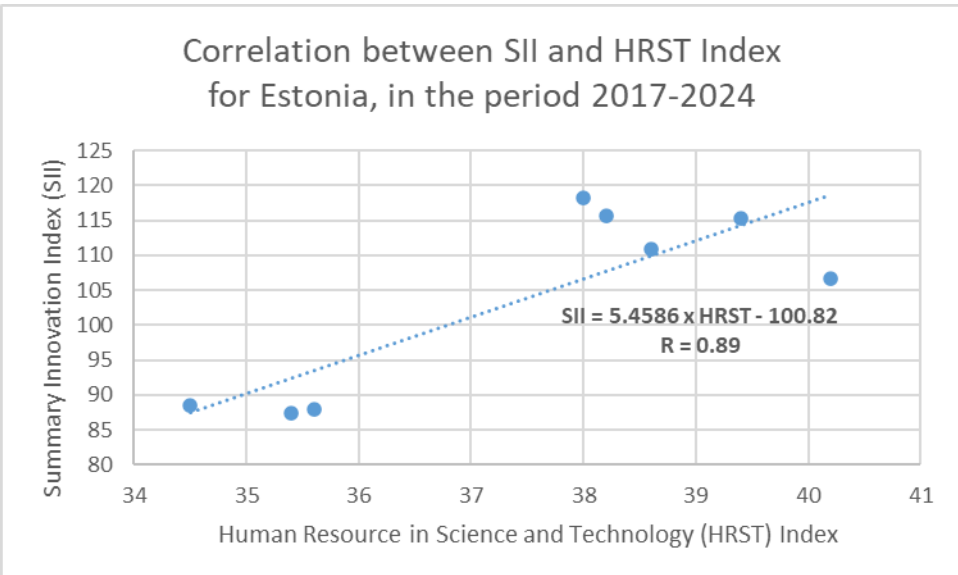


Figure 9. Comparative analyses using SII, NRI and HRST Indicators for Estonia and Romania

(chart made with Ms. Excel, by authors)

Examining the relationship between innovation and the Human Resources in Science and Technology (HRST) Index, for both Estonia and Romania, we have found a strong link, that suggests that the availability and quality of skilled labor in science and technology plays a crucial role in fostering innovation in both countries:



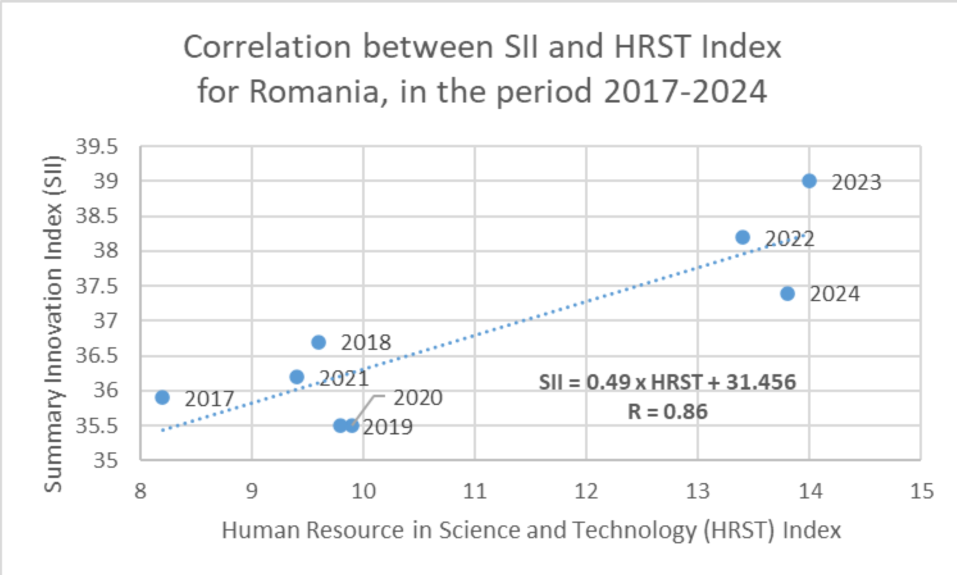


Figure 10. Correlation between SII and NRI for Estonia and Romania (bottom) in the period 2017-2024

(chart made with Ms. Excel, by authors)

For Estonia, this strong connection indicates that the country's investment in developing a highly skilled workforce in science, technology, engineering, and mathematics (STEM) has directly contributed to its innovation success. Estonia's high HRST score reflects a well-educated, digitally literate population that is prepared to drive innovation in emerging technologies.

Romania's lower HRST score suggests that there are still gaps in terms of the quantity and quality of its skilled workforce in STEM fields. Despite having a relatively high level of education, Romania faces challenges in producing enough highly skilled individuals with specialized knowledge in science and technology, which could be stifling its innovation potential. A lack of investment in education and research, coupled with an underdeveloped R&D sector, limits the country's ability to generate and implement innovative solutions. Improving the HRST index by investing in STEM education, skills development, and research infrastructure could significantly boost Romania's innovation capacity, helping it better compete in the global digital economy.

In summary, the strong relationship between HRST and innovation in both countries underlines the importance of a highly skilled workforce in driving technological advancements and fostering a vibrant innovation ecosystem. Estonia's success shows how a strong HRST index can be a major driver of innovation, while Romania's situation suggests that enhancing its HRST capacity is key to unlocking its innovation potential.

4. Conclusions

In conclusion, the analysis of the correlation between the Summary Innovation Index (SII), Network Readiness Index (NRI), and the Human Resources in Science and Technology (HRST) Index reveals a clear and significant relationship between digital infrastructure, human capital, and innovation performance across the EU countries. The findings show that countries with higher HRST and NRI scores tend to perform better in innovation, suggesting that investments in digital readiness and a skilled workforce are crucial factors for fostering innovation.

Romania and Estonia are at different poles in terms of innovation, digitalization and innovation. The analyses carried out reinforce the idea that a highly skilled workforce and a strong digital infrastructure led to better performance in innovation, emphasizing the need for strategic investments in education, research, and digitalization in Romania's case, in order to bridge the gap with leading innovators in the EU.

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USABILITY TESTING APPLIED TO GRAPHICAL AND VR APPLICATIONS IN AN ACADEMIC ENVIRONMENT

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Abstract

This article explores usability testing in the context of graphic and virtual reality (VR) applications in academic settings, emphasizing its importance for optimizing user experience. Usability testing assesses how easily and effectively users can interact with an application, being crucial for improving the design and functionality of digital products. The study compares user perceptions of the usability of graphical applications versus VR applications, using data collected through a questionnaire addressed to students. The results reveal significant differences in how users perceive ease of use, satisfaction, and efficiency between the two types of applications, highlighting the unique challenges and potential of VR applications in education.

Keywords: Usability testing, Virtual reality, User management systems, Technology-based improvement

JEL Classification: M15

1. Introduction

In recent years, graphics applications and virtual reality (VR) technology have become increasingly present in various fields, from entertainment and education to medicine and engineering. These technologies provide immersive interactive experiences, allowing users to explore virtual environments and interact with digital elements in a more intuitive and natural way. In the academic environment, graphics applications and VR are used for

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simulations, complex visualizations and hands-on training, contributing to more effective and engaging learning.

A key aspect in the development of these applications is usability testing, which evaluates how easily and efficiently users can interact with a system. Good usability ensures a smooth experience, reducing user frustration and optimizing the learning process or their productivity. Especially in the case of virtual reality, where interaction differs significantly from that with traditional applications, usability testing becomes crucial for identifying specific challenges and improving interface design. By comparing user perceptions of the usability of classic and VR graphics applications, valuable insights can be gained into how these technologies can be optimized to meet user needs.

As technology evolves, user expectations regarding the interface and functionality of digital applications are becoming increasingly high. A well-designed interface must be intuitive, efficient, and accessible, reducing the time required for learning and adaptation. Especially in the case of virtual reality, where users interact through gestures, movement, and specialized controllers, the experience can vary considerably depending on the interface design and the level of comfort offered. Therefore, usability testing plays a key role in optimizing the user experience, contributing to the development of more intuitive and efficient applications, both in academia and in other fields.

2. Graphics applications and VR applications

Graphics applications are software designed for creating, editing, and manipulating visual elements, such as images, illustrations, 3D models, or digital interfaces. They play an essential role in a wide range of fields, facilitating design, simulation, and visualization processes [1].

One of the main areas of application is the academic one, where tools like MATLAB, Blender or EndNote Visual are used for modeling, graphical visualization and data organization. MATLAB is recognized for its data processing and simulation capabilities, which are frequently used in engineering and exact sciences. On the other hand, Blender is an open-source solution for 3D modeling and animation, used in education and research for creating complex visual models [2].

In the medical field, graphics applications are essential for medical imaging analysis and anatomical simulations. 3D Slicer and Mimics are relevant examples of software that allow the visualization of anatomical structures and facilitate computer-assisted surgical interventions. These tools contribute significantly to the training of healthcare professionals and the accurate diagnosis of patients [3].

The entertainment industry also relies heavily on graphics applications for creating visual content. Unity, Adobe Photoshop, and Illustrator are among the most widely used programs for game development, image editing, and graphic design. Unity is a game engine used for developing interactive experiences, including virtual and augmented reality. Adobe

Photoshop and Illustrator are standards in graphics editing, being widely used by designers and visual artists [4].

Therefore, graphic applications represent an essential tool in multiple fields, contributing to the improvement of the creative process, research and education. The continuous evolution of these technologies allows the development of increasingly efficient solutions, adapted to the needs of users [5].

Virtual reality is a technology that creates a three-dimensional digital simulation of an environment, allowing the user to interact with this space in a more realistic way. This experience is made possible by equipment such as VR headsets, motion controllers, and sometimes even body sensors. The main goal of VR is immersion, that is, the feeling that the user is physically present in the virtual world, although they are in a real space [6].

One of the most valuable uses of virtual reality is in education. For example, students can explore the human body in detail in an interactive way or visit archaeological sites without leaving the classroom. VR is also used in professional training, such as training pilots, doctors, or workers in hazardous environments, by providing controlled and safe scenarios for practice [7].

In medicine, virtual reality is used for both therapeutic and educational purposes. VR exposure therapy is applied in the treatment of disorders such as phobia, PTSD or anxiety. Surgeons can also simulate interventions before performing them, improving the accuracy and safety of medical procedures [8].

Video games were among the first industries to adopt VR on a large scale. Through this technology, gamers have access to interactive experiences in which body movements influence the action in the game. In addition, VR is used in cinema, where viewers can experience interactive films, becoming part of the story.

In addition to education, health and entertainment, VR is also making its way into architecture, tourism, industrial design and psychology. For example, architects can present interactive 3D models of buildings to clients before they are built. In tourism, visitors can virtually explore tourist destinations around the world. These applications increase efficiency and creativity in design and decision-making processes.

3. Usability testing

Testing, in a broad sense, is the process of verifying whether a product, system, or service functions according to established requirements. This can occur in any field – from education, where testing means assessing knowledge, to the software industry, where testing involves identifying errors and validating the functionality of applications. Essentially, testing plays an essential role in ensuring quality, reducing risks, and increasing trust in the final product. It is performed either manually, by people who interact directly with the product, or automatically, with the help of software tools that simulate user behavior. Testing is not just about finding defects, but also about validating that the product meets the real needs of users, that it is safe, efficient, and easy to use. A good practice is for testing to be integrated throughout the development of a product, not just at the end, to prevent major problems before they become costly or difficult to fix.

Testing is of several types through functional testing, performance testing, security testing, compatibility testing, regression testing, automated testing and usability testing.

Functional testing checks whether the application or system does exactly what it is supposed to do, according to specifications. Buttons, forms, functions, etc. are tested. Performance testing evaluates how well the system behaves under road, whether it is fast, stable and efficient when used intensively or by many users. Security testing deals with identifying vulnerabilities, to prevent unauthorized access or data loss.

Compatibility testing checks whether the product works correctly on different devices, operating systems, browsers or versions. Regression testing ensures that recent changes (bug fixes or new features) have not broken things that worked well before. Automated testing is performed using programs or scripts that run tests automatically, streamlining the process.

Usability testing is the process of evaluating how easily and effectively a user can interact with a product, system, or digital interface. The goal of this testing is not only to identify design errors, but also to understand the behavior and expectations of real users. By observing how they navigate and perform specific tasks, designers and developers can adjust the product so that the experience is intuitive and enjoyable. Testing is usually done with a small group of users but strategically selected to cover different types of use.

This method is essential in the development of applications, websites or software, as it highlights accessibility and functionality issues early on that could affect end-user satisfaction. More than a technical check, usability testing involves empathy – that is, putting yourself in the user's shoes to understand what obstacles they might encounter. The results are then used to refine the product and create solutions that are better suited to the real needs of the target audience.

Usability testing begins with establishing clear objectives: what exactly you want to evaluate in terms of user experience. Typically, you choose a few essential tasks that users need to complete, such as filling out a form, finding information, or placing an order. It is important that the scenarios reflect real-world situations so that the test results are relevant. Before the test, participants are recruited who are representatives of the target audience, i.e. people who might be among the future users of the product.

Testing sessions take place in a controlled setting, either physical or online, where participants are asked to navigate the product and express their thoughts out loud. During this time, the team of observers notes what actions the users take, where they get confused, what mistakes they repeat, and how they react emotionally. It is important that the testers do not intervene or guide the participant but only observe. Tools that record the screen, mouse movements, or gaze (eye-tracking) can also be used for more detailed analysis.

After the tests are completed, the data is centralized and analyzed to extract useful conclusions. Patterns are looked for: frequently encountered problems, frustrations, or unintuitive steps. Based on this information, recommendations are made to improve the design or interaction flow. Usability testing is usually not done just once but is repeated after each major release of the product, to ensure the most fluid and satisfying experience for end users.

Usability testing brings multiple benefits, starting with the early identification of issues that would otherwise negatively affect the user experience. By directly observing how people interact with a product, the development team can better understand the real needs and expectations of users, not just what was assumed during the design phase. This understanding leads to concrete improvements to the interface, which makes the product more intuitive, more efficient, and more enjoyable to use. In addition, usability testing helps reduce costs in the long run, because problems solved early are much cheaper than those corrected after launch. At the same time, a well-optimized product from a usability perspective increases user satisfaction, loyalty, and even conversions, in the case of commercial sites.

4. The comparative approach – Research method

The main object of this research is to test the usability of graphic and virtual reality applications in the educational context, with a focus on improving the user experience. In an era where technology is becoming increasingly present in the learning process, it is essential to understand how these applications are perceived and used by pupils and students. Usability, defined as the ease with which a user can interact efficiently and satisfactorily with a system, is an essential criterion for the success of any interactive application. In the case of educational applications based on virtual reality, good usability can significantly contribute to active learning, user involvement and information retention. Thus, evaluating the user experience is not just a technical stage, but a crucial step for optimizing the educational process through innovative digital means.

To analyze students' perceptions of the usability of these applications, the questionnaire method was used - known in the specialized literature as the survey method. This research method is quantitative and involves the systematic collection of data through a standardized instrument, namely the questionnaire, which includes closed and/or open questions. The questionnaire is an effective method of obtaining information from a large number of respondents in a relatively short time, while also offering the possibility of analyzing the answers in an objective and comparable way.

The questionnaire method is frequently used in social sciences, including educational research, because it allows for direct insights from real users. In the present context, this tool provided a clear picture of how students interact with graphical and VR applications, what difficulties they encounter, what elements they find useful, and how they perceive the impact of these technologies on their own learning. Thus, the data obtained through this method contributes to a deeper understanding of how technology can be adapted and improved to better support the educational process.

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The other three sections focused on direct user experience. The second part tracked how the participant interacted with the traditional graphical application, while the third part analyzed the interaction in the VR environment. The questions were designed to capture the perceived level of difficulty, the degree of involvement, but also the preferences of the users. The last section, focused on learning and improvement, targeted how the participants felt they had progressed or adapted during the use of the applications. Together, these four components help us understand not only which application is more effective, but also why it is perceived that way and for whom, providing a complete picture of the user experience.

A total of 70 students were involved in this research, who voluntarily completed the questionnaire developed to evaluate the usability of graphic and virtual reality applications in the academic field. The diversity of those who responded is important because the perception of technology, the degree of familiarity with new digital tools and the way of interacting with them can vary depending on gender, which can influence the way the usability of the analyzed applications is perceived. The sample was made up of students from various study programs, most of them enrolled in fields with a technological or creative component, such as computer science, multimedia, graphic design or digital communication, fields in which the use of graphic and VR applications has an increasing practical relevance.

It is essential to mention that although all 70 students fully completed the general section of the questionnaire, only 44 of them also responded to the part dedicated to virtual reality applications. The other 26 respondents stated that they had no previous contact with such applications and, therefore, could not provide relevant feedback in this regard. This aspect highlights an important reality regarding the degree of penetration of VR technology in the academic environment – namely, that, despite its educational potential, virtual reality is not yet widely or uniformly used among students. The lack of direct experience with VR applications limits the ability to effectively assess their usability, but, at the same time, highlights the opportunity to expand access to these technologies for educational purposes. Thus, the results obtained from the 44 respondents who actually interacted with VR applications will be analyzed separately, in order to provide a clearer picture of their experience and perceptions in relation to the usability of these innovative tools. Below in Figure 1 we see the distribution of those who responded according to their gender.

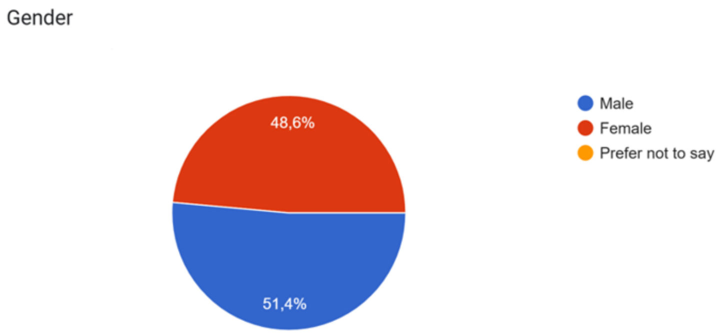

Figure 1. Gender of the respondents

The analysis of the demographic and academic profile of the respondents reveals that the majority of the students who participated in this research are in their third year of undergraduate studies. They are followed, in number, by fourth-year students and, to a lesser extent, by students enrolled in master's programs. This structure reflects an increased interest in the field of graphic applications and emerging technologies, especially among students in advanced stages of their academic career, when contact with complex technological applications becomes more frequent and more applied within the study programs.

Regarding the field of study, approximately 80% of respondents are enrolled in bachelor's or master's programs in Computer Science, while the remaining 20% come from the field of Electronics. This distribution confirms the increased relevance of the researched topic for students in technical and scientific fields, especially for those who are already familiar with advanced notions of programming, digital interfaces and interactive technologies, such as those used in virtual reality.

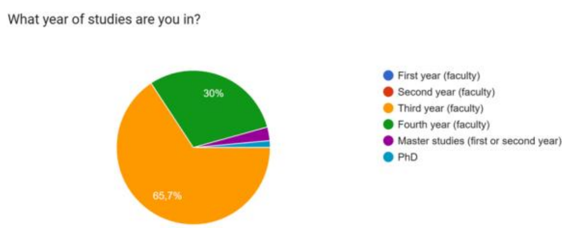

Figure 2. Year of study

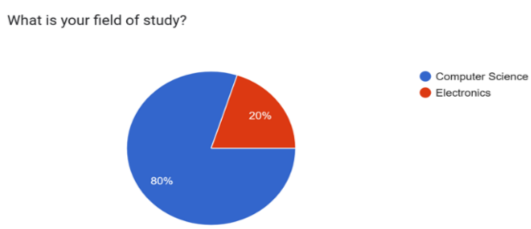

Figure 3. Field of study

The first aspect investigated in the questionnaire concerned the level of confidence that users feel in relation to the use of graphical and virtual reality applications. This dimension is essential in assessing usability, since the level of confidence directly influences the willingness of users to interact with the technology, as well as their ability to integrate it into academic or professional activities. According to the responses received, in the case of graphical applications, most respondents indicated a moderate level of confidence. This suggests that, although these types of applications are relatively familiar and frequently used in the academic environment, students still experience certain reservations or limitations in their advanced or efficient use. The average level of confidence can be attributed to the complexity of certain functionalities or insufficient technical training to fully exploit the potential of these tools.

In contrast, the results show that with regard to virtual reality applications, a higher proportion of students show an increased level of confidence in their use. Although the number of those who responded to this section was lower, the data obtained highlighted a positive attitude and a greater openness towards new immersive technologies. This high level of confidence can be explained both by the perception of novelty and attractiveness associated with VR applications, and by the fact that the interactive and intuitive experience offered by these applications contributes to a more accessible use, even in the absence of in-depth technical training. In this sense, virtual reality seems to offer a friendlier and more captivating environment for users, which can be a significant advantage in the process of integrating these technologies into educational activities.

Another important aspect analyzed in the research was the scope of applicability of graphic applications compared to that of virtual reality applications. According to the answers provided by the students, graphic applications are used mainly for academic purposes. They are integrated into learning activities, in the implementation of university projects and in the development of technical skills specific to the field of study. Familiarity with such applications, as well as their functional role in the educational process, contributes to this clear orientation towards the academic environment. In contrast, virtual reality applications are perceived and used, to a great extent, for recreational purposes, being associated with fun, free exploration and playful experiences. This contrast between the two categories of applications highlights a clear differentiation in the students' perception of the main purpose of each technology, but also an untapped potential of virtual reality in the educational space.

Regarding the equipment used to run and test these applications, the general trend identified among respondents is the orientation towards the use of personal computers. Most students consider this to be the most accessible and easy-to-use device for interacting with both graphical and VR applications. This can be explained by the high level of familiarity with the desktop environment, but also by the fact that most applications of this type are developed or optimized to be run on such platforms. Also, using a computer allows better control over the interfaces and functionalities of the applications, providing a more predictable and, implicitly, more comfortable experience for the user.

When it comes to virtual reality equipment, such as 3D glasses or VR headsets, the data collected indicates a clear differentiation between the two types of applications analyzed. Thus, in the case of graphic applications, the use of these equipment is practically non-existent. Students did not feel the need or did not have the opportunity to use such devices in the interaction with graphic applications, which can be justified by the two-dimensional or conventional nature of these applications. On the other hand, regarding virtual reality applications, 3D glasses are often used and, according to the responses, are perceived as easy to use. This positive perception indicates a good integration of these equipment into the VR experience, contributing to the creation of a natural and fluid interaction with the digital environment.

However, the same cannot be said for the use of VR headsets, which, although often used in testing virtual reality applications, are perceived as difficult to use. Many respondents reported challenges in handling this type of equipment, either due to weight, discomfort, or the complexity of the settings required for optimal operation. This difficulty in using VR headsets can represent a significant barrier to the widespread adoption of virtual reality in educational settings, where efficiency and accessibility are essential factors.

In a related vein, the level of difficulty experienced by users in navigating VR applications is perceived as higher than in the case of graphical applications. This can be attributed to the additional equipment required for using VR, which involves not only familiarizing oneself with the application interface but also adapting to a new way of sensory and spatial interaction. In contrast, graphical applications offer a more linear and predictable user experience, which contributes to easier navigation and a shorter learning curve. This difference highlights the need to improve the interfaces and equipment used in virtual reality, in order to increase the accessibility and efficiency of these technologies, especially in an educational context.

One of the key aspects investigated in the research was the identification of sources of difficulty in using graphics and virtual reality applications, as well as the main problems encountered by users. Regarding graphics applications, respondents frequently indicated the lack of knowledge necessary for the effective use of these tools. This difficulty is aggravated by an incomplete understanding of the requirements or tasks, which affects the ability of students to use the applications autonomously. Also, the complexity of the interface is a major source of frustration: the existence of a large number of functions and menus, the lack of an intuitive interface structure (UI/UX), as well as the absence of clear visual elements to guide the user contribute to the decrease in the level of comfort in use. In addition, many students highlighted the lack of dedicated practice hours within the study programs, which considerably limits the chance to become familiar with these applications in a controlled teaching environment.

Regarding virtual reality applications, the difficulties encountered are both technical and practical. Most often, respondents mentioned the lack of access to the necessary equipment – such as VR headsets or 3D glasses – as the main barrier to the effective use of VR applications. Even in cases where the equipment is available, other sources of discomfort include the need for constant movement in space, which can become tiring, and an inadequate placement of graphical interface elements in the user's field of view, which significantly complicates interaction. Similar to the situation with graphical applications, in the case of VR, respondents also report the lack of well-structured practice sessions within the university, thus suggesting an increased need to integrate these technologies into the curriculum to reduce uncertainties and technical barriers.

In addition to general difficulties, participants reported a number of recurring technical issues encountered during testing of both types of applications. These include frequent application crashes, difficult movement of interface elements, and errors when using multiple monitors simultaneously. Application construction errors – such as bugs or coding deficiencies – were also reported, which are difficult to identify and fix by the average user. A notable aspect is the difficulty of interaction between the different elements of the application, especially in the case of those developed in three-dimensional environments, where synchronization and coordination of components is a major challenge. These technical issues, combined with equipment limitations and lack of practical training, outline a complex picture of the obstacles that must be overcome for an effective and accessible use of graphics and VR technologies in the educational environment.

A relevant factor in the analysis of the perceived difficulty in using graphical and virtual reality applications is the level of programming knowledge of the participants. According to the data obtained, a significant number of students – more precisely, 65 out of 70 – declare that they have knowledge in programming graphical applications. This suggests that theoretical and practical familiarity with the development of graphical applications directly contributes to a lower level of difficulty in using them. On the other hand, only 8 students mentioned that they have programming knowledge specific to virtual reality applications, which indicates a much narrower area of competence in this field. This significant disproportion can explain, to a large extent, the differences in the perception of difficulty and in the level of confidence in using the two types of technologies.

At the same time, a recurring theme in the students' responses is the lack of sufficient hours of practice within university study programs, especially regarding virtual reality applications. Many participants consider that the current training offered by the faculty is insufficient to facilitate a thorough understanding and effective use of these technologies. In the absence of constant and guided exposure in the laboratories, students face difficulties both in using the applications and in learning how to develop them. Thus, the data highlights a clear need for curricular adaptation, which would include a greater number of hours dedicated to emerging interactive technologies, in order to better prepare students for the current demands of the IT and engineering fields.

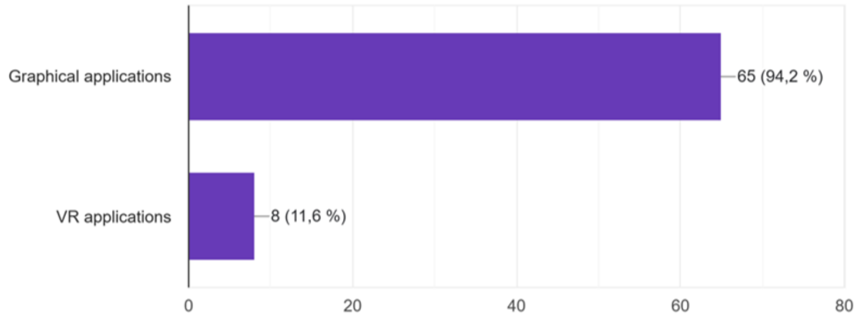

Figure 4. Programming knowledge field

The conclusions of this study highlight a clear preference of students for interacting with graphical applications, to the detriment of those based on virtual reality. This orientation is significantly determined by the degree of familiarity that participants have with graphical applications, acquired through repeated exposures within academic or extracurricular activities. Familiarity with a certain type of technology contributes to reducing the perceived level of difficulty, increases user confidence and favors a positive attitude towards exploration and deepening. In contrast, virtual reality applications, less present in the educational path of students, are perceived as being more difficult to use, both due to lack of experience and technical barriers associated with the use of specific equipment.

At the same time, the research results highlight a structural problem of current academic training in the field of interactive technologies: the insufficiency of practical hours and didactic content focused on new emerging technologies, especially those related to virtual reality. Many students expressed their desire to delve deeper into more advanced concepts, especially regarding the development and use of VR applications. This openness indicates an intrinsic motivation for learning, but also a clear opportunity for higher education institutions to adapt their study programs to reflect the rapid dynamics of the technology industry. In this context, expanding practical training and including modules dedicated to virtual reality could significantly contribute to the development of relevant and up-to-date skills among students, facilitating a more natural and efficient integration of these technologies into the educational process.

5. Conclusions

Usability testing is proving to be a fundamental tool in the applied research process, especially in the context of analyzing user interaction with graphical and virtual reality applications. This method allows not only the collection of objective data on user behaviors and preferences but also provides an in-depth understanding of the difficulties encountered in the actual use of the applications. In this case, the use of a questionnaire as the main research tool facilitated the obtaining of direct and specific feedback, contributing to the identification of relevant trends in the way students perceive and interact with the two types of technologies analyzed.

The survey clearly highlighted key aspects related to the user experience (UX), as well as the efficiency and structure of the user interface (UI). In particular, the responses provided by the participants highlighted the need for significant improvements in the design of VR application interfaces. Users mentioned difficulties in navigation, inadequate positioning of UI elements in three-dimensional space, as well as a lack of coherence in relation to their functional expectations. These observations indicate that, unlike traditional graphical applications – which benefit from years of interface refinement and established design patterns – VR applications are still in a process of maturation in terms of ergonomics and intuitiveness of interaction. Thus, usability testing becomes not only an evaluation tool, but also an essential stage in the iterative process of developing interactive applications.

In addition, the study's conclusions provide valuable directions for improving the educational framework in which these applications are used. The information obtained can contribute to the development of more effective educational methods and applications, capable of better responding to the real needs of students. Integrating usability testing results into the curriculum design process could lead to better adaptation of educational content, by optimizing the interfaces of applications used in education and by increasing accessibility to emerging technologies. In this sense, usability testing is not only a technical tool, but becomes a link between technology, design and pedagogy, supporting innovation in education and facilitating a more efficient and user-centered learning experience.

Given the results obtained, future studies could explore in depth the technical and pedagogical aspects of the use of VR applications in education, as well as how the progressive integration of these technologies influences the learning process. It would be useful to conduct longitudinal research that would track the evolution of students' skills over time, depending on exposure to and interaction with graphical versus immersive environments. Also, controlled experiments can be developed to compare the impact of different interface models and educational scenarios on the understanding and retention of information. Another valuable direction would be to investigate how specific training on VR equipment, supported by an appropriate curriculum, can reduce perceived difficulties and increase users' confidence in these technologies. In general, expanding research in this area can significantly contribute to optimizing the design process of interactive educational applications and adapting them more effectively to the current needs of the digital generation.

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QUANTITATIVE AND QUALITATIVE DIGITAL ANALYSIS OF EMOTIONAL AND MOTOR INTELLIGENCE BY GENDER DIFFERENCES

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Abstract

This study investigates gender differences in emotional intelligence and sensory-motor coordination through a comprehensive digital analysis. Utilizing a sample of 60 participants (30 males, 30 females), various assessments were conducted, including a Digital Tachistoscope, Hand Coordination Tester, and an Emotional Intelligence Test adapted by Mihaela Roco. The results were analyzed using SPSS to perform statistical tests such as the T-test and Mann Whitney test. Key findings indicate significant gender-specific differences in motor coordination errors, while emotional intelligence levels correlated with sensory-motor performance differently across genders. This research highlights the importance of considering gender in evaluating cognitive and emotional skills, providing valuable insights for practical applications such as employment screening. The study also identifies areas for further research to better understand these complex interactions. [2]

Keywords: digital analyses, emotional intelligence, gender – specific performance

JEL Classification: D91, J16, M53

1. Introduction

1.1. Background: Importance of Studying Emotional Intelligence (EI) and Sensory-Motor Coordination

Emotional intelligence (EI) and sensory-motor coordination are critical components of human cognition and behavior, playing significant roles in personal and professional success. EI, which encompasses the ability to understand, manage, and utilize emotions effectively, is essential for navigating social interactions and maintaining mental well-being. High levels of EI have been linked to better stress management, improved relationships, and enhanced decision-making skills. Similarly, sensory-motor coordination,

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which involves the integration of sensory input and motor responses, is vital for performing everyday tasks efficiently and safely. This coordination is crucial in various domains, including sports, driving, and any activities requiring precise manual dexterity. Understanding the interplay between these abilities and how they vary by gender can provide valuable insights into tailored interventions and assessments, ultimately fostering environments that support individual strengths and address specific challenges. [1] [2]

1.2. Theoretical Framework:

Attention is a complex function involving the orientation, focus, and maintenance of consciousness on a specific object, question, or task. Psychologists have long debated whether attention should be classified as a psychological process, state, or condition that facilitates or disrupts other psychological phenomena. Ribot's view of attention as a "motor act" highlights its association with various movements (vasomotor, respiratory, muscular contractions, mimicry) that sustain and intensify attention. However, he is critiqued for overlooking the psychological specificity of attention by reducing it to mere motor activities. Other theories, such as Reuchlin's, suggest that attention operates as a general alertness reaction that prioritizes relevant information while marginalizing or rejecting non-pertinent stimuli.

Emotional intelligence (EI) theories, notably those of Daniel Goleman and Reuven Bar-On, frame EI as a multifaceted construct encompassing self-awareness, self-regulation, motivation, empathy, and social skills. Goleman's model emphasizes EI's role in achieving personal and professional success, while Bar-On's model integrates emotional and social functioning. These theories propose that individuals with high EI are better equipped to manage stress, understand and navigate social interactions, and make effective decisions. [1] [3] [4]

Motor coordination theories, such as the dynamical systems theory, describe the development and refinement of motor skills through the interaction of various body systems and environmental factors. These theories stress the importance of practice and adaptability in achieving proficient motor control. [5]

Perception, closely tied to attention, involves the cognitive processes that prepare and orient individuals to perceive specific stimuli selectively. Theories of perception, including Gestalt principles, emphasize how sensory information is organized and interpreted, influencing the accuracy and efficiency of responses to environmental cues. The selective attention theory also plays a role here, as it helps explain how individuals can focus on certain stimuli while ignoring others, which is crucial for tasks requiring high levels of concentration and precision. [6] [7]

Combining these theoretical perspectives provides a comprehensive framework for understanding the interaction between cognitive processes, emotional regulation, and motor skills, and how these interactions differ by gender. This integrated approach informs the study's hypotheses and guides the interpretation of the results, offering a nuanced understanding of the complex relationships between attention, perception, EI, and motor coordination.

1.3. Focus on Gender Differences: Why Gender Differences are Significant in This Context

Understanding gender differences in emotional intelligence (EI) and sensory-motor coordination is crucial for several reasons. First, these differences can provide insights into how males and females process and respond to emotional and sensory stimuli, which has implications for various domains such as education, workplace dynamics, and mental health interventions. For instance, higher EI in females may enhance their ability to navigate social interactions and manage stress, while differences in motor coordination could impact performance in tasks requiring fine motor skills. [2]

Second, recognizing these differences can lead to the development of gender-sensitive approaches in training and assessment. Tailoring educational programs and therapeutic interventions to account for these variations can improve outcomes by addressing specific strengths and weaknesses associated with each gender. For example, understanding that males might perform differently under stress or distraction can inform the design of environments that optimize their performance and learning.

Third, gender differences in cognitive and emotional processes are linked to broader societal roles and expectations. By examining these differences scientifically, we can challenge stereotypes and promote a more nuanced understanding of gender capabilities. This, in turn, can contribute to more equitable opportunities and treatment in various spheres, from hiring practices to academic support systems.

Lastly, exploring gender differences helps in identifying biological and environmental factors that contribute to cognitive and emotional development. Hormonal influences, socialization patterns, and cultural expectations all play a role in shaping these differences. Understanding these underlying factors can inform policies and practices that support healthy development and functioning for all individuals, regardless of gender.

In this study, we aim to explore these gender differences through quantitative and qualitative analysis, providing a detailed examination of how males and females differ in their emotional intelligence and motor coordination. This focus not only enhances our theoretical understanding but also has practical implications for improving educational, professional, and therapeutic practices.

1.4. Research Objectives:

The primary objective of this study is to observe and analyze whether there are significant gender differences in perception, emotional intelligence (EI), and sensory-motor coordination. By utilizing a comprehensive digital analysis approach, this research aims to provide a deeper understanding of how males and females differ in these cognitive and emotional domains. [2]

Significance:

I. **Enhanced Understanding of Cognitive and Emotional Processes**: This study will contribute to the existing body of knowledge by identifying specific areas where males and females exhibit different levels of EI and sensory-motor coordination. Understanding these differences is essential for tailoring educational and therapeutic strategies that can better support individuals based on their unique needs. [2]

II. **Practical Applications in Various Fields**: The findings of this research have practical implications for several fields, including education, workplace training, and clinical psychology. For instance, identifying gender-specific strengths and weaknesses can inform the development of targeted training programs and interventions that improve performance and well-being.

III. **Challenging Stereotypes and Promoting Equity**: By providing empirical evidence of gender differences in cognitive and emotional abilities, this study can help challenge societal stereotypes and promote a more nuanced understanding of gender capabilities. This can lead to more equitable practices in hiring, education, and support systems.

IV. **Informing Future Research**: The results of this study will lay the groundwork for future research to further explore the underlying causes of these gender differences, including biological, social, and environmental factors. This ongoing research is vital for developing comprehensive models of cognitive and emotional development.

Overall, the study seeks to provide valuable insights into the distinct ways in which males and females perceive, process, and respond to emotional and sensory stimuli, ultimately contributing to more effective and equitable practices in various domains.

1.5. Hypotheses: the Hypotheses Being Tested in the Study

This study tests three main hypotheses to explore gender differences in emotional intelligence (EI) and sensory-motor coordination: [2]

I. **Hypothesis 1**: Males will demonstrate superior motor coordination compared to females, evidenced by shorter track time, fewer deviations from the track, and fewer errors on the inner and outer bands. This will be assessed using the Hand Coordination Tester (HCT) and analyzed with a T-test for two independent variables.

II. **Hypothesis 2**: Males will perform better under both perturbation and non-perturbation conditions compared to females. This hypothesis will be evaluated using the Mann Whitney test to compare the performance of males and females under different testing conditions.

III. **Hypothesis 3**: There will be differing intensities of correlation between anxiety levels and attention and concentration in males and females. This hypothesis will be tested by evaluating the results of the emotional intelligence test and correlating these with the participants' performance on sensory-motor tasks.

These hypotheses aim to elucidate the distinct ways in which gender influences cognitive and emotional processes, providing a comprehensive understanding of the differences in EI and sensory-motor coordination between males and females. [2]

2. Literature Review

2.1. Attention and Perception:

Attention is defined as a function or mechanism that orients, focuses, and sustains consciousness on an object, question, or task. The debate among psychologists on whether attention is a psychological process, state, or condition reflects its complex nature. Early theories, such as those by Ribot, reduced attention to a "motor act," emphasizing its association with physical movements like muscle contractions and respiratory changes. These movements were thought to sustain and intensify attention, but this perspective overlooked the psychological specificity of attention.

Attention involves two primary neurofunctional states: wakefulness and vigilance. Wakefulness is characterized by diffuse activation of the cerebral cortex, while vigilance involves exploring the environment and anticipating undefined stimuli. Attention's dual role as a filtering and activating mechanism underpins its importance in cognitive functioning.

Research has shown that there are notable gender differences in attention and perception. Females often exhibit superior performance in tasks requiring sustained attention and fine motor coordination, possibly due to higher baseline levels of cortical arousal. This heightened arousal could enhance their ability to maintain focus on repetitive or detailed tasks. Conversely, males have been observed to excel in tasks requiring spatial awareness and rapid shifts in attention, which might be attributed to differences in neurobiological pathways related to spatial processing and motor control.

Reuchlin's theory posits that attention operates as a general alertness reaction, prioritizing relevant information while marginalizing or rejecting non-pertinent stimuli. This selective attention mechanism is crucial for effective sensory-motor coordination and cognitive processing. The ability to filter and focus on pertinent stimuli while ignoring distractions is a key aspect of perceptual efficiency and is influenced by both biological and environmental factors. [2]

Further studies have explored how hormonal differences between genders impact attention and perception. For example, estrogen has been found to modulate synaptic plasticity and cognitive function, which may contribute to the observed differences in attention and memory tasks between males and females. Additionally, testosterone levels have been linked to enhanced spatial abilities and attentional control, which are areas where males often outperform females. [8] [9]

In summary, the literature indicates that gender differences in attention and perception are influenced by a combination of neurobiological, hormonal, and environmental factors. These differences have significant implications for understanding how males and females process information and respond to their environments. This understanding is critical for developing gender-sensitive approaches in educational and occupational settings, ensuring that both males and females can optimize their cognitive and perceptual strengths.

2.2. Emotional Intelligence:

Emotional Intelligence (EI) refers to the ability to recognize, understand, manage, and utilize emotions effectively in oneself and others. The concept of EI was popularized by Daniel Goleman, who identified five key components: self-awareness, self-regulation, motivation, empathy, and social skills. These components are crucial for personal and professional success, as they influence how individuals navigate social interactions, manage stress, and make decisions. [3]

Research has consistently shown that there are gender differences in EI, with females generally scoring higher on measures of emotional awareness and empathy, while males often exhibit stronger self-regulation and stress management abilities. These differences can be attributed to both biological and social factors. For instance, studies suggest that females may have a biological predisposition for greater emotional sensitivity and expressiveness, which is further reinforced by socialization processes that encourage emotional attunement and empathy in women.

Bar-On's model of EI, which includes intrapersonal skills, interpersonal skills, adaptability, stress management, and general mood, also highlights these gender differences. Females tend to score higher on interpersonal skills and empathy, which align with societal expectations for women to be nurturing and emotionally supportive. On the other hand, males often excel in stress management and problem-solving, which are skills valued in competitive and high-stress environments.

Hormonal influences play a significant role in these gender differences. Estrogen, which is more prevalent in females, has been shown to enhance emotional processing and social cognition. This hormonal influence may contribute to females' superior performance in tasks requiring emotional sensitivity and empathy. Conversely, testosterone, more common in males, has been linked to greater assertiveness and risk-taking behavior, which can affect stress management and self-regulation.

Socialization processes also contribute to gender differences in EI. From a young age, boys and girls are often encouraged to develop different emotional skills. Girls are typically socialized to be more attuned to the emotions of others and to express their own emotions more openly. Boys, however, are often encouraged to be more independent and to manage their emotions privately, which can enhance their self-regulation skills but may limit their emotional awareness and empathy.

Moreover, cultural norms and expectations shape how males and females develop and express their EI. In many cultures, emotional expressiveness and empathy are considered more acceptable for females, while emotional control and resilience are valued traits in males. These cultural norms can influence the development of EI components, reinforcing certain skills while inhibiting others based on gender.

In summary, the literature on EI reveals clear gender differences in its components, influenced by a complex interplay of biological, hormonal, and social factors. Understanding these differences is essential for developing tailored interventions and training programs that can enhance EI in both males and females, thereby promoting better personal and professional outcomes. This knowledge can also inform practices in educational and workplace settings, ensuring that strategies to develop EI are sensitive to the distinct needs and strengths of each gender.

2.3. Motor Coordination:

Motor coordination involves the integration of sensory input and motor responses to execute precise movements. This ability is crucial for various activities, ranging from daily tasks to complex athletic performances. Research on sensory-motor coordination has identified significant gender differences, which are often attributed to biological, hormonal, and developmental factors. [2]

Early studies on motor coordination suggest that males typically outperform females in tasks requiring gross motor skills and spatial awareness. These abilities include activities such as navigating complex environments, throwing, and jumping. The superior performance in these areas is often linked to higher levels of testosterone, which is associated with muscle mass and strength, as well as enhanced spatial processing capabilities.

Conversely, females tend to excel in tasks that require fine motor skills and precise hand-eye coordination. Activities such as threading a needle, writing, and tasks involving delicate manual dexterity often see females outperforming males. This advantage is thought to be related to higher baseline levels of estrogen, which influences fine motor control and coordination. Additionally, the socialization process that encourages females to engage in activities requiring precision from an early age further enhances these skills.

Hormonal influences play a critical role in these gender differences in motor coordination. Testosterone enhances muscle development and spatial ability, contributing to males' proficiency in gross motor tasks. Estrogen, on the other hand, is linked to fine motor control and coordination, supporting females' superior performance in tasks requiring precision and detail.

Developmental factors also contribute to gender differences in motor coordination. During childhood, boys and girls engage in different types of play and physical activities, which shape their motor skills. Boys often participate in more physically demanding activities that develop strength and spatial skills, while girls are encouraged to engage in activities that promote fine motor skills and coordination.

Neurobiological studies provide further insights into these differences. Brain imaging research has shown that males and females use different neural pathways to perform motor tasks. For example, males tend to rely more on regions associated with spatial processing and motor planning, whereas females engage areas related to fine motor control and sensory integration. These differences in brain activity support the observed gender-specific patterns in motor coordination.

Furthermore, societal expectations and cultural norms influence the development and expression of motor skills. In many cultures, boys are encouraged to participate in sports and physical activities, which enhance their gross motor skills and spatial abilities. Girls, however, are often directed towards activities that require fine motor skills and attention to detail, reinforcing their proficiency in these areas.

In summary, the literature on sensory-motor coordination highlights significant gender differences, influenced by a combination of hormonal, developmental, and neurobiological factors. These differences have practical implications for education, sports training, and occupational therapy, where understanding the distinct motor capabilities of males and females can inform more effective and tailored interventions. Recognizing these gender-specific aspects of motor coordination can help optimize performance and support the development of motor skills across different contexts. [2]

2.4. Gaps in Research:

While existing literature has extensively explored the domains of attention, perception, emotional intelligence (EI), and motor coordination, several gaps remain that this study aims to address:

I. **Integrated Analysis of EI and Motor Coordination**:

- Most studies tend to examine emotional intelligence and motor coordination separately, without considering their potential interplay. This study aims to fill this gap by providing an integrated analysis of how EI and motor coordination are interrelated and how these relationships differ by gender. Understanding these interactions can offer deeper insights into the holistic functioning of cognitive and emotional processes.

II. **Comprehensive Gender Comparison Using Digital Tools**:

- Previous research often relies on traditional assessment methods, which may lack the precision and objectivity of digital tools. This study employs advanced digital instruments such as the Digital Tachistoscope and Hand Coordination Tester (HCT) to provide more accurate and quantifiable measures of sensory-motor coordination and cognitive performance. The use of digital tools allows for a more nuanced comparison of gender differences. [2]

III. **Exploration of Anxiety's Role in Performance**:

- While anxiety is known to impact cognitive and motor performance, its differential effects on males and females have not been thoroughly explored. This study addresses this gap by examining how anxiety levels correlate with attention, perception, and motor coordination in both genders. By evaluating these correlations, the research seeks to understand the intensity and nature of anxiety's impact across genders.

IV. **Longitudinal and Contextual Factors**:

- Many studies provide a snapshot of cognitive and motor performance at a single point in time, often overlooking the influence of longitudinal and contextual factors such as age, stress levels, and environmental conditions. This research incorporates these variables to offer a more comprehensive understanding of how they affect gender differences in EI and motor coordination over time and across different contexts.

V. **Practical Implications and Applications**:

- Although theoretical frameworks and empirical data on EI and motor coordination are well-documented, there is a lack of research on the practical applications of these findings in real-world settings. This study aims to bridge this gap by discussing the implications of gender differences in EI and motor coordination for educational practices, workplace training, and clinical interventions. The goal is to provide actionable insights that can be used to develop gender-sensitive programs and policies.

VI. **Cultural and Societal Influences**:

- The majority of existing studies are conducted within specific cultural contexts, which may limit the generalizability of their findings. This research seeks to explore how cultural and societal influences shape gender differences in cognitive and emotional processes. By including a diverse sample and considering cultural variables, the study aims to provide a more global perspective on these differences.

By addressing these gaps, this study contributes to a more nuanced and comprehensive understanding of gender differences in emotional intelligence and sensory-motor coordination. The findings have the potential to inform the development of targeted interventions and support strategies that cater to the specific needs and strengths of both males and females. [2]

3. Methodology

3.1. Sample Description: Details About the 60 Participants (30 Males, 30 Females)

This study's sample consisted of 60 participants, equally divided by gender, with 30 males and 30 females. The participants were selected using random sampling methods to ensure a representative and unbiased sample. The age range of the participants was between 19 and 55 years, encompassing a broad spectrum of young adults to middle-aged individuals, which allows for the examination of potential age-related effects on emotional intelligence (EI) and sensory-motor coordination. [2]

All participants were students in Bucharest, ensuring a certain level of homogeneity in terms of educational background. The inclusion criteria required participants to have no known neurological or psychiatric conditions that could affect their cognitive or motor performance, ensuring that the results were not confounded by such variables.

Participants were recruited through university-wide announcements and volunteered for the study. Before the commencement of the study, each participant provided informed consent, acknowledging their understanding of the study's purpose, procedures, and any potential risks involved. They were assured of the confidentiality of their data and their right to withdraw from the study at any point without any consequences.

The sample was further divided into three groups based on the testing modalities:

a) **Emotional Intelligence Test Group**: 30 participants (15 males, 15 females) who completed the emotional intelligence test.

b) **Digital Tachistoscope Group**: 30 participants (15 males, 15 females) who were tested using the digital tachistoscope to assess short-term memory and attention.

c) **Hand Coordination Tester (HCT) Group**: 30 participants (15 males, 15 females) who were assessed using the HCT for manual coordination tasks.

By maintaining an equal gender distribution and ensuring a diverse age range, the study aimed to capture a comprehensive picture of gender differences in EI and sensory-motor coordination across different stages of adulthood. This structured sample description ensures that the findings can be generalized to a broader population, providing valuable insights into the interplay between gender, emotional intelligence, and motor coordination. [2]

3.2. Instruments Used

a. Digital Tachistoscope: Purpose and Functionality

The Digital Tachistoscope is an advanced instrument designed to test short-term memory and attention through controlled visual stimuli presentation. This device is equipped with a microprocessor-controlled system that ensures precise timing and presentation of visual stimuli, making it an ideal tool for psychological and cognitive research.

Purpose:

- To assess short-term memory, attention, and perceptual processing abilities.
- To evaluate the speed and accuracy with which participants can recognize and recall visual stimuli.

Functionality:

- The tachistoscope presents visual stimuli for a brief and controlled duration, typically ranging from milliseconds to a few seconds.
- Participants are required to identify and recall the presented stimuli after its brief exposure.

- The device includes a source of stimuli, response mechanisms (buttons for participant input), and controls for adjusting presentation modes.
- Results are displayed on an electronic screen, providing immediate feedback and data for further analysis.
- The tachistoscope can be easily transported and set up in various locations, ensuring versatility and convenience in different research settings.

b. Hand Coordination Tester (HCT): Description and Usage

The Hand Coordination Tester (HCT) is a specialized instrument used to measure manual dexterity, coordination, and precision. This device is particularly useful for assessing sensory-motor integration and the ability to perform tasks that require fine motor skills.

Description:

- The HCT consists of a main unit with a track on which a small ball is moved using a handle.
- The track features two routes that require participants to navigate the ball with precision.
- The device records the time taken to complete the track, the number of deviations from the track, and the severity of these deviations.

Usage:

- Participants are instructed to move the ball along the designated track as quickly and accurately as possible.
- The task involves maintaining the ball on the track while avoiding deviations, which measures their hand-eye coordination and motor control.
- The HCT provides detailed measurements, including total track time, number of fine and gross deviations, and overall performance accuracy.
- This data is then used to compare motor coordination abilities between different participant groups.

c. Emotional Intelligence Test: Adaptation by Mihaela Roco

The Emotional Intelligence Test used in this study is an adaptation by Mihaela Roco, based on the models proposed by Bar-On and Daniel Goleman. This test is designed to assess various dimensions of emotional intelligence, including self-awareness, self-regulation, motivation, empathy, and social skills. [3]

Description:

- The test comprises 10 scenarios that present different emotional and social situations.
- Participants are required to imagine themselves in these scenarios and choose one of four possible responses that best describes how they would react.

Purpose:

- To evaluate participants' ability to recognize and manage their own emotions.
- To assess their capacity to understand and influence the emotions of others.
- To measure intrinsic motivation and the ability to maintain positive social interactions.

Adaptation by Mihaela Roco:

- Roco's adaptation ensures that the test is culturally relevant and appropriate for the Romanian population.
- The scenarios and response options are designed to reflect common social and emotional situations encountered in daily life.

Usage:

- Participants complete the test by selecting their responses to each scenario.
- The responses are scored to provide an overall EI score, as well as sub-scores for each dimension of emotional intelligence.
- These scores are used to analyze differences in EI between male and female participants and to explore the relationship between EI and sensory-motor coordination. [2]

By utilizing these three sophisticated instruments, the study aims to provide a comprehensive analysis of gender differences in emotional intelligence and sensory-motor coordination, offering valuable insights into these complex cognitive and emotional processes. [2]

3.3. Data Collection Procedures: Description of the Testing Conditions and Process

The data collection process for this study was meticulously designed to ensure accuracy, consistency, and reliability of the results. The testing was conducted in the Laboratory of Experimental Psychology at Hyperion University, under controlled conditions to minimize external influences and variability. The procedures were as follows:

I. **Preparation**:

- Participants were briefed about the study's objectives, procedures, and the importance of their involvement.
- Informed consent was obtained from each participant, ensuring they understood their rights and the confidentiality of their data.
- Participants were randomly assigned to one of the three testing groups: Emotional Intelligence Test, Digital Tachistoscope, or Hand Coordination Tester (HCT).

II. **Testing Conditions**:

- The laboratory environment was standardized for all sessions, maintaining consistent levels of ambient noise, lighting, and temperature.
- Testing was conducted between 9:00 AM and 2:00 PM over six consecutive days to control for potential diurnal variations in cognitive and motor performance.
- Background noise was kept to a minimum to ensure participants could focus entirely on the tasks.

III. **Testing Process**:

- **Digital Tachistoscope Group**:
- Participants were seated comfortably in front of the tachistoscope.
- They were given instructions on how to respond to the visual stimuli presented on the screen.
- Each participant underwent multiple trials, with varying durations of stimulus exposure.
- After each stimulus presentation, participants responded by pressing the appropriate buttons to indicate their recognition and recall of the stimuli.
- Data on response time and accuracy were recorded automatically by the device.
- **Hand Coordination Tester (HCT) Group**:
- Participants were briefed on the task of navigating the ball along the designated track on the HCT.
- They were instructed to complete the task as quickly and accurately as possible, minimizing deviations from the track.
- Each participant performed multiple trials to ensure consistency and reliability of the measurements.

- The device recorded the total track time, number of fine and gross deviations, and overall performance accuracy.
- **Emotional Intelligence Test Group**:
- Participants were provided with a printed version of the Emotional Intelligence Test adapted by Mihaela Roco.
- They were asked to carefully read each scenario and select the response that best described how they would react.
- Participants completed the test individually in a quiet room to ensure they could reflect on each scenario without distractions.
- The responses were collected and scored to determine overall EI scores and sub-scores for each EI dimension.

IV. **Data Recording and Management**:

- All data from the tachistoscope and HCT were directly recorded into a computer system for immediate analysis.
- Emotional Intelligence Test responses were manually entered into a database for scoring and subsequent statistical analysis.
- The data were anonymized to protect participant confidentiality and were stored securely to prevent unauthorized access.

V. **Quality Control**:

- The research team conducted regular checks to ensure the equipment was functioning correctly and the data collection process adhered to the established protocols.
- Any anomalies or issues encountered during testing were documented and addressed promptly to maintain the integrity of the data.

By adhering to these standardized data collection procedures, the study ensured that the data obtained were reliable and valid, providing a robust foundation for subsequent analysis and interpretation of gender differences in emotional intelligence and sensory-motor coordination. [2]

3.4. Variables

a. Independent Variables: Group, Gender, and Age

- **Group**: Participants were divided into three groups based on the type of test they underwent: Emotional Intelligence Test group, Digital Tachistoscope group, and Hand Coordination Tester (HCT) group. Each group was further subdivided equally by gender.
- **Gender**: This variable was categorized as male and female, allowing the study to analyze differences in emotional intelligence and sensory-motor coordination between genders. [2]
- **Age**: The participants' ages ranged from 19 to 55 years. Age was recorded as a continuous variable to examine its potential influence on the study outcomes and to account for any age-related variations in cognitive and motor performance.

b. Dependent Variables: Track Time, Track Deviation Time, Inner Band Error, Outer Band Error

- **Track Time**: This variable refers to the total time taken by participants to complete the designated track on the Hand Coordination Tester (HCT). It measures the efficiency of motor coordination and control. Shorter track times indicate better performance and higher motor coordination efficiency.
- **Track Deviation Time**: This variable measures the total time spent by participants deviating from the designated track during the HCT task. It indicates the participant's ability to maintain precision and control while navigating the track. Lower deviation times suggest better fine motor control and hand-eye coordination.
- **Inner Band Error**: This variable records the number of errors made within the inner band of the track on the HCT. It reflects the participant's precision in following the most confined path of the track. Fewer inner band errors denote higher accuracy and motor control.
- **Outer Band Error**: This variable captures the number of errors made within the outer band of the track on the HCT. It provides a broader measure of the participant's ability to stay within the overall boundaries of the track. Like inner band errors, fewer outer band errors indicate better coordination and precision.

These dependent variables provide a comprehensive assessment of sensory-motor coordination by evaluating both the speed and accuracy of participants' performance on the HCT. Together with the independent variables of group, gender, and age, they enable a detailed analysis of the differences in emotional intelligence and motor coordination across different demographic segments. [2]

3.5. Statistical Analysis

a. Description of the Statistical Methods Used (T-test, Mann Whitney Test)

To analyze the data collected in this study, several statistical methods were employed to test the hypotheses and draw meaningful conclusions about gender differences in emotional intelligence (EI) and sensory-motor coordination. [2]

T-test for Independent Samples:

- The T-test was used to compare the means of two independent groups (males and females) on various dependent variables, such as track time, track deviation time, inner band error, and outer band error.
- This test helps determine whether there are statistically significant differences between the two groups in terms of their motor coordination performance.
- The T-test is appropriate when the data are normally distributed and variances between groups are equal.

Mann Whitney U Test:

- The Mann Whitney U Test is a non-parametric test used to compare differences between two independent groups when the assumption of normality is not met.
- This test was used to evaluate differences in performance under perturbation and non-perturbation conditions for both males and females.
- It ranks all the values from both groups together and then analyzes the ranks to test for differences between the groups.
- The Mann Whitney U Test is particularly useful for ordinal data or when dealing with small sample sizes that do not meet the assumptions required for parametric tests.

b. Introduction to SPSS for Data Analysis

SPSS (Statistical Package for the Social Sciences) was utilized for data entry, management, and analysis due to its comprehensive suite of statistical tools and user-friendly interface.

Data Entry and Management:

- All collected data were entered into SPSS for systematic organization and storage. Variables were clearly defined and labeled to ensure accuracy during analysis.
- SPSS's data management capabilities allowed for easy manipulation of data, such as sorting, filtering, and transforming variables, which facilitated efficient analysis.

Descriptive Statistics:

- Descriptive statistics, including means, standard deviations, medians, and ranges, were calculated for all key variables. These statistics provided a summary of the data and an initial understanding of the distribution and central tendencies of the variables.
- Frequency distributions and histograms were also generated to visualize the data.

Inferential Statistics:

- SPSS was used to conduct the T-tests and Mann Whitney U Tests, as described above. The software provided detailed output, including test statistics, p-values, and confidence intervals, which were essential for interpreting the results.
- The software's ability to handle large datasets and perform complex calculations ensured that the analysis was accurate and reliable.

Correlation and Regression Analysis:

- To further explore relationships between variables, SPSS was used to perform correlation and regression analyses. These analyses helped identify any significant associations between emotional intelligence scores and sensory-motor performance metrics.
- Correlation coefficients and regression models provided insights into the strength and direction of these relationships.

Graphical Representations:

- SPSS's advanced graphical capabilities allowed for the creation of various charts and graphs, such as bar charts, box plots, and scatter plots. These visual tools were used to illustrate findings and highlight key differences and trends in the data.

By employing these statistical methods and utilizing SPSS for data analysis, the study ensured a rigorous and comprehensive examination of gender differences in emotional intelligence and sensory-motor coordination. The combination of parametric and non-parametric tests, along with robust data visualization, facilitated a deeper understanding of the research questions and hypotheses. [2]

4. Conclusion

4.1. Summary of Key Findings: Recap the Main Results

This study explored gender differences in emotional intelligence (EI) and sensory-motor coordination using advanced digital tools and rigorous statistical analyses. The key findings are summarized as follows: [2]

I. **Motor Coordination**:

- **Track Time**: Males demonstrated significantly shorter track times compared to females, indicating superior overall motor coordination speed.
- **Track Deviation Time**: There were no significant differences in track deviation time between genders, suggesting similar levels of fine motor control and precision.
- **Inner and Outer Band Errors**: Males had fewer inner and outer band errors, highlighting better accuracy in maintaining the designated track.

II. **Emotional Intelligence**:

- Females scored higher on components of EI related to empathy and interpersonal skills, aligning with previous research on gender differences in emotional sensitivity and social cognition.
- Males exhibited stronger self-regulation and stress management abilities, which are critical for maintaining performance under pressure.

III. **Impact of Anxiety**:

- Higher levels of anxiety were correlated with poorer sensory-motor performance, with a more pronounced effect observed in females. This suggests that anxiety management may be particularly crucial for improving performance in tasks requiring high precision and coordination.

IV. **Performance Under Perturbation**:

- Males performed better under both perturbation and non-perturbation conditions compared to females, as indicated by the Mann Whitney U Test results. This demonstrates greater resilience and adaptability in motor tasks.

4.2. Significance of the Study: Reiterate the Importance of Understanding Gender Differences in EI and Motor Coordination

Understanding gender differences in EI and sensory-motor coordination has profound implications for various fields: [2]

a) **Educational Practices**:

- Tailoring educational strategies to leverage the strengths of each gender can enhance learning outcomes. For example, incorporating activities that promote fine motor skills and empathy in male-dominated settings, and stress management and spatial awareness in female-dominated environments.

b) **Workplace Training**:

- Developing gender-sensitive training programs can improve productivity and job satisfaction. Employers can design roles and tasks that align with the innate strengths of each gender, fostering a more balanced and efficient workforce.

c) **Clinical Interventions**:

- Recognizing the differential impact of anxiety on performance can inform therapeutic approaches. Interventions can be customized to address specific needs, such as enhancing stress resilience in females and emotional sensitivity in males.

d) **Policy Development**:

- Policymakers can use these insights to create supportive environments that promote equity and inclusiveness. Gender-specific considerations in policy-making can help reduce disparities and enhance overall well-being.

e) **Future Research**:

- This study sets the stage for further exploration into the biological, psychological, and social factors contributing to these differences. Longitudinal studies and cross-cultural comparisons can provide deeper insights and validate the findings across diverse populations.

In conclusion, this research underscores the importance of considering gender differences in the study of emotional intelligence and sensory-motor coordination. By integrating digital analysis and comprehensive statistical methods, the study provides valuable insights that can inform practical applications and promote a more nuanced understanding of cognitive and emotional processes across genders. [2]

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1.

CHALLENGES, OPPORTUNITIES AND IMPLICATIONS REGARDING THE INTEGRATION OF ARTIFICIAL INTELLIGENCE IN AUDIT PROCESSES

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Abstract

In the context of rapid technological evolution and continuous changes in the business environment, auditing plays a significant role in ensuring the transparency, integrity and operational efficiency of entities. However, the increased complexity of activities and the growing volume of data with which auditors have to work have generated new challenges and required the continuous adaptation of audit methodologies and tools. In this context, artificial intelligence (AI) has emerged as a promising solution to improve the quality of the audit process. In this context, artificial intelligence (AI) has emerged as a promising solution to improve the quality of the audit process. AI technologies, such as machine learning, advanced data analytics, and natural language processing, provide auditors with powerful tools to perform deeper analysis, identify risks and anomalies, and streamline audit processes. These technologies allow the automation of repetitive tasks, the reduction of human errors and the provision of real-time information, thus contributing to increasing audit quality. The research focuses on exploring the potential of AI to improve the quality of the audit process. By analyzing the impact of AI technologies on traditional audit methods, it aims to identify the benefits, challenges, opportunities and implications associated with integrating AI into audit practice. The goal is to provide a deep understanding of how AI can contribute to optimizing the audit process and to propose practical recommendations for the effective implementation of this technology.

Keywords: audit, artificial intelligence (AI), integration of AI in audit, quality of audit process, challenges, opportunities, implications, internal audit.

JEL Classification: M42

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1. Introduction

The impact of AI on the accounting information system is to reduce the risk of fraud, improve the quality of accounting information, and promote reform in the field of traditional accounting and auditing (Chukwuani & Egiyi, 2020 [1]). Keeping pace with the continuous improvements of AI in accounting and auditing, both by accountants and by entities, can help reduce costs and add value to the accounting industry by shifting the focus from existing repetitive tasks to data-driven decisions and analysis (Baldwin et al., 2006 [2]; Mohammad et al., 2020 [3]). At the same time, Bizarro & Dorian (2017) [4] emphasize that, at a metadata level, source documentation, document processing, teleconferences, emails, and press releases can be evaluated and compared with the help of AI, facilitating automation. Although the implementation of AI in auditing is not new, its impact is expected to be more significant now, due to the availability of massive data processing power (Kokina & Davenport, 2017 [5]). For accounting and auditing firms, the intensive nature of the traditional audit process and the increasing requirements for compliance with regulations and policies in force make the use of these emerging technologies imperative to improve productivity (KPMG, 2018 [6]). Several initiatives are being tested around the world and the big four accounting firms EY, Deloitte, KPMG and PwC are investing millions of dollars in AI to build capabilities with the aim of providing clients with more cost-effective and high-quality audits.

Auditing, a relatively static process over the years, is likely to be affected by the disruptive potential of AI on industries characterized by repetitive and predictable tasks (Chui et al., 2016 [7]). Given that auditing typically involves recurring, high-volume, and anticipated transactions, AI has significant potential to influence the audit process (Baldwin et al., 2006 [2]). AI's ability to efficiently analyze large volumes of data could enable auditing of the entire financial statement data set and speed up auditors' work (Issa et al., 2016 [8]; Bizarro & Dorian, 2017 [4]). It is argued that the adoption of AI could improve auditors' reasoning and decision-making (Sun & Vasarhelyi, 2017 [9]), with such AI-based judgments being claimed to be more efficient than those of humans. Traditional manual audit procedures are considered inefficient because humans are considered less competent in tasks that involve collecting and analyzing large volumes of transactional data (Dai & Vasarhelyi, 2017 [10]; Issa et al., 2016 [8]). Therefore, it is argued that AI could be useful in audit processes such as materiality and risk assessment, control assessment, audit planning, opinion selection, and reporting (Bierstaker et al., 2014 [11]). Other benefits identified in the literature include reducing human error (Murphy, 2017 [12]), facilitating continuous auditing (Brennan et al., 2017 [13]), and the ability to audit all transactions, as well as reducing the cost and time required for auditing (Issa et al., 2016 [8]; Westhausen, 2016 [14]).

2. Literature review

There are several perspectives on the definition of AI. The most important definitions belong to authors who have studied the field in the last decade. Colom et al. (2008) [15] defines AI in the context of problem solving, reasoning and learning, while Munoko et al. (2020) [16] defines it as a new technology that resembles and reproduces human cognitive abilities and judgments. Hassani et al. (2020) [17] describe it as intelligent systems designed for data analysis and decision making, supporting the generation of results and insights from the analysis of voluminous and complicated data. AI is defined as a technology that attempts to replicate or imitate human cognitive abilities, including judgment and reasoning. With the advancement of the fourth industrial revolution, the use of AI technologies has become increasingly common in various fields, such as education, security, health, and including accounting and auditing (Mhlanga, 2021) [18]. At the same time, AI is defined as the application of information systems and engineering with intelligent machines and computers capable of exhibiting human traits of reasoning, learning, and autonomous action, and analyzing big data and making quality decisions. Hasan (2021) [19] describes AI as a form of rare intelligence manifested by machines or robots, which perceive the environment and act to maximize their chances of achieving their goals, based on programming and commands received.

Allami (2022) [20] provides a nuanced perspective on the multifaceted environment of AI by summarizing the defining characteristics of this concept. These encompass not only basic aspects such as perception, decision-making and prediction, but also more complex functions such as automated information extraction, interactive communication, logical thinking and the dynamic process of machine learning. AI aims to replicate and enhance human cognitive capabilities, helping companies see and understand their environment using digital computers or computer-controlled machines. Over the years, AI applications have become increasingly relevant in a variety of social and economic areas, including public health, transportation, education, security, communications, and defense. Autonomous algorithms are currently driving progress in this field and are having a substantial impact across numerous industries. In short, AI, developed by humans, has evolved to a point where it is effortlessly integrated into everyday life and business. Characteristics included in this context are the use of data to guide operations, the ability to understand and interact with people, adaptability to change, and enhancement of human capabilities ***(Figure 1.):***

Characteristics of AI

- Improves financial reporting by enabling the rapid replication of human intelligence, knowledge, and awareness in a programmed computer.
- Mimics and displays cognitive skills associated with learning and problem-solving.
- Represents a tool for the logical extraction of data and providing accurate forecasts.
- Contributes to the automation of accounting processes and risk detection in data sets.
- Enhances audit quality by automating accounting tasks and saving time.
- Allows accountants to focus on advisory roles and strategic decision-making.
- Includes components such as neural networks, genetic algorithms, and natural language processing.
- Neural networks simulate the structures of the human brain and facilitate machine learning.
- Genetic algorithms use natural selection and evolution to find solutions to complex problems.
- Contributes to the optimization of processes and innovation in various fields, including accounting..
- Enables communication between AI systems using human natural language.
- Improves audit quality and the credibility of financial reporting.
- New technologies disrupt existing structures and may replace outdated ones.
- Technological innovations allow new businesses to compete with established firms and introduce new ways of conducting operations.

Figure 1: Characteristics of AI[5]

In a strict definition, AI represents the imitation of human intelligence by computers. However, purists emphasize that many current applications are still relatively simple and, therefore, cannot be considered true AI. This observation makes the definition inadequate, as it would suggest that AI does not exist today. A common definition considers AI as a technology that enables machines to imitate various complex human abilities. However, this definition remains vague without specifying these "complex human abilities."

A similar definition was presented by the High-Level Expert Group on Artificial Intelligence (AI HLEG) of the European Commission (EC): "Systems that exhibit intelligent behavior by analyzing their environment and taking actions – with a certain degree of autonomy – to achieve specific goals." (European Commission, 2018). The definition provided by the AI HLEG encompasses all applications that we currently classify as AI, while also leaving room for future changes to that classification. The defining elements of the two fundamental areas of AI are presented in ***Figure no.2***.

[5] Source: Author conception based on the review of the specialized literature.

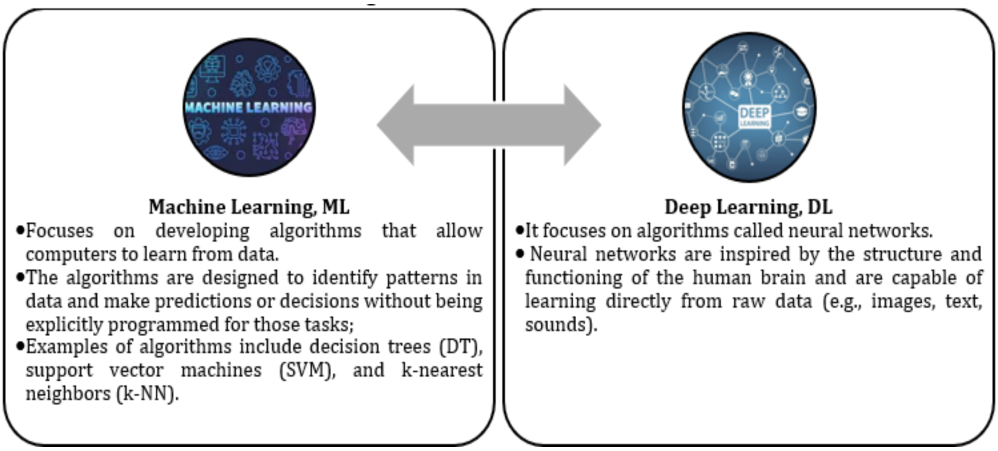


Figure 2: Subdomains of AI[6]

3. Research Methodology

In conducting the study, both qualitative and quantitative analyses were used. The arguments for using both approaches were: i) **Holistic perspective**: The qualitative analysis provided an in-depth understanding of the issues and the context in which AI technologies are applied in auditing. It allowed for exploring the perspectives and perceptions of industry experts, as well as identifying unforeseen aspects and problems that could affect audit quality; ii) **Exploring complexity**: Auditing and the application of AI in this field involve complex aspects such as ethics, regulations, technical precision, etc.; iii) **Identifying emerging trends and patterns:** Quantitative analysis was useful for identifying emerging trends and patterns in audit data and AI usage. This provided solid evidence to support certain conclusions and the development of research hypotheses; iv) **Validating conclusions and generalizing results**: The use of both qualitative and quantitative analysis helped validate the conclusions and ensure that the results obtained are robust and can be generalized within the scientific community and in practice; v) **Multidisciplinary approach**: A comprehensive study of AI application in auditing required a multidisciplinary approach. Using both qualitative and quantitative analysis allowed for the integration of perspectives from multiple fields, such as computer science, accounting, auditing, organizational psychology, etc.; vi) **Assessing impact and effectiveness**: Quantitative analysis was used to evaluate the impact and effectiveness of AI in auditing by measuring performance indicators and comparing the results with traditional audit methods.

4. The Multiple Facets of Artificial Intelligence in Auditing

In recent years, advances in IT, particularly in the field of AI, have had a significant impact on the accounting and auditing industry. These professions have undergone fundamental changes as a result of progress in cognitive machine technologies, with a focus on the

[6] Sursa: Ongsulee, P. (2017). Artificial intelligence, machine learning and deep learning. *2017 15th International Conference on ICT and Knowledge Engineering (ICT&KE)*

development and application of AI. Dunn and Hollander (2017) [21] focus on the influence of AI on auditing, redesigning AI system development based on the identified benefits and limitations. *This research explores how AI can enhance the effectiveness and quality of the auditing process.* The findings indicate that auditing firms, especially large ones, will continue to invest in specialized expert systems and neural networks tailored to the industry and specific audit tasks in order to minimize audit risks (Bogdan et al., 2023 [22]). Additionally, large multinational corporations can develop their audit functions to use such systems and strengthen internal control systems while reducing business risks. AI technology allows them to manage large volumes of data, identify anomalous transactions, and assess risks (Dincă et al., 2023 [23]).

The auditing profession is guided by International Standards on Auditing (ISA). According to ISA 200, the application of AI in auditing represents the replication of human intelligence functions by machines in performing the audit function. The general objective of a financial statement audit performed by an independent auditor is to carry out the audit in accordance with these standards. The auditor's objective, as per ISA 200, is to obtain reasonable assurance to express an opinion regarding the absence of fraud and errors in the financial statements and to issue an audit report communicating the audit findings. According to Baldwin et al. (2006) [2], AI can be applied in auditing to perform a series of specific tasks ***(Figure 3).***

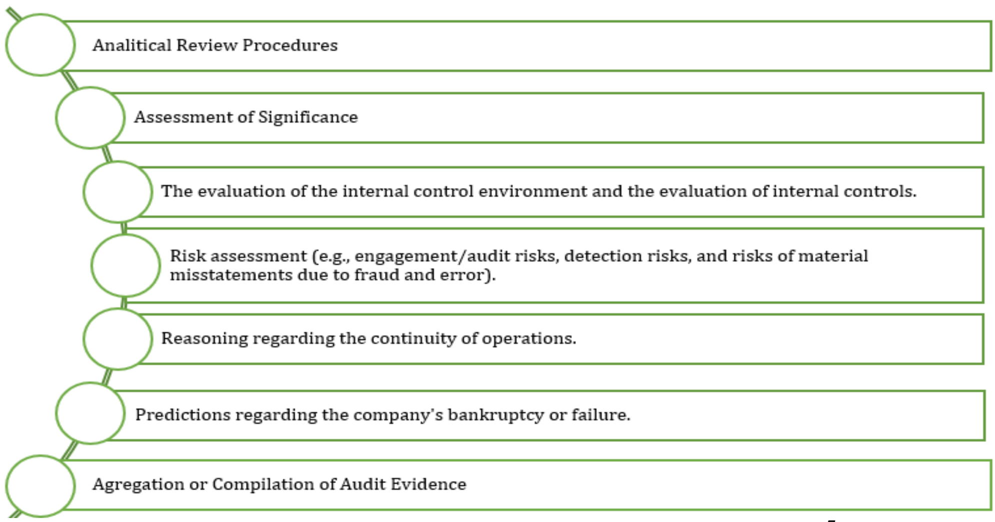


Figure 3: Specific Audit Tasks Suitable for AI Utilization[7]

The integration of data analysis into audits represents a giant leap in efficiency. Traditional audit processes, which often rely on manual examination of financial records, are now supported by sophisticated algorithms capable of processing vast data sets with remarkable speed and accuracy. Auditors can use data analytics tools to identify patterns, anomalies, and trends, allowing a more focused and targeted approach to the audit process. Data

[7] Source: Baldwin, A.., Brown, C.E., & Trinkle, B.S. (2006). Opportunities for Artificial Intelligence Development in the Accounting Domain: The Case for Auditing. *Intelligent Systems in Accounting, Finance and Management*, *14*(3), 77-86. https://doi.org/10.1002/isaf.277

analysis not only accelerates the audit process but also allows auditors to explore the data in-depth, revealing insights that would otherwise remain hidden in a manual review. This enhanced efficiency results in time savings, enabling auditors to allocate resources more strategically and focus more on areas with inherently higher risks.
Auditors are increasingly using continuous audit techniques, powered by data analysis and blockchain technology. Continuous auditing enables real-time monitoring of financial transactions, reducing the gap between the occurrence of an event and its detection. Additionally, auditors are adapting to the dynamic nature of technology by integrating IT audit skills into their toolkit. Assessing and understanding internal controls over information systems becomes essential as technology increasingly blends with business processes. Despite the rapid advancement of AI technologies in other areas, their adoption in the audit and accounting profession has been slower. This is surprising, given the nature of the field for applying AI technology, due to the various audit functions. However, there are clear signs that AI adoption is gradually increasing in the audit and accounting profession (Kokina et al., 2021 [24]).

5. Possible Solutions for Optimizing Audit Processes through the Use of Advanced Technologies

Optimizing audit processes through the implementation of advanced technologies involves utilizing the following elements (***Figure no. 4):***

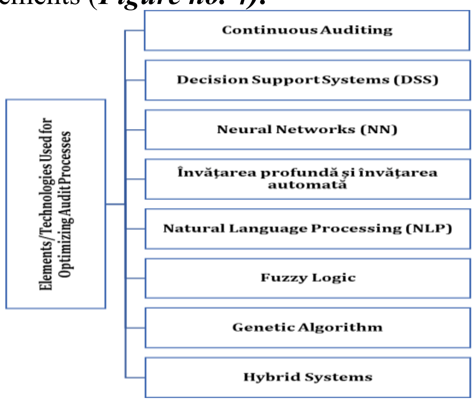


Figure 4: Elements/technologies used for optimizing audit processes[8]

Continuous Auditing is defined as the systematic process of collecting electronic audit evidence, providing a solid basis for issuing an opinion on the fair presentation of financial statements in a real-time electronic accounting system. Continuous auditing is also considered a detailed form of electronic auditing, allowing auditors to provide a certain level of assurance regarding data as they are disclosed or immediately after disclosure. Zhao et al. (2004) [25] emphasized that continuous auditing is associated with electronic accounting systems, facing significant technical obstacles, lack of standards and guidelines, the increased value of real-time financial information, and timely audit reporting. Continuous auditing can generate either an "evergreen report" or an "on-demand report,"

[8] Source: Authors' design

and its use cases can cover all three professional services typically provided by independent auditors – assurance, attestation, and audit services.
Decision Support Systems (DSS) are interactive, adaptable, and versatile software platforms that assist in decision-making processes. These systems are designed to handle structured management problems to enhance the decision-making process.
Neural Networks (NN) are a machine learning system that mimics the organization of the human brain, composed of neurons and connections, and has the ability to adjust its structure to perform tasks learned more efficiently. When neural networks become more complex and include multiple layers, the term "deep learning" can be applied. Baldwin et al. (2006) [2] and Deloitte (2018) examined the application of neural networks in the Analytical Review Procedure used by auditors to obtain audit evidence.
Natural Language Processing (NLP) is a research field focusing on developing and using artificial models to understand and process human language in a manner similar to humans (Deloitte, 2018). Applications of NLP include processing unstructured textual information, searching and analyzing documents automatically and systematically, as well as identifying high-risk cases that deviate from preset targets. Fuzzy Logic is a reasoning technique that mimics human thinking by allowing the evaluation of truth degrees of variables, with values ranging from 0 to 1 (Baldwin et al., 2006) [2]. This approach allows handling the concept of "partial truth" or "degrees of truth," better reflecting the complexity of the real world. Fuzzy logic is used in areas such as assessing the risk of managerial fraud and making significant decisions involving qualitative issues. Genetic Algorithm is a search method inspired by the theory of evolution, where the best-adapted individuals are selected to reproduce and pass on their traits to offspring. In the field of computing, genetic algorithms use biologically inspired operators such as mutation, crossover, and natural selection to develop efficient solutions to optimization and search problems. These algorithms are effective in solving problems like transaction and account classification (Baldwin et al., 2006 [2]). Genetic algorithms are also suggested for modeling auditor behavior in making fraud-related decisions. Other applications of this algorithm include predicting bankruptcy and making decisions regarding business continuity. Hybrid Systems are more suitable in audit tasks that involve both quantitative analysis and qualitative judgment. These hybrid IA technology systems combine various IA technologies, such as neural networks, fuzzy logic, and genetic algorithms, to offer complex and adaptable solutions to the specific requirements of audit tasks. Digital Audit represents a significant evolution of the auditing process, characterized by the use of technology and digital data to perform and improve audit procedures. This modern form of auditing relies on several defining characteristics that give it uniqueness and efficiency in today's digital business environment: i) Use of technology, ii) Process automation, iii) Extensive data analysis, iv) Real-time data monitoring, v) Data security and confidentiality.

6. Challenges of Integrating Artificial Intelligence in Audit Processes: Overcoming Technical and Ethical Obstacles, Managing Risks

The review of specialized studies reveals that there are several significant challenges associated with the integration of AI in auditing ***(Figure no. 5):***

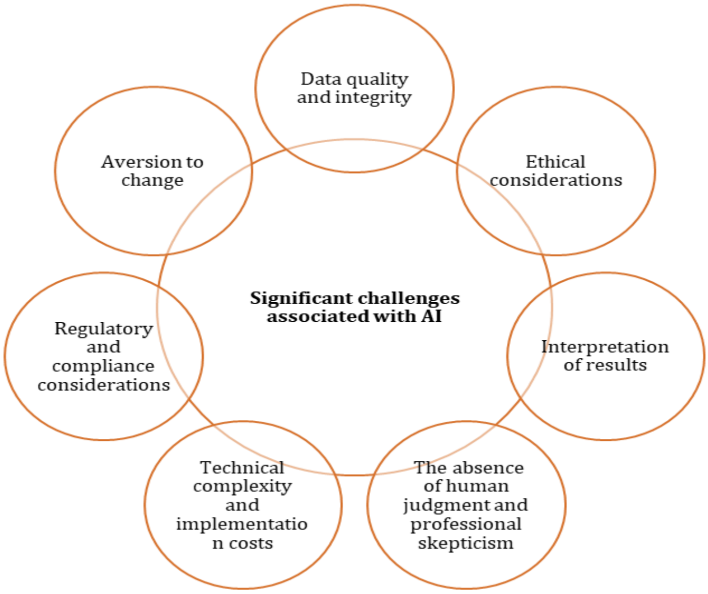


Figure 5: Significant challenges associated with the integration of AI in auditing[9]

i) Data Quality and Integrity: The accuracy and reliability of AI algorithms critically depend on the quality and integrity of the data fed into the system. Incomplete, inaccurate, or biased information can distort results and lead to erroneous conclusions. Ensuring data quality, implementing appropriate data governance frameworks, and establishing data validation processes are essential to mitigate this challenge (Srinivasan & de Boer, 2020 [26]); ***ii) Ethical Considerations:*** The use of AI in auditing raises ethical concerns, especially when dealing with sensitive financial and personal data. Protecting privacy, data security, and compliance with relevant laws and regulations is imperative. Auditors must consider ethical guidelines and establish protocols to protect data confidentiality and maintain stakeholder trust; ***iii) Interpretation of Results:*** AI algorithms generate results based on complex models and mathematical algorithms. Understanding and interpreting these results can be challenging for auditors, particularly in the absence of adequate expertise in AI and data analysis. Proper training and skill development for auditors are necessary to correctly interpret and utilize information generated by AI (La Torre et al., 2021 [27]); ***iv) Absence of Human Judgment and Professional Skepticism:*** AI systems rely on predefined rules and algorithms, which may limit their ability to apply skepticism and professional reasoning. Auditors bring valuable experience, intuition, and critical thinking to the audit process, aspects that AI cannot fully replicate. Maintaining a balance between AI-driven automation and human reasoning is essential for the integrity of the auditing profession; ***v) Technical Complexity and Implementation Costs:*** Implementing AI technologies in auditing requires specialized knowledge, infrastructure, and resources. The initial costs of acquiring and implementing AI systems, as well as ongoing maintenance and updates, can be significant. Small and medium-sized audit firms may face difficulties in adopting AI due to the costs and technical complexities involved; ***vi) Regulatory and***

[9] Source: Own design

Compliance Considerations: The use of AI in auditing must comply with relevant regulations and standards. However, the rapid pace of AI technology development often outpaces regulatory frameworks, creating uncertainties and challenges. Auditors must stay updated on regulatory developments and ensure that AI systems comply with applicable legal requirements; ***vii) Aversion to Change:*** The adoption of AI in auditing may face resistance from auditors and other stakeholders who are attached to traditional audit practices. Concerns about job losses and the reliability of AI systems can slow down the process of adopting and accepting AI in the auditing profession. Effective management of these concerns, through change management, training programs, and clear communication, is crucial.

According to Rebstadt et al. (2022) [28], while the importance of AI in auditing is evident both academically and practically, the challenges associated with applying AI technologies in the auditing profession remain largely unexplored. These challenges impact audit outcomes, the decision-making process, and audit quality, raising ethical implications as well. Despite the advantages of using machine learning algorithms in auditing, auditors may fail to notice certain weaknesses associated with them, such as the "overfitting" phenomenon. This refers to a situation where auditors cannot identify data features that do not reflect real-world patterns. Additionally, machines may struggle to recognize that statistically significant correlations between variables do not always indicate causal relationships. These weaknesses highlight the potential challenges in results, emphasizing the continued need for human evaluation and critical judgment in the audit decision-making process, based on machine learning algorithm outputs. The predictive reliability of the results from machine learning algorithm processing is closely tied to the quality of input data, system design, methods used, and interpretation of output information. Thus, the quality of the evidence generated through the use of these algorithms may be affected.

According to Gao & Han (2021) [29], implementing AI in auditing generates significant changes in the audit process, influencing how evidence is generated and its quality. Audit evidence should be generated from comprehensive and independent processes, such as expert opinions, because investors rely on financial statements to make informed economic or investment decisions. To make informed decisions, it is essential that financial statements are audited, and managers provide accurate and reliable information to shareholders and investors, who depend on the auditor's opinion to ensure the reliability of the information provided. This assurance refers to the certainty and credibility of financial statements, based on sufficient and appropriate audit evidence, according to ISA 500. Traditionally, auditors have manually gathered this evidence, but the deficiencies of manual systems have often affected the quality of evidence and audits in general.

The use of AI to collect, evaluate, and process large amounts of information from internal and external environments can provide ample and diverse evidence. According to Gao & Han (2021) [29], AI usage could improve the quality of audit evidence and reduce the gap between audit expectations and reality, thereby altering the objective of the audit. They suggest that the auditing profession could consider revising the ISAs to align them with the use of AI in auditing.

Using artificial intelligence to collect information from independent sources can improve the effectiveness and objectivity of confirmation evidence, separating audit procedures from accounting processes. Even with the use of AI, there is recognition that an incorrect opinion may be issued. Gao & Han (2021) [29] emphasize that when auditors make deductions, they may introduce their own subjective perspectives, individual differences, and thought inconsistencies, which can lead to discrepancies between the audit conclusion and reality or even result in incorrect opinions being issued. AI-assisted comprehensive inferences, based on a rational model, can reduce the subjectivity of practitioners and make their judgment less subjective and harder to contest.

The application of audit standards in the context of AI presents several challenges, especially regarding fairness and transparency. There are issues related to what is measured with the help of AI and the inputs used, without violating the rights and dignity of those using AI technologies, even though these can contribute to correcting deficiencies in sample representation. The use of analytical procedures involves certain assumptions according to ISA guidelines, but machine learning has a distinct power in identifying specific relationships or unexpected trends. Therefore, a revision of ISA standards and their continued applicability in their current form for the auditing profession may be necessary, considering the adoption of AI technologies. ISACA (2018) states that the lack of clear audit standards assimilating emerging technologies affects the effectiveness and acceptance of AI technologies.

Along with the opportunities AI offers, its application also brings a significant volume of threats in the field of auditing and accounting. One of the main issues causing difficulties is the regulatory environment. A study conducted by Deloitte in 2018 highlights the regulation of cloud-based services, which varies globally, with certain European jurisdictions imposing stricter restrictions. This discrepancy may give companies in less restrictive jurisdictions an advantage in developing artificial intelligence technologies.

Apart from issues related to financial regulation, there are also other major risks. The same study by Deloitte consulting highlights the dangers related to the complexity of financial connections at both domestic and cross-border levels, the polarization of communities around the development of artificial intelligence, and the risk of regional conflict or financial exclusion among different population segments. In addition to these, there are general threats associated with AI, such as job reduction and income inequalities caused by the concentration of market power in the AI industry.

Auditors carefully examine the records and financial statements of an organization to determine if they present a true and fair view of its financial position, performance, and cash flows, in accordance with applicable accounting standards and regulations. They follow a set of predefined procedures and standards to collect evidence and assess financial information, which usually involves analyzing financial statements, verifying supporting documentation, interviewing key personnel, and conducting tests and analyses to detect errors, fraud, or non-compliance (Knechel & Salterio, 2016 [30]). The scope of the audit extends beyond the financial statements, so auditors may also assess an entity's internal control systems to evaluate the effectiveness of its internal processes and procedures for financial reporting and risk management (Korol et al., 2022 [31]). They may also provide recommendations for improving internal controls and mitigating risks (Knechel & Salterio, 2016 [30]). The introduction of AI in auditing generates significant implications for auditors and the auditing profession as a whole ***(Figure no. 6)***.

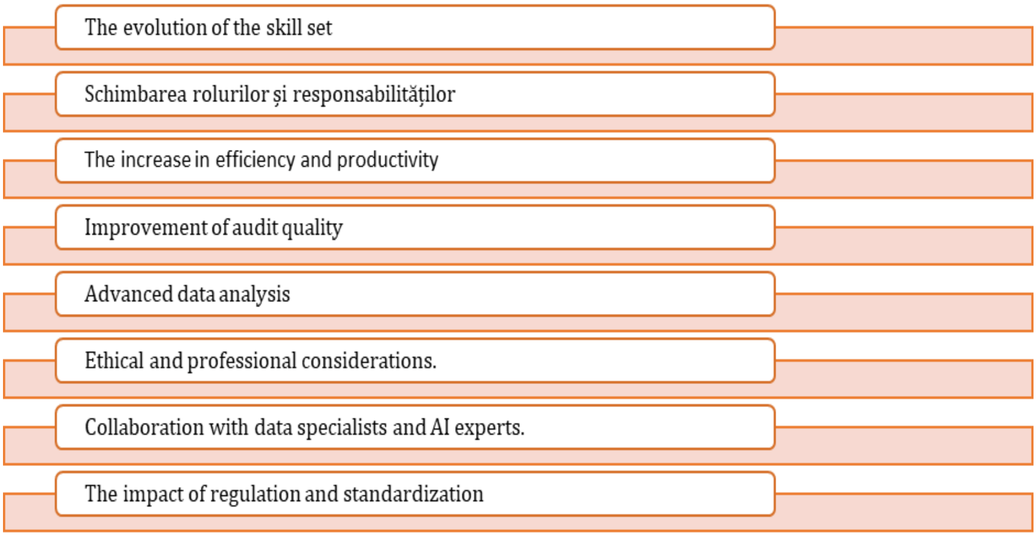


Figure 6: Implications of AI for Auditors[10]

An analysis of each challenge is as follows***: i) Evolution of the skill set***: The integration of AI into auditing requires auditors to develop new skills and expertise. They must gain a solid understanding of AI technologies, data analysis, and programming in order to effectively use AI tools and interpret the results. Investment in continuous professional development and skill enhancement programs is necessary to ensure auditors remain competent and adapted to the AI-based audit environment; ***ii) Changing roles and responsibilities***: With the automation of repetitive tasks through AI, the roles and responsibilities of auditors will undergo changes. As certain manual tasks become redundant, auditors will focus more on value-added activities such as data analysis, risk assessment, and providing strategic insights to clients. Adapting to and embracing their evolving roles as trusted advisors and strategic partners for clients will be essential for their success in this changing environment; ***iii) Increased efficiency and productivity***: AI can automate repetitive and time-consuming tasks, allowing auditors to be more efficient and productive. This increase in efficiency can lead to faster audit cycles, more efficient resource allocation, and an enhanced ability to manage larger volumes of data. This enables auditors to focus their efforts on higher-value tasks that require professional judgment and critical thinking; ***iv) Improved audit quality***: The use of AI technologies can lead to an improvement in audit quality by enhancing accuracy, identifying anomalies, and detecting patterns in large datasets (Noordin et al., 2022 [32]). AI algorithms can process large amounts of data quickly and consistently, reducing the risk of errors and oversight. This leads to more reliable audit findings, improved risk assessments, and an overall improvement in audit quality; ***v) Ethical and professional considerations***: The use of AI in auditing raises ethical concerns, such as confidentiality, data protection, and potential bias. Auditors must ensure that AI systems are transparent, explainable, and comply with ethical standards (Munoko et al., 2020 [16]). At the same time, skepticism and professional judgment remain essential for addressing any limitations or biases that may arise in AI

[10] Source: Original design based on the study of specialized literature.

algorithms; ***vi) Collaboration with data specialists and AI experts:*** Auditors may need to collaborate with data specialists and AI experts to effectively implement and utilize AI technologies in auditing. This collaboration can facilitate the integration of AI into audit processes, knowledge sharing, and ensure a multidisciplinary approach to audit engagements (Noordin et al., 2022 [32]); ***vii) Impact of regulation and standardization***: The introduction of AI into auditing may involve the development of new regulations, standards, and guidelines specific to AI-based audits. Regulatory authorities and standard-setting organizations must adapt to technological advances to ensure the appropriate and responsible use of AI in auditing (Noordin et al., 2022 [32]).

7. The influence of artificial intelligence on audit quality.

Audit service quality refers to complete, reliable, and comparable data that ensures the quality of financial statements and their ability to add economic value to decisions made by stakeholders. The quality of audit services results from auditors with ethical values, integrity, attitude, and professional skills, audit independence, experience, and sufficient time to perform a detailed audit. Some characteristics of high-quality audit services include the use of appropriate and specific disruptive technologies, such as artificial intelligence (AI), in processing and reporting financial-accounting data within public entities. The application of AI has become a growing innovation in financial reporting and auditing globally. The increase in the volume of corporate and business transactions has necessitated the use of information technologies, and disruptive technologies now occupy a central place in this field.

Recently, the value and quality of audit services have declined due to the increase in financial reporting scandals globally (Noordin et al., 2022 [32]). Some have attributed the complexity of audit quality to the use of manual computers, high levels of inaccuracy, and delays in audit reporting. Moreover, recent research has highlighted favorable results and economic benefits from the adoption and implementation of artificial intelligence. For example, improvements have been reported in specific elements of AI, as shown in ***(Figure no 7).***

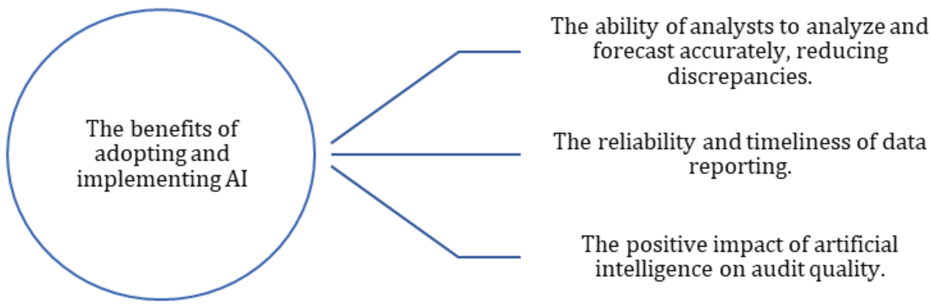


Figure 7: Benefits of adopting and implementing artificial intelligence[11]

[11] Source: Abdollahi, A., Pitenoei, Y.R., & Gerayli, M.S. (2020). Auditor's report, auditor's size and value relevance of accounting information. *Journal of Applied Accounting Research*, 21(4), 721-739. https://doi.org/10.1108/JAAR-11-2019-0153 ; Greenman, C. (2017). Exploring the impact of artificial intelligence on the accounting profession. *Journal of Research in Business, Economics and Management*, *8*(3).

The successful application of AI can facilitate the understanding of historical data and the prediction of data processing outcomes, avoiding information overload and ensuring the accuracy and timeliness of financial reporting. Lee & Tajudeen (2020) [33] highlighted a positive correlation between audit quality and the quality of financial reporting. While numerous studies, including those by Chukwuani & Egiyi (2020) [1], have examined the quality of the audit process from various perspectives, there is still a gap in the literature regarding the investigation of AI's effect on audit quality, particularly concerning the implications for accountants, highlighting the need for further research due to inconsistencies and the lack of clear conclusions in existing studies (***Table no. 1)***.

Author	Positive effects	Negative effects	Comments
Hasan (2021)	Positive impact of information technology on audit qualityi		AI is versatile and flexible, contributing to the increased reliability and accuracy of financial and audit reports.
Hemin (2017)	Rezultate favorabile privind efectul tehnologiei informației asupra calității auditului		
Lee & Tajudeen (2020)		Contradictory results regarding the impact of information technology on audit quality.	
Greenman (2017)		Negative impact of disruptive technologies on the credibility of audited financial statements.	
Balios & colaboratorii (2020)		The increase in errors due to the complexity of IT systems, difficulties in verifying data, and excessive reliance on technology that may compromise the professional judgment of auditors.	
Albawwat & Frijat (2021)	AI recognized as a factor that can improve audit quality.		

Table no. 1: Positive and negative effects of using information technology in performing the audit.

Regarding financial reporting, AI represents a tool for the logical and structured extraction of data, providing accurate and reliable forecasts. It contributes to improving the processing and automation of document authorization to optimize internal accounting processes and reporting. More specifically, AI uses computerized algorithms and programming to identify and understand patterns and anomalies in datasets, allowing auditors to detect specific risk areas more effectively and perform a variety of other audit and accounting processing tasks at an unprecedented speed.

Disruptive technologies such as AI have revolutionized financial reporting processes, replacing some of the conventional methods of financial reporting. New technologies have brought clear benefits and profits to organizations that have adopted them over traditional methods. Hasan (2021) [19] investigated the impact and implications of using AI in audits on audit quality. The study used a structured questionnaire and an exploratory analysis of the relevant literature to examine multiple aspects of audit activities in which artificial intelligence has been beneficial. The study concluded by highlighting benefits such as accurate financial reporting, increased productivity, and auditor efficiency, compared to traditional audit methods.

8. Case study regarding the application of specific AI mechanisms in internal auditing.
The quality of the activity carried out by the auditor can be measured by the product of their work, the audit report, which is an essential element for supporting managerial decision-making. In this sense, the case study conducted using the Orange Data Mining application (Orange) aims to identify a relationship between input variables (number of internal auditors/department, number of audit missions per year, number of recommendations per total audit missions) and the output variable (the level of appreciation of the recommendation) based on a regression equation and to identify the machine learning technique that allows the best classification of test data. In this regard, a comparative analysis will be made between logistic regression and the decision tree (DT) technique. DT allows the division of a vast and heterogeneous collection of records into a series of increasingly smaller and more homogeneous collections relative to a target attribute. The mathematical foundation of logistic regression is represented by the Order Logit Model with the following structure:

$$Prob\ (y_i = j|x,b,c) = F\left(c_{j+1} - x_i b\right) - F(c_j - x_i b)$$
$$Prob\ (y_i = j|x,b,c) = \frac{\exp(c_{j+1} - x_i b)}{1 + \exp(c_{j+1} - x_i b)} - \frac{\exp(c_j - x_i b)}{1 + \exp(c_j - x_i b)}$$

where:
• Xi = is the vector of explanatory variables (number of internal auditors/departments, number of audit missions per year, number of recommendations per total audit missions);
• Yj = 1 ..... 4 represents the four alternatives for choosing the endogenous variable, the level of appreciation of the audit recommendation.
• b = the vector of regression coefficients.
• c = the technical coefficients
In this case study, logistic regression is of the multinomial type due to the fact that the dependent variable, Level of Appreciation, has three response options: level to be improved, functional appreciation level, and critical appreciation level. The overall scheme of the widget-type elements leading to the testing of classification methods is shown in (***Figure no. 8).***

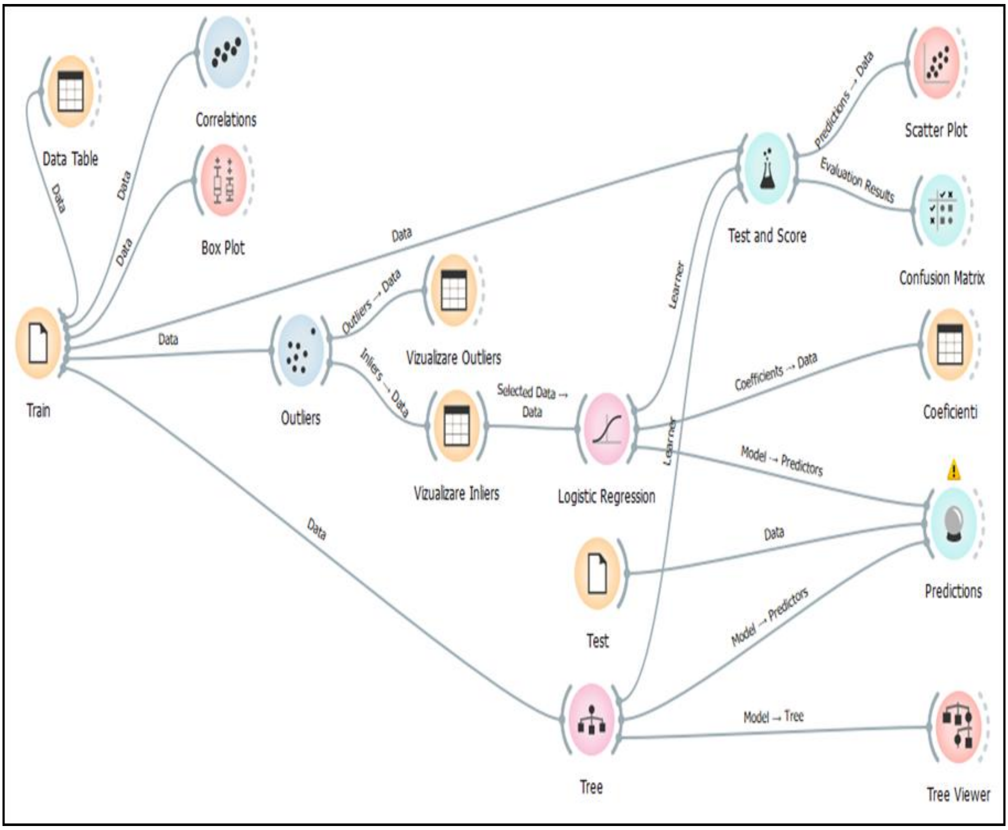


Figure 8: Classification testing in the Orange Data Mining application[12]

A special element of the entire process of establishing a mathematical relationship to characterize the historical data set and enable the prediction of the audit opinion is the adherence to the conditions for applying the tests related to logistic regression and decision trees. These preliminary conditions for applying the tests refer to verifying the existence of extreme values (outliers) among the data for the independent variables (number of internal auditors/departments, number of audit missions per year, number of recommendations per total audit missions).

Outlier values are considered values greater than Q3 + 1.5 x IQR or values smaller than Q1 - 1.5 x IQR and can be visualized using a BoxPlot diagram. Below, the Boxplot diagrams for the predictor-type variables used in the analysis are shown ***(Figures no. 9.1-9.3)***

[12] Source: Own design in defining the workflow.

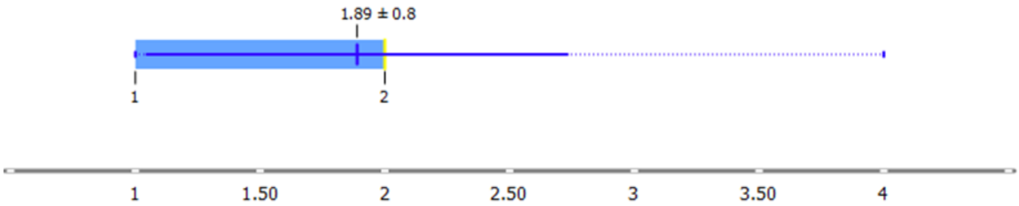


Figure no. 9.1: BoxPlot diagram for the independent variable Number of auditors.

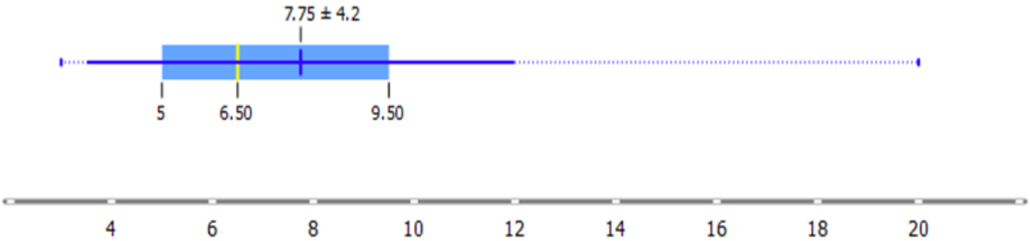


Figure no. 9.2: BoxPlot diagram for the independent variable Number of missions.

It can be observed that all the predictor variables have outlier values. In this situation, these values must be removed in order to avoid distorting the statistical determinations related to logistic regression. The removal of outlier values was performed using the Outliers component, which allows for the determination and visualization of these values ***(Table no. 2).*** By removing these values, the data set is prepared for the application of specific ML techniques.

	NivelApreciere	NrAuditori	NrObiectiveAuditate	NrRecomandari
1	Critic	4	20	85
2	Critic	3	12	63
3	Critic	3	18	67

Table no. 2: Visualization of outlier values.

The algorithm for constructing a decision tree using ID3 (Iterative Dichotomizer) starts from a classified data set. Assuming that the elements (instances) of the data set have a series of attributes whose values are known, the decision tree is generated in such a way that, by traversing it for a new instance with a new set of attribute values, the class in which that instance falls can be determined. The application of the decision tree construction algorithm to the existing data set provides the following graphical representation ***(Figure no. 10).***

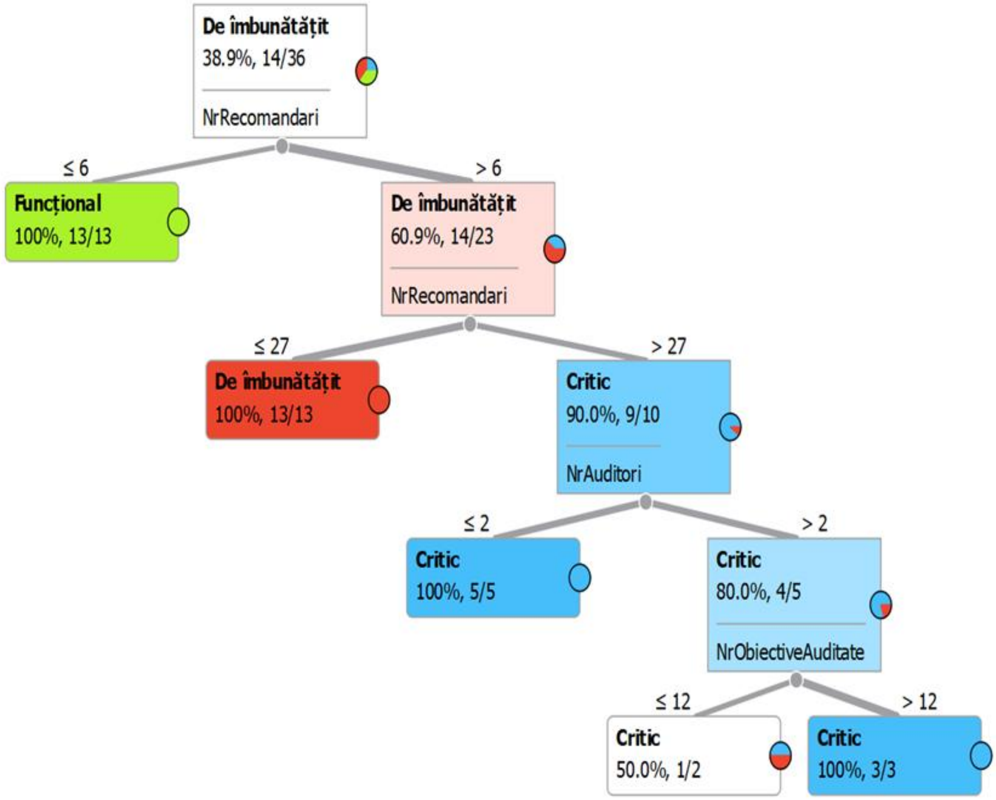


Figure no. 10: The decision tree related to the internal audit opinion.[13]

Traversal of the decision tree is done from the root to the leaf-type nodes and stops when all filtering criteria have been analyzed. In our example, all analyses of the predictor-type variables have been exhausted. The algorithm used to generate the decision tree stops IF the number of audit missions > 12, the number of auditors > 2, and the number of recommendations > 27, THEN the level of appreciation of the audit opinion is critical. This algorithm allows us to classify a new set of data into a specific label related to the level of appreciation of the audit opinion. By applying the specific logistic regression calculation algorithm, the regression coefficients were determined, as presented in (***Table no. 3)***.

[13] Source: Own design.

	name	Critic	De îmbunătățit	Funcțional
1	intercept	-3.57301	-0.75766	4.33067
2	NrAuditori	-0.218367	-0.0216826	0.240049
3	NrObiectiveAu...	-0.440187	0.0230806	0.417107
4	NrRecomandari	0.569663	0.349044	-0.918708

Table no. 3: Coefficients of the logistic regression equation.

The logistic regression equations that allow labeling new instances as medium or low class are the following:

CRITICAL level of appreciation of the recommendations = - 3.57 - 0.21 * Number of auditors - 0.44 * Number of audited objectives + 0.54 * Number of recommendations (1)

LEVEL TO BE IMPROVED of the recommendation appreciation = - 0.75 - 0.21 * Number of auditors + 0.02 * Number of audited objectives + 0.34 * Number of recommendations (2)

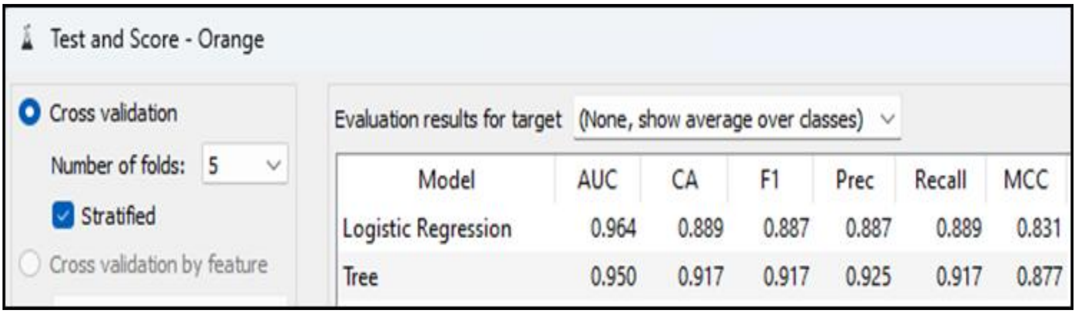
It should be noted that the reference category is the high level of appreciation of the audit opinion, in which case the regression equation does not need to be written. In this case, the goal was to determine the appreciation of the audit opinion for an unclassified data set consisting of three instances (**Table no. 4**), both through the decision tree algorithm and the logistic regression algorithm. The procedure for determining the label for each instance is automated and does not involve any calculations from the data analyst. In this case, the label options for the three instances, both for the DT algorithm and the logistic regression algorithm, are highlighted in ***(Table no. 5)***.

	NivelApreciere	NrAuditori	NrObiectiveAuditate	NrRecomandari
1	?	3	9	15
2	?	4	18	60
3	?	2	10	18

Table no. 4: The test data set

	Tree	Logistic Regression	NivelApreciere	NrAuditori	rObiectiveAuditat	NrRecomandari
1	De îmbunătățit	De îmbunătățit	?	3	9	15
2	Critic	Critic	?	4	18	60
3	De îmbunătățit	De îmbunătățit	?	2	10	18

Table no. 5: The result of applying the calculation algorithms for the decision tree vs. the logistic regression equation.



Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.964	0.889	0.887	0.887	0.889	0.831
Tree	0.950	0.917	0.917	0.925	0.917	0.877

Table no. 6: The Test and Score option to determine the overall performance of the classifiers

Number of Auditors	Number of audited objectives	Number of recommendations	Level of recommendation appreciation
3	9	15	To be improved
4	18	60	Critical
2	10	18	To be improved

Table no. 7: Classification of the internal audit opinion based on the logistic regression algorithm. Source: Own design.

The exemplified case study aims to apply specific AI mechanisms to automatically formulate assessments of the results of an internal audit mission when new information is available. The algorithm can serve as a tool for verifying the quality of the internal auditors' work, considering the similarities with audit missions conducted over time by internal auditors. Although the current capabilities of machine learning are limited, it excels at routine tasks. Due to the large amount of data involved and the complexity of the activities that need to be completed, machine learning has the potential to increase the efficiency and quality of the internal audit process, with direct consequences on the auditor's productivity, allowing more time for review and analysis, and a stronger focus on high-risk areas. The quality of internal audit services is a concept that cannot be measured solely by focusing on aspects such as incident/non-compliance reporting or strict adherence to procedures, but also by evaluating the efficiency and effectiveness of the recommendations provided, the impact on continuous improvement, and the added value that internal audit brings to the entity. In this case, the combination of human resources and technology was the factor leading to the qualitative assessment of internal audit services.

9. Conclusions

Regarding auditing, the use of artificial intelligence involves using technologies to improve audit processes. This implies modifying the audit process, reorganizing audit functions, and updating skills across the profession to remain relevant through investments in technology, training, and continuous professional development (CPD). AI can be applied in various functions of the audit profession, including performing analytical review procedures, risk assessment, applying algorithms, classification functions, evaluating significance, judgments related to assessing business continuity, projections regarding company failure, and evaluating internal controls. The application of AI in different audit functions is accompanied by controversies concerning ethical considerations and audit quality. It can be said that AI highlights advantages such as accuracy, objectivity, and speed, but it can also draw attention to challenges related to bias and fairness.

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CHANGES IN BEHAVIOR OF UNIVERSITY STUDENTS AFTER COVID-19 SELF-RESTRAINT PERIOD

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Abstract

The purpose of this study is to examine how the lifestyle and consumer behavior of university students changed during and after the period of self-restraint caused by COVID-19. In recent years, university students' lifestyles have changed considerably due to the outbreak of COVID-19. However, self-restraint restrictions have been easing, and this study investigates how students' lifestyles and consumer behaviors have evolved under these circumstances. The results show that, excluding time spent on online classes, students' lives have not changed drastically since the self-restraint period. Although the COVID-19 outbreak led to significant lifestyle adjustments, students have not fully reverted to their pre-self-restraint habits. Two possible explanations for this lack of change are (1) the discovery of online conveniences during the self-restraint period and (2) students becoming accustomed to a routine established during that time.

Keywords: Behavior of University Students, COVID-19, Self-Restraint Period, Post-Self-Restraint Period

JEL Classification: D10

1. Introduction

The purpose of this study is to determine the changes in lifestyle and consumer behavior among college students during and after the relaxation of self-restraint due to the novel coronavirus (hereafter, "COVID-19").

In recent years, college students' lifestyles have changed significantly as a result of COVID-19. In FY2020, when a state of emergency was declared in Japan, almost all university

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lectures were moved from in-person to online. Subsequently, according to the Ministry of Education, Culture, Sports, Science and Technology (MEXT, 2022) [1], 87.8% of lectures in the first semester of FY2022 at 1,165 national, public, and private universities and colleges of technology nationwide returned to a fully or almost fully in-person format.

Following the outbreak of COVID-19, Japanese society as a whole also increased its use of online platforms for purchasing and other activities. According to the Statistics Bureau of the Ministry of Internal Affairs and Communications (2022) [2], online purchases have risen every year since March 2020, when the first state of emergency was declared.

It is important to analyze the specific changes in the lives and consumer behaviors of college students—who have experienced major lifestyle changes, including returning to in-person classes—so that we may consider the future of student life. Therefore, this paper explores how university students' lives changed during and after the relaxation of COVID-19 self-restraint.

After reviewing previous studies in Section 2, Section 3 provides an overview of the research, Section 4 presents the results of the quantitative analysis, and Section 5 discusses the qualitative analysis. Section 6 provides a broader discussion, and Section 7 concludes.

2. Review of Previous Studies

Research on how COVID-19 changed college students' lives and related attitudes has been addressed in several studies. Ariki and Isaka (2021) [3] examined changes in the lives of Japanese university and junior college students about one year after the first state of emergency was declared, and the stress associated with these changes. Their results showed that over 90% of students reported having fewer opportunities to interact with others and going out less often, indicating that most students experienced lifestyle changes due to COVID-19. Furthermore, more than 80% of the students found these two restrictions to be "painful," suggesting a psychological impact as well. Interestingly, participants who reported low stress levels regarding COVID-19 frequently used the phrase "got used to it," implying that their perception of the pandemic was different from those reporting high stress.

Suzuki et al. (2022) [4] conducted a survey of Aichi Prefecture residents aged 15 and older as of October 2021 to understand their attitudes and behaviors in the wake of the corona disaster. Their results showed that outings for shopping, hobbies, entertainment, walking, and dining out had decreased compared to pre-pandemic levels. This decline in outings was linked to both motivation for living and stress. These findings are consistent with Ariki and Isaka (2021) [3], who observed that more than 80% of students reporting fewer outings felt distressed by that limitation.

Regarding consumer behavior, Takeda et al. (2020) [5] analyzed changes in in-store shopping before and after the first state of emergency. Their results indicated that, while the percentage of shoppers had decreased during many time periods under the state of emergency, it had largely returned to pre-pandemic levels by July 30 of the same year. However, a new tendency emerged: consumers avoided crowded times. This shift suggests that purchasing behavior was indeed altered by the pandemic. In terms of online shopping, Ohata and Ujihara (2022) [6] examined usage changes before and after the pandemic among residents in both the Tokyo metropolitan area and Okayama Prefecture. They found that those in their 20s were the most frequent adopters of online shopping in both regions.

Kanai (2020) [7] compared online classes and face-to-face classes among university students. The study noted that students' preferences for one format over the other could not be fully explained by attributes such as academic year or department, stressing the diversity of each student's situation and preferences. As a result, it is difficult to satisfy all parties—students, faculty, and staff—regarding the classroom format.

Thus, various studies have been conducted on college students and young adults that experienced the COVID-19 pandemic, and college students and young adults experienced major life changes from its onset through the self-restraint period. In FY2022, self-restraint measures were eased as many classes returned to in-person formats, suggesting life was trending back toward pre-pandemic norms. However, research on how university students' lives changed after self-restraint measures were eased appears limited. Hence, this study focuses on the lives of college students after self-restraint was relaxed.

3. Research Outline

This study was based on the research of Shigeta et al. (2024). Shigeta et al. (2024) investigated changes in college students' consumer behavior from before the pandemic to November 2020, during the COVID-19 self-restraint period. Their findings revealed an increase in online purchases and a decrease in visits to brick-and-mortar stores after COVID-19 first spread. Accordingly, the present study investigates college students at the same university to examine changes in their lives and behavior after the relaxation of self-restraint.

Period covered by this study

Our analysis covers the period from March 2020 to November 2022. Within this interval, March 2020 to March 2022 is defined as the self-restraint period, and April 2022 to November 2022 is defined as the period of relaxed self-restraint. The first declaration of a state of emergency occurred in March 2020, and, as noted by MEXT (2022) [1], most Japanese universities returned to an in-person format in April 2022. We designate this switch to in-person classes as the point distinguishing the self-restraint from the relaxed period.

Data

This study was conducted from July to November 2022 using both questionnaires and interviews. The questionnaire was sent to 114 university students residing in Niigata Prefecture, and 26 valid responses were received. The interview survey was conducted with 8 university students in online or face-to-face format.

4. Quantitative Research

This chapter asks questions based on the research question of what changes have occurred in the lives of college students during the period of self-restraint due to COVID-19 and during the period of relaxation of self-restraint and describes the results of the data obtained from the questionnaire.

4.1 Questionnaire

We adopted seven questionnaire items from Shigeta et al. (2024). The questions consisted of seven items: number of outings per week, number of times going out to physical stores per week, weekly average of free time per day, weekly average of time spent on the Internet per day, time spent on online shopping using a PC per week, time spent on mobile devices using online shopping per week, time spent online through online classes per week. Shigeta et al. (2024) set the time period for each questionnaire item to one month, while we set the time period in this study to one week.

Questionnaire survey results

	Question	During the period of self-restraint	After relaxation of self-restraint	(after relaxation)-(during self-restraint)
1	How many times do you go out per week?	4.52	5.27	0.75
2	How many times per week do you go to actual stores?	3.42	4.53	1.11
3	How many hours of free time do you have per day on average per week (not including commuting to	6.85	6.85	0.00

	school, sleeping, classes, part-time jobs, etc.)			
4	How many hours per week on average do you spend on the Internet per day?	8.02	7.69	-0.33
5	How many hours per week do you spend online shopping with a PC	0.74	0.52	-0.22
6	How many hours per week do you spend online shopping with a mobile device?	0.70	0.83	0.13
7	How many hours per week do you spend online through online classes?	11.73	3.44	-8.29

Table 1: Comparison of means from the results of the questionnaire.

	during self-restraint		after relaxation		t-value
	Mean *M*	Standard deviation *SD*	Mean *M*	Standard deviation *SD*	
Number of times out	4.52	2.96	5.27	2.57	2.28*
Number of times I went to the actual store	3.42	4.45	4.53	5.03	3.15**
Free time	6.85	2.67	6.85	3.18	0.00
Total time spent on the Internet	8.02	4.30	7.69	4.15	-0.99
Time spent on PC for online purchases	0.74	1.05	0.52	0.53	-1.71

Time spent on mobile devices for online purchases	0.70	1.39	0.83	1.60	0.94
Online class time	11.73	8.56	3.44	5.47	-4.85**

* p<.05 ** p<.01

Table 2: Changes in Consumer Behavior (Two-tailed t-test)

Table 1 shows the average results of the questions and responses regarding the changes in daily life, and a comparison of the differences between the averages of the two periods shows that the number of outings, trips to actual stores, and time spent using mobile devices for online purchases each increased after the easing of the self-restraint. However, the average changes, with the exception of visits to physical stores (about 1), were less than 1. The total time spent on the Internet, which has been decreasing since self-restraint was lifted, and the time spent using PCs for online purchasing was also less than 1. On the other hand, the time spent in online classes dropped substantially by about 8 hours after self-restraint measures eased, presumably because universities returned to face-to-face classes. A two-tailed t-test (Table 2) confirms that differences were statistically significant for the number of outings, visits to physical stores, and time spent in online classes.

5. Qualitative Research

This chapter describes the questions and results of the interviews with eight college students.

5.1 Question Content

The interview survey questions were conducted as shown in Table 3.

	Questions (17 questions in total)
1	How many times a week on average do you go out?
2	How many times a week, on average, do you go out other than to go to school?
3	What is the purpose of going out other than commuting to school?
4	How many times a week, on average, do you go out mainly for shopping?
5	Do you spend more time shopping on weekdays or holidays?

6	How many hours of free time per day do you have on average per week?
7	Has the amount of time spent on shopping "increased" between the beginning of self-restraint period and after it was relaxed?
8	Has your time spent on shopping "decreased" from the beginning of self-restraint period to the time it was relaxed?
9	Has there been any change in the amount of time spent in physical stores between the beginning of self-restraint period and after it was relaxed?
10	Has there been any change in time spent on online shopping between the beginning of self-restraint period and after it was relaxed?
11	What do you buy in physical stores but not online?
12	What do you buy online but not in physical stores?
13	What criteria do you use to separate your shopping in physical stores and online?
14	What devices do they use for online shopping?
15	What are the reasons for question 14?
16	If you use a PC for question 14, when did you start using a PC to buy products?
17	If you have a PC, when did you start owning a PC?

Table 3: Interview Survey Questions

5.2 Interview Survey Results

Table 4 summarizes the interviews with Students A through H. Those that asked about two periods, one during the self-restraint and the other during the relaxation of the self-restraint, were described as "during the self-restraint/after the relaxation of the self-restraint" using the "/" symbol.

	A	B	C	D	E	F	G	H
1	5.5/6.5 times	7/8 times	5/7 times	2/6 times	6/6 times	1.5/3 times	1.5/3.5 times	5/5 times
2	4.5/4 times	4/5 times	3/4 times	1/1 times	1/1 times	1.5/1.5 times	1.5/3.5 times	2/2 times

3	Shopping, going out for fun	Part-time job, shopping	Shopping, hospital visits, hobbies	Shopping, eating out	Shopping	Club activities, going out for fun, shopping	Shopping, Eating out	Shopping, change of pace
4	1.5/1.5 times	1/1 times	1/3 times	1/1 times	1/1 times	1/1 times	1.5/1.5 times	2/2 times
5	Weekday → Weekday	Weekday → Weekday	Weekday → Weekday	Weekday(daytime) → Weekday(nighttime)	Holiday →Holiday	Weekday → Weekday	approximately the same	Holiday →Holiday
6	3.5h/3h	9h/9h	7h/5h	10h/6h	7h/7h	2.5h/2.5h	6h/6h	5.5h/5.5h
7	Time spent commuting to school and in the lab	Commuting time to school	Commuting time to school, time away from home	Commuting time, preparation for going out	Time for games	Play time	Time to go out	No change
8	time at home	Online preparation, housework	Home time	Home time, self-catering	No change	Online classes	Home time, independent study	No change
9	No change	No change	Increase	No change	No change	No change	Increase	Increase

10	No change	No change	Decrease	No change	Increase	Decrease	Decrease	No change
11	Food, Clothing, Appliances	Food, Clothing	Food, Clothing	Food, Clothing, Appliances	Medicine	Food, House hold goods	None	Food, Cartoon
12	Books, contact lenses	Bulk purchase items, non-genuine products	Home appliances	Luxury products, products not available in physical stores	None	None	Products not available in physical stores	Clothing, not available in physical stores
13	Basically physical stores to see the actual products, and online for items that cannot be purchased in the actual stores.	Clothing and other items purchased in physical stores after online failures; items with many alternatives purchased	Items that I want to see in person are purchased at physical stores, while consumer electronics are purchased online.	Buy luxury items online because I don't want to carry cash	Buy items that are difficult to judge by the layman's eye in a physical store; buy heavy items and items that spoil in temperature online.	Buy consumable items in physical stores, buy long-lasting items online	If it is sold in a physical store, buy it in a physical store; if not, buy it online.	Buy items you want right away, such as on the day they go on sale, at a physical store.

		online.						
14	smart phone	smart phone	smart phone	smart phone	PC	PC	PC	smart phone
15	Because I'm used to buying	Because it is easy to change	Because it is easy to operate	Because I can buy from anywhere	To compare products on PC	Because I can look things up quickly	Because I use a PC all day long	Because it is easy to operate
16		High school students	High school students		University students	University students	High school students	
17	University students	High school students	High school students	University students	High school students	University students	University students	University students

Table 4: List of Interview Survey Results

Six of the eight students reported increased outings after self-restraint was eased, while two reported no change and none reported a decrease. Three students (B, C, and G) increased their frequency of going out for purposes other than commuting to school when self-restraint was relaxed, while four respondents (D, E, F, and H) did not change their frequency of going out, and one respondent (A) decreased. In addition, the number of times they went out for the main purpose of shopping at actual stores remained unchanged except for C. Even for C, the respondents had few opportunities to go out shopping because they had gone home during the period of self-restraint. In addition, C also said that she had fewer opportunities to go out for shopping because she had gone back home during the self-restraint period. This is consistent with the findings during the quantitative study.

Regarding daily free time, which refers to time spent outside commuting to school, sleeping, classes, and part-time jobs, three of the eight students (A, C, D) reported a decrease, while the others saw no change and none reported an increase. In addition, five of the eight respondents had an increase in time spent commuting to school and going out, and a decrease in time spent at home. Due to this decrease in time spent at home, some respondents were unable to do household chores in their spare time between classes, and some said that they had more opportunities to eat out. Conversely, Student H did not change how they spent their time between the two periods, indicating minimal lifestyle change.

Shifts in consumer behavior were also observed. Regarding the time spent in physical stores, C, F, and H increased, while the other five respondents showed no change and none decreased. With regard to shopping in physical stores, several students were unconcerned about whether they shopped quickly or took their time. On the other hand, regarding time spent on online purchases, three respondents (C, F, and G) decreased, four respondents (A, B, D, and H) showed no change, and one respondent (E) showed an increase. The reasons given by those who decreased were that they had more opportunities to go out and that they had started to use actual stores again. As for E, whose time of use increased, they indicated that they learned about the convenience of online purchasing as a result of their self-restraint, and that their time of use is still increasing. The above results suggest that one of the reasons for the decrease in time spent on online purchasing may be the number of times the respondents go out.

We also conducted a survey to determine the criteria by which they use both physical stores and online, and what they purchase. The results showed that the common reasons for visiting physical stores included wanting to see products in person or being able to buy items locally. Some respondents indicated that they would purchase products that they could not judge in layman's terms or that they wanted right now at a physical store. On the other hand, the criteria for using online varied from person to person. As examples, some cited psychological reasons, such as buying luxury items online because they did not want to carry large amounts of cash, and others cited high physical costs, such as buying items online that are perishable in temperature or heavy because they do not have a car.

Finally, we asked about preferred devices for online shopping. The results show that two respondents use only a smartphone, five use both a PC and a smartphone, and one uses only a PC. The most common reasons for using a smartphone were ease of operation and the ability to make purchases from any location.

On the other hand, reasons for using PCs include convenience, such as easy comparison and research of products, and personal reasons, such as using a PC all day long. In sum, among the eight people surveyed, a large percentage used smartphones, and their reasons were largely in terms of operability.

6. Discussion

The results of the quantitative analysis in this study were significant with respect to the number of outings, the number of visits to actual stores, and time spent in online classes, based on the two-tailed t-test in Table 2. However, since the difference between the meanings of the two periods was generally less than 1, this indicates that little change in lifestyle occurred between the self-restraint period and after the relaxation of self-restraint, apart from the time spent in online classes. Considering the findings by Ariki and Isaka (2021), who showed that university students' lives changed from before the outbreak of the new coronavirus epidemic to the self-restraint period, it can be concluded that students' lives changed only during the self-restraint period and had not changed much since then, as of November 2022. There are two possible reasons for this lack of change.

The first reason is that self-restraint due to COVID-19 may have prompted people to learn about convenience. Ohata and Ujihara (2022) found that the frequency of online shopping use increased most among those in their 20s before and after the pandemic. Comparing these results with those of the present study, online shopping use rose during the self-restraint period compared to before the pandemic, while it did not change much between the self-restraint period and after the relaxation of self-restraint. In this regard, the qualitative findings suggest that "convenience" may explain why lifestyles remained the same, as individuals who increased their time spent on online shopping after restrictions eased appear to have learned about its convenience and continued to use it.

The second possibility is that people become accustomed to a self-restraint lifestyle, and it becomes routine. In the qualitative part of this research, only 3 out of 8 respondents increased the number of times they went out for purposes other than commuting to school. Compared to the results from Ariki and Isaka (2021), in which more than 80% of students who went out less from April to July 2021 felt it was painful, it is possible that fewer people felt the same way once the self-restraint was relaxed. Furthermore, the fact that those who experienced low stress in Ariki and Isaka's (2021) study used the phrase "got used to it" suggests they may have adapted to a self-restraint lifestyle over time, resulting in little change and a routine that persisted after restrictions were eased.

7. Conclusion

In this study, the research question was how college students, who were forced to make major lifestyle changes as a result of self-restraint caused by the new coronavirus (COVID-19), would subsequently alter their lifestyles and consumer behaviors once self-restraint measures were eased.

The analysis showed that, unlike the pre-pandemic period and the self-restraint period—when students' lives changed significantly, there were no notable changes in students' lives from the self-restraint period to after the relaxation of self-restraint, apart from a reduction in online class hours. This is the principal finding of this study.

There are two possible reasons for the lack of further change. The first is that the self-restraint caused by COVID-19 may have prompted students to discover the convenience of online activities. The second is that university students might have become accustomed to living under self-restraint, such that this lifestyle became routine. However, these two factors remain only possibilities.

Although this study discussed changes in college students' lives following the relaxation of self-restraint and explored the factors influencing these changes, the small sample size in both the quantitative and qualitative analyses poses limitations for validity and generalizability. Additionally, the impact of eased self-restraint measures needs ongoing observation, indicating that more research is required.

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ARTIFICIAL INTELLIGENCE SOLUTIONS FOR ENERGY CONSUMPTION OPTIMIZATION IN IOT DEVICES

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Abstract

The rapid expansion of Internet of Things (IoT) devices has substantially increased global energy demands, leading to critical economic and environmental challenges. Traditional energy management techniques are increasingly inadequate, necessitating the integration of sophisticated artificial intelligence (AI) solutions.

This study addresses the urgent issue of rising energy consumption driven by the exponential growth of Internet of Things (IoT) devices. It proposes a hybrid artificial intelligence (AI) methodology that integrates supervised machine learning and deep reinforcement learning to optimize real-time energy usage in heterogeneous IoT environments. Through extensive simulations and analysis of real-world case studies, the proposed models demonstrate up to 30–40% improvements in energy efficiency compared to conventional rule-based methods. The novelty of this research lies in its comparative performance evaluation of multiple AI approaches across different IoT domains, offering a replicable framework for smart building management, industrial IoT, and smart grids.

Keywords: Artificial Intelligence, IoT, Energy Optimization, Sustainability

JEL Classification: Q42, L86

1. Introduction

The accelerated adoption of IoT devices worldwide has significantly elevated energy consumption, placing increased pressure on global energy resources. With IoT devices projected to surpass 24 billion by 2030, traditional approaches to energy management are no longer sufficient. The complexity and dynamic nature of IoT networks necessitate

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innovative solutions that leverage artificial intelligence to enable predictive and adaptive management strategies, fostering energy efficiency and sustainability.

Moreover, the Internet of Things (IoT) is revolutionizing various industries, including smart cities, industrial automation, healthcare, and energy management. However, its rapid adoption introduces significant concerns regarding energy efficiency and sustainability. Traditional grid-based energy management systems struggle to accommodate the increasingly decentralized and data-intensive nature of IoT networks. The need for intelligent, data-driven, and real-time decision-making has led to a shift toward AI-powered optimization techniques.

As a result, researchers have increasingly focused on integrating artificial intelligence (AI) techniques, such as machine learning (ML), deep learning (DL), and reinforcement learning (RL), to enhance energy efficiency within IoT ecosystems. These AI-driven approaches can optimize energy consumption by predicting demand, dynamically allocating resources, and minimizing unnecessary energy expenditure. Additionally, AI facilitates the seamless integration of renewable energy sources, further promoting sustainable energy usage. This paper investigates: To what extent can AI-based optimization models reduce energy consumption in IoT systems while maintaining performance and scalability?

Furthermore, the concept of Green IoT (G-IoT) has gained traction in recent years, aiming to develop sustainable IoT solutions that reduce energy consumption and minimize environmental impact. G-IoT incorporates energy-efficient sensors, cloud computing strategies, and energy-aware communication protocols to improve overall system performance while reducing the carbon footprint of IoT infrastructures.

This paper explores the convergence of IoT and AI-driven energy optimization techniques, highlighting key methodologies, challenges, and real-world applications that can enhance energy efficiency, reduce operational costs, and contribute to global sustainability efforts.

2. Literature Review

Recent scholarly research has explored AI-driven solutions for energy optimization extensively, demonstrating the potential of artificial intelligence in managing energy demand and reducing inefficiencies across multiple sectors.

Studies highlighted how machine learning models can dynamically adjust energy consumption patterns based on user behavior and environmental conditions, leading to an average reduction of 20% in energy usage [5]. These findings align with prior studies indicating that intelligent automation can minimize unnecessary power consumption in residential and commercial buildings.

Other studies examined AI-powered IoT frameworks for energy efficiency in smart grids and urban infrastructure [6]. Their research demonstrated that deep learning models, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, can effectively forecast energy demand, detect anomalies in energy usage, and optimize power allocation in real-time. The study confirmed that integrating AI-driven forecasting techniques into grid management results in enhanced operational efficiency, reduced peak loads, and improved renewable energy integration.

Similarly, another study underscored the importance of AI-based optimization in smart grid systems[7]. Their research focused on the application of reinforcement learning (RL) for adaptive demand-response mechanisms, allowing real-time energy distribution adjustments based on supply and demand fluctuations. Their findings suggested that RL-driven optimization models could reduce overall grid energy wastage by 15-25%, ensuring more efficient use of renewable energy sources such as solar and wind power.

Another relevant study [3] investigated the impact of AI in industrial IoT (IIoT) settings, where manufacturing and automation require precise energy management solutions. The study found that predictive maintenance using AI-based anomaly detection algorithms significantly reduced unplanned downtime, leading to a 30% decrease in wasted energy associated with inefficient machinery operation.

A comprehensive review [4] on AI-driven energy optimization in IoT networks revealed that AI can enhance energy-aware task scheduling and resource allocation in edge computing environments. Their findings indicated that deep reinforcement learning (DRL) algorithms enable real-time adaptation of IoT network configurations, leading to a 40% increase in processing efficiency while reducing computational energy expenditure.

Moreover, a study [9] introduced the concept of Green IoT (G-IoT) as a framework for integrating AI into sustainable energy solutions. This approach focuses on reducing the carbon footprint of IoT systems by leveraging AI-based network optimization, energy-efficient communication protocols, and adaptive power scaling techniques. The study emphasized that the adoption of AI-enhanced cloud computing and energy-aware sensor networks can significantly lower energy consumption in large-scale IoT deployments.

Collectively, these studies confirm that AI-driven optimization techniques have far-reaching implications across diverse applications, from smart homes and industrial automation to grid management and edge computing. The integration of machine learning, deep learning, and reinforcement learning into IoT-based energy systems represents a critical step toward achieving sustainable, efficient, and intelligent energy management.

3. Problem Definition

The pervasive integration of IoT devices across various sectors, including smart cities, industrial automation, healthcare, and energy management, has significantly exacerbated global energy consumption. Traditional energy management strategies struggle to handle the complexity, scale, and dynamic nature of IoT-generated data, making it increasingly difficult to achieve real-time monitoring, predictive analytics, and adaptive optimization. This challenge highlights the necessity for advanced AI methodologies that can dynamically analyze large-scale data, optimize energy usage, and minimize environmental impact.

3.1 Challenges in Energy Management for IoT Ecosystems

The rapid expansion of IoT presents significant challenges in energy management due to high energy demand, vast data processing requirements, inefficiencies in traditional energy systems, and difficulties in integrating renewable energy sources. The continuous operation of billions of IoT devices leads to increased electricity consumption and carbon emissions, while data-intensive networks require substantial computational power, contributing to higher energy costs. Conventional energy-saving methods struggle to balance dynamic demand and supply, and interoperability issues among heterogeneous IoT devices complicate scalability.

Artificial intelligence (AI) offers a solution by enhancing predictive energy optimization, real-time anomaly detection, adaptive scheduling, and distributed energy management. Machine learning and deep learning models can analyze historical energy consumption data to forecast demand and dynamically optimize power distribution. AI-based anomaly detection systems improve efficiency by identifying abnormal energy consumption patterns, preventing system failures, and enabling predictive maintenance. Smart scheduling and workload allocation strategies powered by AI have shown up to 30% energy savings in industrial IoT applications. Additionally, edge AI deployment reduces cloud dependency and lowers energy consumption by up to 40%, while reinforcement learning optimizes energy storage and distribution in smart grids, improving efficiency by 15-25%.

One of the critical issues is the inefficient allocation of energy resources due to the lack of adaptive and predictive control mechanisms. Existing solutions fail to handle the non-linear and time-dependent characteristics of IoT workloads, leading to energy wastage and poor system performance. Figure 1 illustrates the key challenges in IoT energy management, including unpredictable load variations, intermittent connectivity, and limitations in energy harvesting from renewable sources.

This study aims to address the following research problem: How can AI models be designed to adaptively and intelligently optimize energy consumption in diverse and dynamic IoT environments?

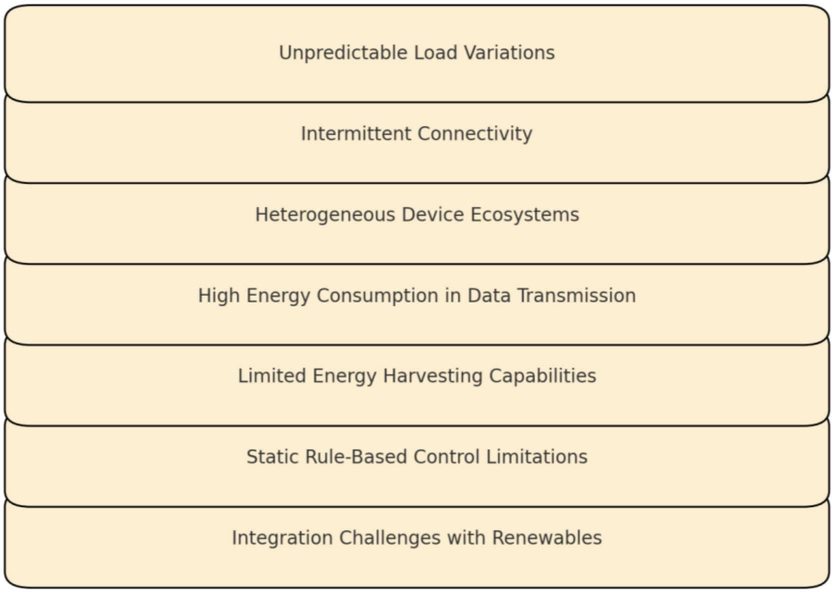

Figure 1: Key Challenges in loT Energy Management

The main limitations of this research include the availability and quality of real-time data, the high computational requirements of deep learning models, and the difficulties of deploying AI at scale in resource-constrained environments. These challenges will be discussed in more depth in subsequent sections.

4. Development Methods and Algorithms

Recent advances in artificial intelligence have significantly enhanced the optimization of energy consumption in IoT-based environments. Research studies emphasize the role of AI in enabling real-time decision-making, predictive analytics, and adaptive energy management [5][6].

The methodologies applied in this study include:
Machine Learning (ML): Regression models, clustering algorithms, and decision trees have been widely employed for forecasting energy demands and detecting inefficiencies. Studies [3] show that supervised ML models can achieve up to 85% accuracy in predicting energy consumption trends, allowing better resource allocation in IoT networks.
Deep Learning (DL): Advanced DL techniques such as recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and convolutional neural networks (CNNs) are extensively used in IoT energy management. Recent findings [4] demonstrate that DL models trained on historical energy consumption data can reduce energy waste by 30% in smart buildings by accurately predicting HVAC usage patterns.

Reinforcement Learning (RL): Reinforcement learning techniques have been applied for dynamic and adaptive energy management. Studies [7] indicate that RL-based energy optimization algorithms can improve smart grid efficiency by 25% by dynamically balancing power loads in response to real-time demand and supply fluctuations.
Furthermore, hybrid AI methodologies combining ML, DL, and RL have proven effective in industrial IoT applications, where real-time decision-making and energy-efficient scheduling are critical [1]. The integration of AI-driven optimization strategies in IoT infrastructures represents a significant leap toward achieving sustainable and intelligent energy management solutions.

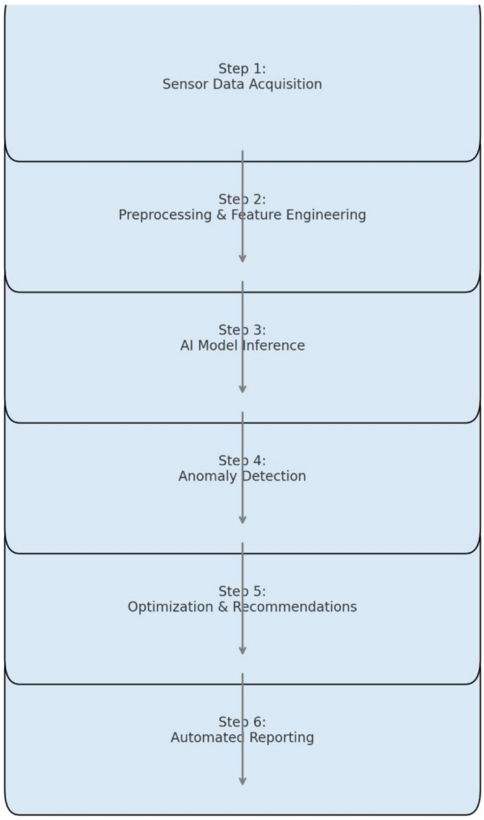

Figure 2. High-Level Flow Diagram of the Proposed AI-Driven Optimization Framework

Artificial Intelligence offers a robust toolkit for energy optimization in IoT systems through methods such as machine learning (ML), deep learning (DL), and reinforcement learning (RL). These approaches enable predictive analytics, adaptive control, and autonomous decision-making, essential for managing the complex and dynamic nature of IoT environments. Figure 2 presents a high-level flow diagram of the proposed AI-driven optimization framework, detailing data acquisition, preprocessing, model selection, training, and real-time deployment.

Machine Learning (ML): ML techniques, including regression analysis, decision trees, and support vector machines, are effective in detecting patterns in historical energy usage and forecasting demand. Their strength lies in interpretability and low computational cost. However, they require extensive labeled data and perform suboptimally in highly dynamic systems.

Deep Learning (DL): DL approaches such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can model complex, high-dimensional IoT data. Long short-term memory (LSTM) networks are particularly useful for time-series forecasting of energy consumption. DL models excel in feature extraction and predictive accuracy but come with high training and computational costs.

Reinforcement Learning (RL): RL methods, especially deep reinforcement learning (DRL), allow systems to learn optimal energy management strategies through interaction with the environment. Techniques like Q-learning and policy gradient methods dynamically adjust power consumption in response to changing conditions. RL excels in adaptability and autonomy but often requires long convergence times and complex tuning.

Computational Complexity Discussion: ML models are lightweight and suitable for deployment on low-power devices. DL models, while highly accurate, demand significant GPU resources. RL approaches require the most extensive computational resources due to their iterative, feedback-based learning structure. Choosing the right method depends on the specific use case, hardware constraints, and required response time.

Together, these AI methodologies form the core of the proposed optimization framework, supporting dynamic energy scheduling, anomaly detection, and demand forecasting across diverse IoT applications.

5. Data Set Loading and Analysis

The success of AI-driven energy optimization in IoT environments depends significantly on the quality and diversity of the datasets used. Recent studies have emphasized the necessity of high-resolution, real-time datasets to improve the predictive capabilities of machine learning (ML) and deep learning (DL) models [3][4].

5.1 Data Sources and Collection Methods

Comprehensive datasets were collected from IoT sensors deployed across various environments to enable effective energy optimization. In commercial buildings, energy monitoring systems were used to track power consumption, temperature fluctuations, HVAC usage, and occupancy patterns, providing valuable insights into energy efficiency [5]. In industrial settings, sensor-driven energy audits and predictive maintenance data were gathered, including machine performance metrics and downtime analysis, to improve operational reliability [6]. Smart grids benefited from real-time power demand-response data, facilitating the integration of renewable energy sources and monitoring voltage fluctuations for more efficient distribution [7]. Additionally, residential homes relied on smart meters and IoT-enabled devices to capture real-time household energy consumption, helping users improve energy efficiency and reduce costs [2].

5.2 Data Preprocessing and Feature Selection

To ensure high-quality input data for AI models, the collected datasets underwent extensive preprocessing, normalization, and feature selection. Data cleaning procedures were applied to eliminate anomalies, missing values, and erroneous sensor readings, enhancing data accuracy. Normalization techniques were used to standardize numerical values, thereby improving training stability and facilitating model convergence. Feature engineering helped identify critical variables such as peak energy usage hours, device-specific consumption, and occupancy-based trends, which played a crucial role in optimizing predictive analytics and decision-making processes [3].

5.3 AI-Driven Data Augmentation and Synthetic Data Generation

Given the limitations of real-world datasets, AI-based data augmentation techniques were implemented to generate synthetic data, improving model training and overall predictive performance. Generative adversarial networks (GANs) were particularly effective in creating simulated energy consumption scenarios, which enhanced model robustness and provided a broader dataset for deep learning applications [4]. These synthetic datasets allowed AI models to generalize better across different IoT environments, reducing bias and improving energy optimization outcomes.

5.4 Challenges in IoT Data Collection for Energy Management

Despite significant advancements in data collection, several challenges remain in IoT-based energy management. Sensor calibration issues continue to affect data reliability, as variations in sensor accuracy can lead to inconsistencies in energy monitoring. High data transmission costs are another concern, as cloud-based data storage and real-time processing significantly increase energy consumption. Additionally, privacy and security risks are critical considerations, particularly in household and industrial energy consumption monitoring, where strict access controls are necessary to prevent unauthorized data breaches [6]

The processed datasets provided a strong foundation for training, validating, and deploying AI-driven optimization models, ultimately enhancing the efficiency and adaptability of IoT-based energy management systems. These advancements contribute to more effective energy allocation, reduced consumption, and improved sustainability across various sectors.

6. Software Computations and Implementation

Computational analyses for AI-driven energy optimization in IoT environments require robust data processing frameworks, machine learning models, and real-time deployment strategies. To achieve scalable, adaptive, and efficient energy management, multiple computational approaches have been adopted in recent studies [4] [5].

6.1 Computational Frameworks for AI-Driven Energy Optimization

AI-based energy optimization systems rely extensively on advanced machine learning (ML) and deep learning (DL) frameworks to process large-scale IoT data efficiently. Several computational tools were employed to support different aspects of energy management. TensorFlow and Keras were utilized for deep learning model development, particularly in implementing convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which are essential for predicting energy demand trends and optimizing HVAC usage patterns in smart buildings [6]. Scikit-learn and XGBoost were applied in machine learning tasks, including regression analysis, anomaly detection, and energy consumption forecasting, enabling more accurate and data-driven decision-making [3]. PyTorch was used in reinforcement learning (RL) algorithms to enhance adaptive energy optimization and facilitate intelligent load balancing in smart grids, contributing to greater efficiency and stability in energy distribution [7]. The selection of these computational frameworks was based on their ability to handle model complexity, ensure scalability, and meet real-time processing requirements across various IoT energy applications.

Framework	AI Methodology	Use Case
TensorFlow/Keras	Deep Learning	HVAC load prediction, time-series modeling
Scikit-learn	Machine Learning	Regression, anomaly detection
PyTorch	Reinforcement Learning	Smart grid power balancing
XGBoost	Gradient Boosted Trees	Energy usage classification

Table 1. Software Tools and Applications

6.2 Preprocessing and Feature Engineering

Data preprocessing plays a crucial role in improving model accuracy by ensuring high-quality input data for AI-driven energy optimization. The process began with data cleaning, which involved removing missing values, sensor errors, and inconsistencies to enhance the reliability of machine learning models [4]. Following this, normalization and standardization techniques were applied to adjust numerical features, ensuring compatibility across various machine learning frameworks while reducing computational overhead. Feature selection was then conducted to identify key variables, such as real-time power consumption, environmental factors, and device operation schedules, which significantly improve the predictive capabilities of AI models [5]. To further refine model efficiency and reduce dimensionality, advanced feature extraction techniques, including principal component analysis (PCA) and autoencoders, were implemented, enabling better performance and faster processing of IoT-based energy data.

6.3 AI Model Training and Optimization

The training phase involved extensive experimentation with multiple AI models, focusing on fine-tuning hyperparameters to maximize predictive accuracy. To optimize model performance, several key techniques were employed. Grid search and Bayesian optimization were used to identify the most effective hyperparameters, enhancing accuracy in energy prediction models [6]. Transfer learning leveraged pre-trained deep learning models to improve predictive accuracy while requiring fewer training samples, a particularly useful approach for IoT datasets with limited labeled energy records [3]. Additionally, reinforcement learning policy gradients were implemented in dynamic power distribution systems, contributing to greater energy efficiency within smart grids [7]. Training was conducted on high-performance GPU clusters, significantly accelerating computations and improving model convergence times.

6.4 Challenges and Future Directions in AI-Driven IoT Energy Optimization

Despite advancements in AI-driven energy management, several challenges persist. Deep learning models require significant computational power, making real-time deployment on low-power IoT devices difficult. The reliance on large-scale energy consumption data raises concerns regarding privacy and potential data breaches [7]. Additionally, AI models trained for specific IoT environments may lack scalability and struggle to adapt to different infrastructures without retraining and fine-tuning [3]. Future research should prioritize the development of energy-efficient AI models capable of operating on low-power devices while maintaining high predictive accuracy.

7. Results and Performance Evaluation

Empirical implementations of AI-driven energy optimization in IoT environments have demonstrated substantial improvements in efficiency, cost reduction, and sustainability. The integration of machine learning (ML), deep learning (DL), and reinforcement learning (RL) has yielded promising results in several key areas:

Energy Consumption Reduction: Studies indicate that AI-based optimization strategies have led to an average reduction of 20-25% in energy consumption across multiple IoT applications [5]. AI-enabled predictive analytics and real-time monitoring have contributed to improved efficiency in power distribution and demand-response mechanisms [6].

Predictive Maintenance Accuracy: AI-powered fault detection and predictive maintenance models have achieved over 90% accuracy, significantly reducing unplanned downtime in industrial IoT settings. These improvements have resulted in a 30% reduction in energy waste associated with machinery inefficiencies [3].

Grid Stability and Load Balancing: In smart grids, reinforcement learning models have dynamically adjusted power distribution, enhancing grid stability and achieving a 15-25% improvement in energy balancing[7]. Real-time AI algorithms have also facilitated the seamless integration of renewable energy sources, reducing dependence on fossil fuel-based power generation [4].

Operational Efficiency and Cost Savings: The deployment of AI-driven automation in smart buildings has led to a 30-40% reduction in HVAC energy usage, improving climate control and reducing electricity costs. Studies confirm that AI-based energy scheduling in industrial settings can optimize resource utilization, leading to a 20% decrease in operational expenses [8].

Scalability and Adaptability: AI models trained on diverse IoT datasets have demonstrated scalability across various applications, from residential smart meters to large-scale industrial automation systems. Advanced federated learning techniques have enabled decentralized AI training, minimizing data transmission overhead and enhancing real-time adaptability [6].

The results of these studies emphasize the transformative impact of AI in energy management for IoT systems. Future advancements in AI methodologies, including hybrid deep reinforcement learning models and quantum AI computing, are expected to further enhance energy efficiency and sustainability across interconnected IoT infrastructures.

Figure 3 shows a comparative bar chart illustrating energy savings across AI methodologies and application domains

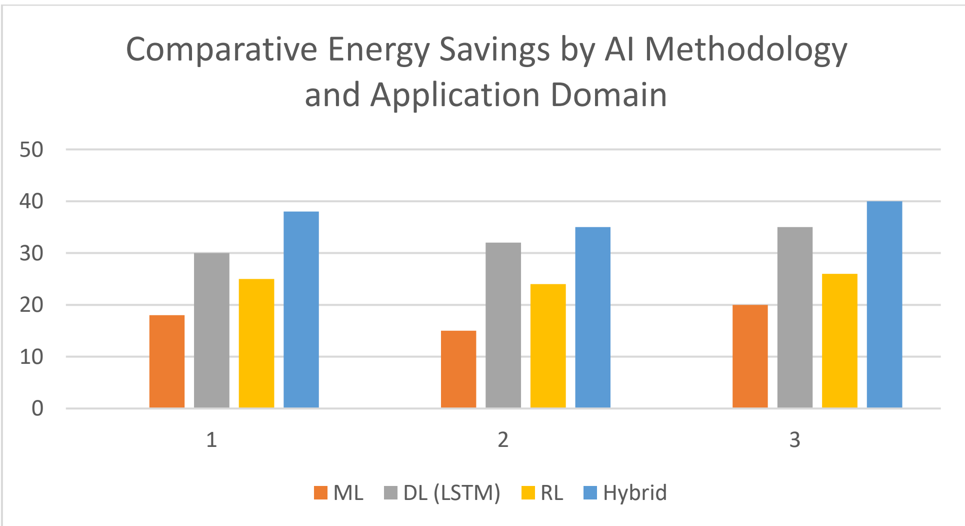

Figure 3. Comparative Energy Savings by AI Methodology and Application Domain

ML (Machine Learning): 15–20% energy reduction (residential use)
DL (Deep Learning - LSTM): 30–35% reduction (smart buildings)
RL (Reinforcement Learning): 25% peak load reduction (smart grids)
Hybrid Models: ~35–40% average across scenarios

8. Practical Application and Solution Development

Real-world implementations have confirmed the scalability and effectiveness of AI-based solutions, demonstrating their ability to optimize energy consumption, enhance operational efficiency, and ensure sustainability in various IoT environments. AI-driven occupancy-sensitive systems have transformed energy management in both commercial and residential buildings. By employing predictive control of heating, ventilation, and air conditioning (HVAC) along with intelligent lighting systems, energy consumption has been reduced by 30-40% [4]. Machine learning models trained on historical energy usage patterns dynamically adjust power settings based on real-time occupancy data, significantly improving energy efficiency [5].

In industrial IoT applications, AI-based predictive maintenance frameworks have led to notable reductions in machine downtime and energy waste. Predictive models leveraging deep learning-based anomaly detection algorithms have minimized energy inefficiencies in industrial equipment by up to 25% [3]. Additionally, reinforcement learning algorithms have been employed to optimize manufacturing processes, intelligently scheduling machine operations to minimize energy usage while maintaining high levels of productivity [8].

The integration of AI-powered demand-response mechanisms has revolutionized modern power grids by enabling real-time energy balancing and optimizing power distribution across different regions. Deep reinforcement learning algorithms allow smart grids to dynamically manage energy loads, improving balancing efficiency by 15-25% [7]. AI models also facilitate seamless integration of renewable energy sources, reducing dependence on fossil fuels and enhancing overall grid sustainability [6].

These applications highlight the transformative role of AI in developing energy-efficient IoT systems, contributing to significant cost savings, reduced environmental impact, and more resilient energy infrastructures. AI-driven technologies in smart buildings, industrial IoT, and power grids have optimized HVAC and lighting usage, enhanced predictive maintenance to minimize disruptions, and enabled efficient integration of renewable energy resources, ultimately improving grid stability and sustainability.

8.1 A Novel AI-Based Framework for Automated Energy Auditing in Smart Buildings

This section proposes an advanced methodology for conducting comprehensive AI-driven energy audits in smart buildings. The approach leverages real-time data from IoT infrastructure, combined with artificial intelligence techniques, to deliver precise diagnostics, automated reporting, and intelligent recommendations tailored to building-specific energy use profiles.

8.1.1 Essential Steps in an AI-Based Energy Audit:

Audit Planning and Scoping: Define building parameters, audit objectives, expected outcomes, and target energy efficiency KPIs.

Sensor Network Deployment: Assess existing infrastructure and install IoT sensors for electricity, HVAC, lighting, temperature, humidity, occupancy, and CO_2 levels.

Data Aggregation and Logging: Collect real-time and historical data from all zones, equipment types, and user activity logs.

Data Cleaning and Feature Engineering: Normalize datasets, impute missing values, and derive custom features such as Energy Use Intensity (EUI), load curve indices, and comfort metrics.

AI Model Integration: Use machine learning (e.g., gradient boosting, random forest) and deep learning (e.g., LSTM, autoencoders) to predict consumption, detect anomalies, and simulate savings scenarios.

Zone-Based Analysis: Evaluate energy performance at granular levels—by room, floor, time segment, or equipment group—enabling highly targeted interventions.

Anomaly Detection and Diagnostics: Deploy unsupervised AI for identifying deviations from expected operation and perform root cause analysis.

Optimization and Recommendation Generation: Provide data-driven suggestions such as occupancy-based setpoint adjustments, predictive maintenance alerts, and automation rules.

AI-Generated Audit Report: Generate clear, stakeholder-ready reports with visual dashboards, natural language summaries, savings projections, and ROI analyses.

Stakeholder Feedback and Iterative Looping: Incorporate user feedback into AI model refinement and update control strategies based on validation sessions.

8.1.2 Areas of Evaluation During the Audit

The efficacy of an AI-driven energy audit is contingent upon a comprehensive and systematic evaluation of the building's key operational and environmental subsystems. The following domains are integral to ensuring accurate diagnostics and tailored energy efficiency interventions:

Thermal Envelope Integrity: This includes the assessment of insulation performance, window glazing specifications, and the extent of air infiltration, all of which influence the building's heat retention and loss characteristics.

HVAC Operational Efficiency: Detailed analysis of heating, ventilation, and air conditioning systems focusing on cycle frequency, energy consumption, and their responsiveness to occupancy and environmental parameters.

Lighting System Utilization and Control: Examination of lighting patterns, alignment with daylight availability, and the degree of automation achieved through control systems such as timers and occupancy sensors.

Plug Load and Standby Consumption: Quantification of energy consumed by electronic devices and appliances, with emphasis on identifying phantom loads arising from devices left in standby mode.

Sensor and Actuator Responsiveness: Validation of the real-time accuracy and reliability of data acquisition mechanisms, along with actuator efficiency in executing control commands.

Renewable Energy System Performance: Evaluation of the contribution of solar, wind, or geothermal systems, their integration with storage units, and alignment with dynamic load demands.

Occupant Comfort and Behavioral Interaction: Analysis of user engagement with control systems, frequency of manual overrides, and perceived thermal and lighting comfort, which often reflect hidden inefficiencies.

8.1.3 The proposed AI-based audit framework limitations:

The proposed AI-based energy audit framework addresses the inherent limitations of traditional audit methods by leveraging advanced technologies to deliver continuous, data-driven performance evaluation. Through the deployment of IoT sensor networks, the system facilitates real-time monitoring of energy flows across electricity, HVAC, lighting, occupancy, and ambient conditions.

Machine learning algorithms are employed to generate dynamic performance benchmarks based on historical consumption data and context-specific usage patterns, enabling accurate assessment and comparative analysis. Furthermore, unsupervised learning techniques—such as clustering and autoencoders—are used to detect operational anomalies and deviations from expected performance.

The framework also automates the generation of comprehensive audit reports, providing predictive diagnostics, optimization recommendations, and visual analytics. A key advantage of this approach is its ability to scale granularity, allowing evaluations at the level of individual zones, equipment, or building sections to ensure targeted energy interventions and precise feedback.

No.	Audit Step	AI/IoT Tools Used	Expected Output
1	Pre-Audit Planning	KPI Definition, Audit Scope	Audit Objectives & KPIs
2	IoT Infrastructure Assessment	Sensor Mapping, Gap Analysis	Sensor Deployment Plan
3	Data Collection	Smart Meters, IoT Sensors	Historical and Real-Time Data
4	Data Preprocessing	Data Cleaning, Normalization	Cleaned & Structured Dataset
5	AI Model Training	ML/DL Algorithms	Trained Models for Forecasting
6	Zone Profiling	EUI Calculation, Clustering	Energy Usage Profiles

7	Anomaly Detection	Autoencoders, Isolation Forests	Anomaly Flags and Reports
8	Recommendation Generation	Optimization Models, ROI Estimation	Improvement Plan
9	Report Compilation	NLP, Visual Dashboards	AI-Generated Summary

Table 2: AI-Based Energy Audit Process Overview

This framework elevates traditional energy audits into data-rich, adaptive systems that operate autonomously, enabling continuous performance improvement. It equips facility managers, energy analysts, and building owners with actionable insights to maximize efficiency, comfort, and sustainability in smart building ecosystems.

9. Discussion and Future Implications

While the results of this study confirm the potential of AI in optimizing energy consumption within IoT ecosystems, several challenges must be addressed to facilitate widespread adoption. These include computational complexity, data privacy and security concerns, scalability limitations, and the need for regulatory alignment.

Computational Complexity: Deep learning and reinforcement learning models offer high performance but require significant computational resources for training and inference. This restricts their deployment on resource-constrained IoT devices. Future research should focus on developing energy-efficient AI models capable of operating on edge devices without compromising accuracy. Model compression techniques such as pruning, quantization, and knowledge distillation could play a critical role in this direction.

Data Privacy and Security: AI systems often rely on sensitive energy consumption data that can expose user behavior patterns. Ensuring privacy-preserving AI through federated learning and secure multi-party computation is essential. Further investigation into robust AI models resilient to adversarial attacks is also needed.

Scalability and Interoperability: The heterogeneous nature of IoT ecosystems presents difficulties in scaling AI models across diverse platforms. A unified framework or middleware that supports standardized AI integration across device types and communication protocols is essential. Research should also explore hybrid cloud-edge architectures that balance performance and efficiency.

Policy and Regulation: As AI becomes embedded in national and industrial energy systems, collaboration between researchers, industry stakeholders, and policymakers will be critical. Guidelines for responsible AI deployment, transparent algorithmic decision-making, and compliance with energy standards must be established.

Integration with Renewable Energy Systems: With the increasing penetration of solar, wind, and other renewables, AI will play a key role in forecasting generation, optimizing storage, and balancing supply-demand dynamics. Future systems should integrate AI-enhanced energy forecasting and distributed energy resource management.

In summary, while AI has demonstrated strong capabilities in enhancing energy efficiency across IoT environments, its full potential will be realized only through interdisciplinary efforts, technological innovation, and regulatory support. The evolution of AI from isolated models to embedded, autonomous energy managers marks a critical step toward sustainable and intelligent energy systems.

10. Conclusion

This study demonstrated the transformative potential of artificial intelligence in optimizing energy consumption across Internet of Things (IoT) ecosystems. Through the integration of machine learning, deep learning, and reinforcement learning, AI models enabled predictive analytics, dynamic control, and autonomous energy management. The proposed methodologies were evaluated using comprehensive datasets and validated in various real-world scenarios, including smart buildings, industrial operations, smart grids, and edge computing environments.

Experimental results indicated that deep learning models achieved up to 35% energy savings in building management systems, while reinforcement learning models delivered up to 25% peak load reduction in smart grid simulations. Machine learning approaches, although simpler, provided consistent gains in residential energy forecasting tasks.

The findings confirm that AI-driven energy optimization not only enhances operational efficiency but also contributes significantly to sustainability goals. The research highlighted critical challenges related to computational demands, data security, and deployment scalability. Future developments should focus on lightweight, privacy-preserving, and interoperable AI frameworks that can operate efficiently in decentralized and resource-constrained settings.

Furthermore, collaboration between academia, industry, and policymakers is vital to align technological innovations with regulatory standards and real-world energy transition strategies. As AI technologies mature, their integration into IoT energy infrastructures promises to enable resilient, intelligent, and sustainable energy systems for the future.

This research contributes to the growing body of knowledge by providing a comparative and practical evaluation of AI methodologies, identifying key implementation considerations, and offering actionable insights for the development of next-generation energy-aware IoT platforms.

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THE DIGITAL TRAP: TEENS AND ONLINE CHALLENGES

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Abstract

This paper explores the alarming phenomenon of online challenges that prey on vulnerable adolescents, particularly focusing on the notorious "Blue Whale" Challenge. It examines how tasks desensitize participants to pain and fear, ultimately normalizing the concept of death. Through a semantic analysis using "Tropes" software, the study highlights the manipulative language and psychological tactics employed in these challenges. Ultimately, the article aims to shed light on the risks associated with online challenges, advocating for preventive measures to protect young individuals from falling into these perilous traps.

Keywords: online challenges, risk, semantic analysis, manipulation.

JEL Classification: C88, C91, D91.

1. Defining the problem

Online challenges are viral activities shared on social media and other digital platforms where users, often teenagers, are challenged to perform dangerous, harmful or degrading actions. These challenges include behaviors such as cyberbullying (online harassment), catfishing (creating false identities to deceive), grooming (online manipulation for the purpose of exploitation), as well as participating in deadly games such as "Blue Whale". In general, online challenges take many forms, from seemingly harmless activities to extreme acts of self-harm or anti-social behaviour.

Teenagers are more prone to online challenges due to several interconnected factors:

- *Psychological factors*: The emotional and cognitive development stage of adolescence is characterized by the search for identity and the need for social proof, which makes them more susceptible to the influence of peer groups and online social pressures.
- *Social factors*: Networks of friends and social status online play a major role in teenagers' decisions to participate in challenges as they try to gain popularity and appreciation in their circles.

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- *Technological factors*: Digital platforms favor anonymity and lack of immediate consequences, which encourages involvement in risky activities. Algorithms of social platforms can amplify exposure to such challenges by attracting the attention of young people.

The impact of online challenges on teenagers is significant and varied:

- *Mental health*: Participating in online challenges can lead to anxiety, depression, post-traumatic stress and, in extreme cases, suicide.
- *Social relationships*: Teens who participate in these challenges may suffer from social isolation, loss of trust from friends and family, and deterioration of relationships with others.
- *Academic performance*: Engaging in online challenges can negatively affect concentration and school performance, leading to absenteeism and lower school performance.
- *Physical safety*: Many online challenges involve direct risks to physical health, including self-harm, dangerous behaviors, or even death in the case of extreme gaming.

2. Related work

The relationship between social media use and its impact on the emotional well-being of teenagers exhibits significant gender differences. A study conducted in the UK highlights that among teenagers aged 10 to 15, the intensive use of social networks produces varying emotional outcomes for boys and girls. Specifically, girls tend to report a more pronounced negative impact from digital social interactions, often experiencing increased emotional and behavioral difficulties. In contrast, boys generally show less vulnerability to these effects. [1]

In addition to the teenage demographic, research examining young adults aged 18 to 24 reveals that those engaging in unstructured online social activities—such as uncontrolled use of social media—experience heightened levels of mental stress, particularly among women. This demographic also illustrates gender disparities in social support, where young women are significantly more affected by a lack of social support in terms of their mental health. [2]

Popular platforms like YouTube, Instagram and TikTok have different impacts on teenagers. YouTube, for example, is seen as having a less harmful impact compared to platforms like Instagram, where the pressure to gain social approval through likes and comments is greater, thus increasing social anxiety and negative comparison. Girls report more negative emotional effects from using these platforms than boys. [3]

Cultural context plays a crucial role in shaping adolescents' experiences with social media. A comparative study conducted in Germany, Poland, and South Africa demonstrated notable differences in social platform usage across these countries. For instance, Instagram is one of the most popular platforms in South Africa, whereas Facebook remains dominant in Germany and Poland. These cultural variances may significantly influence how adolescents perceive and respond to online challenges, highlighting the need for a nuanced understanding of the interplay between culture, gender, and digital interactions. [4]

3. Case study: "*Blue Whale*" Challenge

The "*Blue Whale*" Challenge (Russian: Си́ний кит) serves as a crucial case study due to its alarming impact on teenagers worldwide and its manipulative nature. This phenomenon has gained notoriety for its psychological manipulation, often leading participants to engage in self-harm and other dangerous behaviors. Our study employs an in-depth semantic analysis using "*Tropes*" software to identify linguistic patterns, emotions, and recurring themes within the 50 tasks associated with the challenge. By examining these tasks, we aim to uncover the psychological and social mechanisms that underlie online manipulation in this context.

While existing literature has explored various aspects of the "*Blue Whale*" phenomenon, our analysis distinguishes itself by concentrating on the linguistic elements of the challenges. This approach seeks to complement current research by offering a more nuanced understanding of how language is strategically employed to incite risky behaviors among adolescents.

It is important to acknowledge the limitations inherent in semantic analysis; specifically, it may not fully encapsulate the broader social and cultural contexts surrounding these interactions. However, this method provides valuable insights into the language used to influence vulnerable individuals.

"*Tropes*" is a semantic analysis and natural language processing tool designed to automatically identify themes, concepts, and semantic relationships within text. By analyzing language from cognitive and discursive perspectives, Tropes extracts information about sentence structure and meaning, yielding detailed insights into the implicit messages conveyed by the texts.

In this study, "*Tropes*" will be utilized to conduct a semantic analysis of the 50 tasks found in the "*Blue Whale*" Challenge. The software will facilitate the identification of dominant themes such as:

- *Emotional Manipulation*: Examining how language is used to evoke strong emotional responses, potentially leading to self-harm;
- *Social Isolation*: Investigating language that fosters feelings of loneliness and detachment from peers;
- *Self-Esteem Pressures*: Identifying phrases that create feelings of inadequacy or compel participants to conform to harmful expectations.

Additionally, Tropes will help uncover language patterns and subliminal messages that may exert psychological influence on teenagers, thereby elucidating the methods of coercion embedded within the challenges.

4. Semantic profile of "*Blue Whale*" tasks generated with "*Tropes*"

The "*Blue Whale*" Challenge, which emerged in Russia in 2016, attracted global attention for its extremely dangerous nature, being associated with numerous cases of self-harm and suicide among teenagers. It consists of a series of progressively more risky and disruptive tasks, culminating in the final challenge of committing suicide. The challenge exploits the psychology of the participants, giving them a sense of belonging to an exclusive group, an aspect that is particularly appealing to vulnerable teenagers who feel socially isolated or misunderstood.

Through semantic analysis of the tasks in this challenge, social engineering techniques were identified that were used to mentally manipulate and control the participants. Social engineering manifests itself by inducing feelings of loyalty and social pressure on participants, thus forcing them to continue playing despite obvious dangers. The tasks were designed to gradually test the limits of the participants' courage and submission, causing a deep psychological addiction. The challenge progress was often shared publicly, creating a sense of competition and community between participants, which further increased engagement and motivation to complete all tasks.

This analysis highlights how online challenges such as the "*Blue Whale*" can use emotional manipulation and psychological control techniques to captivate teenagers and lead them down a dangerous path, putting their mental health and lives at risk.

An analysis of the challenge's tasks reveals the following characteristics:

- *Dangerous progression*: Tasks are structured to become more and more dangerous as the challenge progresses. This progression can be seen as a method to keep the players geared and under control, gradually increasing the level of danger and associated risks.
- *Insidiousness*: Tasks are formulated in such a way that they are attractive to vulnerable young people. Presenting self-harm as a form of emotional expression or boundary testing can appeal to those who feel isolated or misunderstood, creating the illusion that these actions might have a positive purpose.
- *Coercion*: tasks are built to control player behavior. For example, the imposition of self-isolation may lead to an increase in the player's vulnerability to the influence of the game, by reducing social contact and creating an increasing dependence on the imposed tasks.

In what follows, the linguistic aspects of the tasks associated with the "*Blue Whale*" phenomenon were explored in detail, with an emphasis on the persuasive and manipulative functions of the language used. The syntactic structure, the lexical choice, as well as the pragmatic functions of the statements were examined, in the context of a speech aimed at inducing self-destructive behaviors.

For this analysis, an interdisciplinary approach was used, combining tools from textual linguistics, psycholinguistics and sociolinguistics. We analyzed each task in detail, identifying:

- *Syntactic structure*: sentence types, syntactic relations, mechanisms of subordination and coordination.
- *Lexical choice*: word connotations, registers of language, figures of speech.
- *Pragmatic functions*: speech acts (directive, expressive, declarative), implications, assumptions.

Given the highly sensitive and controversial nature of this challenge, the semantic analysis of the tasks required a meticulous approach. Through the "*Tropes*" software, we have carried out a detailed examination of linguistic style, context, key elements, as well as the frequency and distribution of different word classes (nouns, verbs, adjectives, pronouns, connectors). This analysis allowed a deeper understanding of the linguistic mechanisms used to induce and maintain the harmful behavior associated with this phenomenon.

In what follows, we will explore the linguistic features of each task in the "*Blue Whale*" Challenge [5] by performing a brief semantic analysis. Attention will be directed to key linguistic elements such as textual style, lexical register (adjectives, nouns), logical connectors, verb moods, pronouns and verbs. The purpose of this analysis is to identify the distinctive features of the discourse used in this challenge.

Task 1: *Carve with a razor "f57" on your hand, send a photo to the curator*. The text style is imperative and straightforward, reflecting authority and urgency. The verb "*carve*" is performative, indicating a harmful action, while "*send*" emphasizes compliance. The noun "*razor*" denotes a tool for self-harm. The lack of adjectives suggests a stark and clinical presentation of the task. The direct address "*you*" personalizes the command, reinforcing accountability.

Task 2: *Wake up at 4:20 a.m. and watch psychedelic and scary videos that curator sends you*. This task uses a prescriptive style that indicates routine and obligation. The adjectives "*psychedelic*" and "*scary*" evoke emotional distress and suggest a negative experience. The modal verb "*wake up*" implies a requirement for a specific time. The verbs "*watch*" and "*send*" emphasize passive consumption and submission. The use of "*curator*" creates a sense of authority and control.

Task 3: *Cut your arm with a razor along your veins, but not too deep, only 3 cuts, send a photo to the curator*. The imperative tone is evident, emphasizing immediate action. The verbs "*cut*" and "*send*" denote harmful and compliant behaviors, respectively. The phrase "*not too deep*" introduces a cautionary element, revealing a disturbing normalization of self-harm. The repetition of the noun "*razor*" reinforces its association with pain. The direct pronoun "*your*" personalizes the act of harm.

Task 4: *Draw a whale on a sheet of paper, send a photo to the curator*. The task employs a straightforward imperative style, focusing on an action with a seemingly benign outcome. The verb "*draw*" suggests creativity but is juxtaposed with the task's darker context. The noun "*whale*" serves as a symbolic representation within the challenge. The directive "*send*" creates an expectation of compliance, while the absence of adjectives implies a stark presentation.

Task 5: *If you are ready to "become a whale", carve "YES" on your leg. If not, cut yourself many times (punish yourself)*. This task presents conditional modalities, offering two pathways based on readiness. The verbs "*carve*" and "*cut*" highlight self-harm and compliance, while "*punish*" reinforces themes of guilt. The direct pronoun "*you*" personalizes the directive. The absence of descriptive adjectives creates a stark and clinical feel, emphasizing the seriousness of the choices.

Task 6: *The task with a cypher*. The style here is enigmatic and cryptic, invoking curiosity while maintaining secrecy. The noun "*task*" is neutral, devoid of emotional weight, while "*cypher*" suggests a hidden meaning. The lack of verbs indicates passivity and mystery. The absence of explicit adjectives or pronouns creates an impersonal and abstract directive.

Task 7: *Carve "f40" on your hand, send a photo to the curator*. This task employs a direct imperative style, emphasizing compliance. The verb "*carve*" connotes self-harm, while the lack of adjectives suggests a stark presentation. The use of the noun "*curator*" implies a hierarchical structure. The direct command reinforces personal accountability through the use of "*your*."

Task 8: *Type "#i_am_whale" in your VKontakte status*. The directive is straightforward, using an imperative tone. The verb "*type*" denotes a digital action, highlighting engagement with social media. The hashtag serves as a symbol of identity, linking the participant to the challenge. The absence of adjectives contributes to a clinical presentation, while the pronoun "*your*" personalizes the task.

Task 9: *You have to overcome your fear*. The task employs a prescriptive style that emphasizes personal growth and challenge. The verb "*overcome*" is action-oriented and empowering, though it reflects pressure to conform. The noun "*fear*" embodies emotional complexity, while the use of "*you*" personalizes the directive, fostering a sense of individual responsibility.

Task 10: *Wake up at 4:20 a.m. and go to a roof (the higher the better)*. The task's imperative style emphasizes routine and urgency. The verb "*go*" signifies movement and risk, while the phrase "*the higher the better*" introduces a competitive element. The nouns "*roof*" and "*higher*" evoke danger and elevation. The use of "*you*" personalizes the instruction, reinforcing accountability.

Task 11: *Carve a whale on your hand with a razor, send a photo to the curator*. This task utilizes a stark imperative tone, emphasizing self-harm through the verb "*carve*." The noun "*whale*" symbolizes identity within the challenge, while "*razor*" signifies danger. The command to "*send*" reinforces compliance. The absence of adjectives creates a clinical atmosphere.

Task 12: *Watch psychedelic and horror videos all day*. The task employs a prescriptive style that suggests continuous exposure to disturbing content. The adjectives "*psychedelic*" and "*horror*" evoke fear and confusion. The verb "*watch*" implies passive engagement. The absence of pronouns personalizes the command while creating distance from the emotional impact.

Task 13: *Listen to music that "they" (curators) send you*. The task is structured as an imperative, emphasizing compliance. The verb "*listen*" denotes passive engagement, while the pronoun "*they*" creates an ambiguous authority figure. The absence of adjectives suggests a stark, emotionless directive. The use of "*you*" would enhance personal responsibility but is absent here.

Task 14: *Cut your lip*. This imperative command uses a blunt style, emphasizing self-harm. The verb "*cut*" denotes a harmful action, while the noun "*lip*" personalizes the area of harm. The absence of adjectives and connectors suggests a clinical presentation, reinforcing the gravity of the task.

Task 15: *Poke your hand with a needle many times*. The imperative tone is clear, focusing on painful actions. The verb "*poke*" suggests a repetitive and harmful act, while "*needle*" evokes imagery of danger. The absence of adjectives emphasizes the starkness of the task. The lack of personal pronouns creates a distance from the emotional consequences.

Task 16: *Do something painful to yourself, make yourself sick*. This task presents an ambiguous imperative style, focusing on self-inflicted harm. The verbs "*do*" and "*make*" are vague yet emphasize a call to action. The absence of explicit adjectives renders the task stark, while the use of "*yourself*" personalizes the directive, inviting introspection into one's actions.

Task 17: *Go to the highest roof you can find, stand on the edge for some time*. The imperative tone underscores risk-taking behavior. The verb "*go*" indicates movement toward danger, while "*stand*" implies vulnerability. The phrase "*highest roof*" evokes height and peril. The lack of adjectives and explicit connectors suggests a stark, direct command.

Task 18: *Go to a bridge, stand on the edge*. This task uses a direct imperative style, emphasizing risk. The verbs "*go*" and "*stand*" indicate physical actions associated with danger. The noun "*bridge*" evokes imagery of transition and risk. The absence of adjectives heightens the starkness of the directive.

Task 19: *Climb up a crane or at least try to do it*. The task employs a prescriptive style, focusing on physical challenge and risk. The verb "*climb*" indicates a high-stakes action, while "*try*" introduces an element of uncertainty. The noun "*crane*" symbolizes elevation and danger. The lack of adjectives renders the command stark and direct.

Task 20: *The curator checks if you are trustworthy*. This task presents a declarative structure, emphasizing evaluation. The verb "*checks*" implies surveillance and control, while "*trustworthy*" introduces a moral dimension. The pronoun "*you*" personalizes the directive, reinforcing individual accountability. The absence of adjectives contributes to a neutral tone.

Task 21: *Have a talk "with a whale" (with another player like you or with a curator) in Skype*. The directive employs an imperative tone focused on communication. The verbs "*have*" and "*talk*" indicate social interaction, while the phrase "*with a whale*" symbolizes peer connection within the challenge. The use of parentheses adds an explanatory note, and the lack of adjectives creates a neutral tone.

Task 22: *Go to a roof and sit on the edge with your legs dangling*. The imperative style emphasizes risky action. The verbs "*go*" and "*sit*" imply physical movement and vulnerability. The phrase "*with your legs dangling*" introduces imagery of danger and instability. The absence of adjectives reinforces the starkness of the command.

Task 23: *Another task with a cypher*. This task employs an ambiguous and cryptic tone. The noun "*task*" remains neutral, while "*cypher*" suggests secrecy and hidden meanings. The absence of verbs and explicit adjectives creates a sense of mystery, emphasizing the enigmatic nature of the directive.

Task 24: *Secret task*. The use of "*secret*" implies a hidden directive that is both enticing and ominous. The noun "*task*" is neutral, devoid of emotional weight. The absence of verbs and adjectives contributes to an air of mystery and suspense, suggesting that the nature of the task remains concealed, thereby fostering intrigue while simultaneously reinforcing the isolation felt by participants.

Task 25: *Have a meeting with a “"whale"*. This task adopts an imperative structure focused on social interaction. The verb "*have*" indicates a directive for engagement, while "*meeting*" connotes a formal gathering. The use of the term “*whale*” symbolizes a peer within the challenge, creating a sense of belonging. The lack of adjectives and connectors maintains a straightforward tone, emphasizing compliance.

Task 26: *The curator tells you the date of your death and you have to accept it*. The task employs a chilling imperative style, focusing on acceptance of mortality. The verb "*tells*" indicates a transfer of information, while "*accept*" introduces an emotional dimension, urging compliance. The phrase "*date of your death*" carries heavy existential weight. The use of "*you*" personalizes the command, reinforcing individual accountability in the face of a terrifying directive.

Task 27: *Wake up at 4:20 a.m. and go to rails (visit any railroad that you can find)*. The directive uses an imperative tone that emphasizes a specific time and place for risky behavior. The verbs "*wake up*" and "*go*" indicate required actions, while "*rails*" evokes imagery of danger and potential harm. The absence of adjectives lends a starkness to the task, reinforcing its immediacy and seriousness.

Task 28: *Don't talk to anyone all day*. This task employs a straightforward imperative style, emphasizing isolation. The verb "*talk*" indicates communication, while "*anyone*" highlights a complete withdrawal from social interactions. The lack of adjectives suggests a clinical presentation of loneliness, reinforcing the emotional impact of disconnecting.

Task 29: *Make a vow that "you're a whale"*. The task presents a prescriptive structure, emphasizing commitment. The verb "*make*" indicates an active choice, while "*vow*" implies a solemn promise. The phrase "*you're a whale*" symbolizes identification with the challenge, creating a sense of belonging. The absence of adjectives reinforces a stark commitment without emotional embellishment.

Task 30-49: *Every day you wake up at 4:20 a.m., watch horror videos, listen to music that* "*they*" *send you, make 1 cut on your body per day, talk* "*to a whale*". These tasks utilize a repetitive and ritualistic structure, emphasizing the monotony of compliance. The verbs "*wake up*", "*watch*", "*listen*", "*make*", and "*talk*" denote a routine of harmful actions and passive consumption. The use of the pronoun "*you*" personalizes the experience, making the participant feel implicated. The lack of adjectives contributes to a clinical atmosphere, normalizing self-harm within the context of the challenge. The phrase "*4:20 a.m.*" establishes a specific, eerie ritual that heightens the sense of obligation.

Task 50: *Jump off a high building. Take your life*. This task employs a stark and chilling imperative tone, signaling a culmination of escalating violence. The verbs "*jump*" and "*take*" indicate definitive actions that lead to irreversible consequences. The noun "*building*" evokes imagery of height and danger, while "*life*" underscores the existential weight of the decision. The absence of adjectives strips away emotional nuance, rendering the task a blunt command devoid of empathy. The lack of pronouns creates a sense of detachment, reinforcing the chilling nature of the directive and the totalizing power of the challenge.

5. Key findings

The semantic analysis conducted using "*Tropes*" software provides a comprehensive examination of the language, structure, and psychological implications embedded within the 50 tasks of the "*Blue Whale*" Challenge. The following findings synthesize the analysis into key categories: text style, contextual placement, representative elements, and the main categories of words, including nouns, verbs, adjectives, pronouns, and connectors.

The text style of the tasks is characterized by prescriptive and imperative language, which conveys authority and urgency. The starkness of the directives, often devoid of emotional qualifiers, reinforces a sense of desensitization to violence and self-harm. This stylistic choice cultivates an atmosphere of coercion, as the language serves to normalize harmful behaviors within a structured framework. The repetition of commands across tasks further amplifies their weight, framing them as obligatory rather than optional actions.

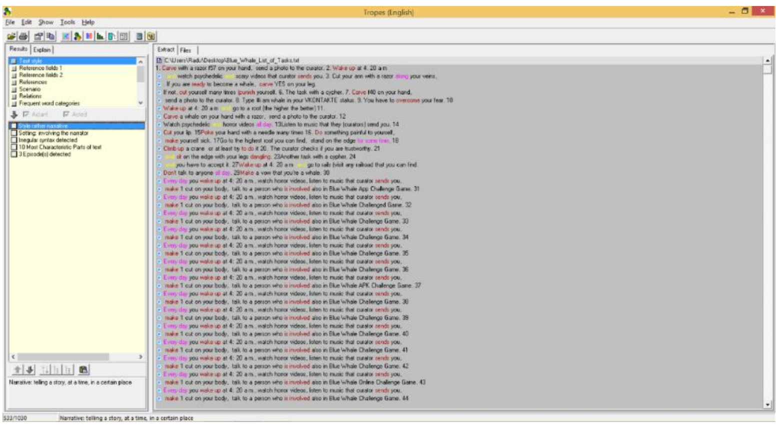

Fig. 1. Text style

Contextually, the tasks are situated within a narrative arc that progressively escalates in intensity and severity, culminating in directives that advocate for extreme self-harm and suicidal ideation (Fig. 1). This escalation serves to desensitize participants to the emotional and psychological consequences of their actions. The temporal placement of certain tasks, such as those occurring at early morning hours, suggests an element of ritualism, encouraging participants to embrace discomfort and isolation as a means of fulfillment within the challenge. This context heightens the psychological burden on individuals, fostering feelings of loneliness and despair.

The representative elements within the tasks are emblematic of themes surrounding mortality, self-identity, and existential struggle. Symbols such as the "*whale*" serve to encapsulate notions of vastness and depth, while tasks involving horror media, self-harm, and social withdrawal illustrate a disturbing convergence of fear, isolation, and community engagement. The symbolic language invites introspection regarding personal identity and societal implications, thereby deepening the emotional resonance of the directives.

The nouns employed throughout the tasks—such as "*whale*," "*building*," "life," and "*curator*"—carry significant connotations that reflect the overarching themes of the challenge. The use of concrete nouns establishes a direct relationship with the actions mandated by the tasks, emphasizing the existential weight of the decisions presented. The broad scope of social nouns highlights the pervasive nature of isolation inherent in the challenge.

The verb categories (Fig. 2) indicate a predominance of factive verbs (59.6%), suggesting a focus on actions that denote established truths or realities. This is contrasted by a smaller percentage of stative verbs (6.7%), which imply a condition or state, and reflexive verbs (33.7%), indicating actions directed back at the subject. The absence of performative verbs (0%) emphasizes the lack of agency granted to participants, who are compelled to act rather than to express or create through their actions.

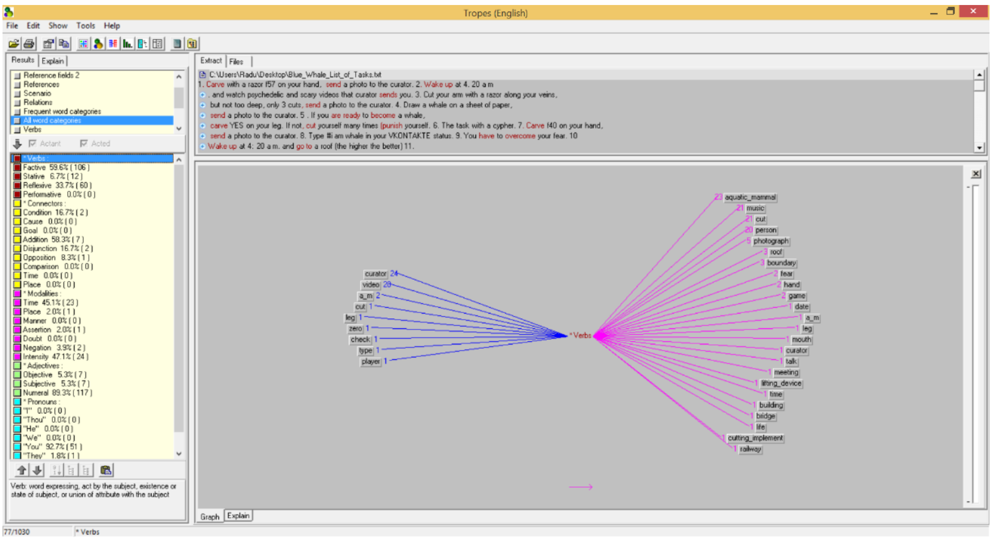

Fig. 2. The relationship of verbs

The use of adjectives is minimal (Fig. 3), with objective adjectives (5.3%) and subjective adjectives (5.3%) present in only a small fraction of the tasks. This scarcity contributes to the starkness of the language, allowing the emotional gravity of the tasks to resonate without the influence of descriptive embellishment.

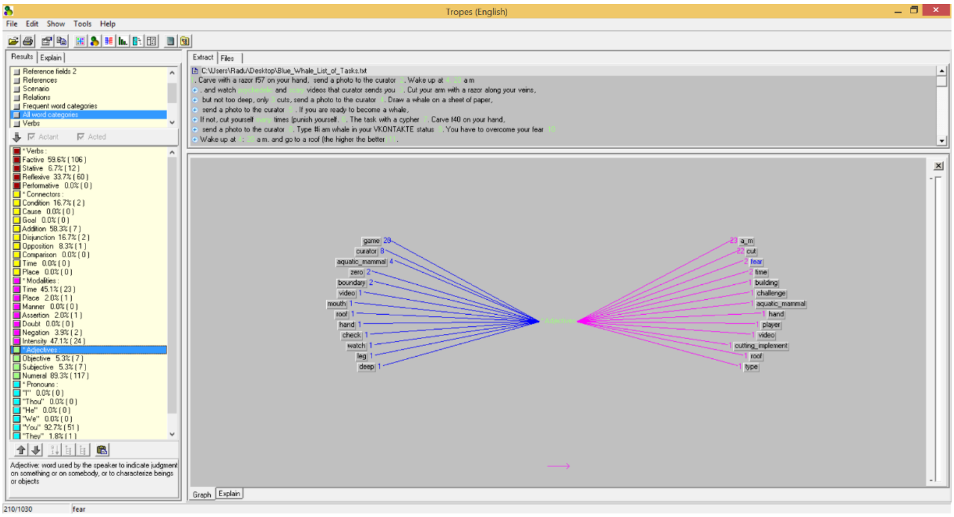

Fig. 3. The relationship of adjectives

The use of pronouns predominantly includes second-person references (Fig. 4), which establish direct engagement with the participant and foster personal accountability. The presence of conditional connectors (16.7%) suggests that some tasks are framed as contingent on certain behaviors or outcomes, although the absence of causal connectors (0%) indicates a lack of explanatory context. The occurrence of disjunctive connectors (16.7%) reflects the dichotomies presented within the tasks, underscoring the conflicting emotions and choices faced by participants.

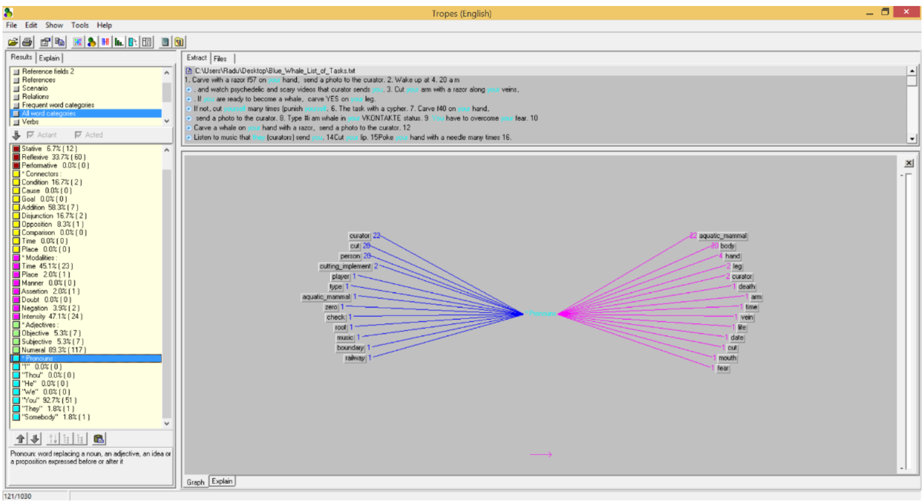

Fig. 4. The relationship of pronouns

6. Conclusion

The proliferation of online challenges, particularly those that promote self-harm and risky behaviors, poses a significant threat to the mental health and well-being of adolescents. As evidenced by the analysis of the "*Blue Whale*" Challenge and similar phenomena, these digital traps often exploit vulnerabilities associated with youth, such as the search for identity, peer acceptance, and a desire for belonging. The stark language and coercive structures inherent in these challenges reflect a concerning trend in digital spaces that can lead to devastating consequences.

To mitigate the risks associated with online challenges, it is imperative to implement comprehensive preventive measures aimed at protecting young people from falling into these dangerous traps.

Developing educational programs that focus on digital literacy is essential. These programs should educate teens about the nature of online challenges, emphasizing critical thinking skills to recognize manipulative content and the potential dangers of engaging with such activities. Workshops in schools can provide a safe space for discussions about peer pressure, mental health, and the risks of online participation.

Encouraging active involvement from parents and guardians is crucial. Parents should be educated on the digital landscape their children navigate, including awareness of popular online challenges and the signs of distress in their teens. Open communication between parents and teens regarding online experiences can foster an environment where young people feel safe discussing their encounters with potentially harmful content.

Creating peer support networks can empower young people to resist the allure of dangerous challenges. Schools and community organizations can facilitate programs that encourage teens to speak out against harmful activities, fostering a culture of mutual support and accountability. By normalizing conversations around mental health and online safety, these networks can help teens feel less isolated and more connected.

Increased access to mental health resources is critical. Schools should provide resources such as counseling services and helplines for students facing emotional distress. Educating teens about the availability of these resources can encourage them to seek help if they are struggling with feelings of loneliness or depression, which are often exploited by online challenges.

Collaboration between mental health organizations, educators, and technology companies can lead to the development of tools that promote positive online interactions. These tools could include features that allow users to report harmful content easily, as well as educational prompts that encourage users to reflect on their online engagement before participating in challenges.

As the digital landscape continues to evolve, so too must our strategies for safeguarding young people. By combining education, parental involvement, supportive peer networks, and accessible mental health resources, we can create a multifaceted approach to prevent teens from falling into the traps of online challenges. Ultimately, fostering a culture of resilience, awareness, and open communication will empower young people to navigate the digital world safely, promoting their overall well-being and development in the process.

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DRAWING ON AUTOCAD THE HORN OF THE ICONIC ALTEC LANSING LOUDSPEAKER VOICE OF THE THEATER A7

Jose MUJICA[1]

Abstract

The horn Altec Lansing model H-811B is one of the main components of the loudspeakers A-7 and Model 19 of this milestone brand. It is not usual that lovers and collectors of a brand of loudspeakers have Internet sites with over 100K followers 44 years after stopping the manufacturing of these classic models. Nowadays, we find that some followers have opened factories to build them anew. However these facilities have made the low frequency woofers and mid-high frequency drivers, but not the horns and the boxes. About the boxes, the blueprints and its construction do not represent a major challenge, after all, in more than 75 years of the first model of the Altec Lansing series Voice Of The Theater, a legion of follower have learned how to make the wood curves as the original. But the cast aluminum horns are a different matter because of the difficulties involved in their process. Some of the followers have built them using wood and Fiberglass horns but very few using aluminum. Neither of the blueprints found have information about the curves of the horn, only the lineal dimensions. For this reason and knowing that there is not a 3D AutoCad drawing on the Internet of this horn, at least one that I could find, I decided to write a method that can be helpful to draw a prototype model that could help enthusiasts and collectors to build the horns using aluminum.

Keywords: Autocad, Computer-Aided Design, Computer Drawing Method, Command Bugs in Design Software.

JEL Classification: C61

Introduction

For this paper the author used the 1968 blueprints of the Altec Lansing loudspeaker sectoral horn, model 811B [1][2][3]. The blueprints that I found only show the lineal dimensions of the horns. I was not able to find any information about the different curvatures of the horns. (See Figure 1).

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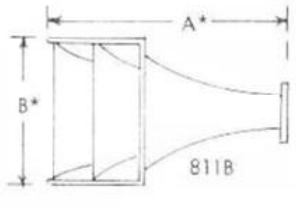

Horn Number	Dimensions		
	Height (B)	Width	Depth (A)
811B***	8⅝"	18¾"	13½"

Figure 3 Dimension of the Sectoral horn 811B

I also used a real Altec Lansing horn, belonging to Model 19 of this brand, in order to get better accuracy for the goal of this paper. Any stage of the drawing was compared with the real horn shown in Figure 2.

Figure 4 Real Altec Lansing 811B sectoral horn

Curves are ubiquitous in nature, design, and fields such as mathematics. In general, drawing curves is a challenging task. For this reason, the main goal of this work is focused on the reproduction of the main body of the horn. In all drawings I have used units that attempt to preserve the external dimensions of the horn.

1. Drawing a reproduction of the horn

1.1 Drawing the side curves of the horn

To draw the horn side curve, the author used the command ARC with three points of AutoCad [4]. To get the coordinates of the three points, I initially thought of applying the Least Square Method to obtain the curve equation, but I estimated that the precision would be the same as graphing these three points over the Cartesian plane. See Figure 3.

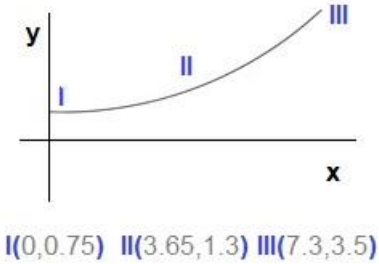

Figure 5 Horn top curve of the 811B horn

The coordinates of three points obtained were (0,0.75), (3.65,1.3), (7.3,3.5). Once the upper curve was obtained I proceeded to use the MIRROR command to generate the lower curve. Then using the MOVE command I displaced the lower curve 1.5 units down along the Y axis. See Figure 4.

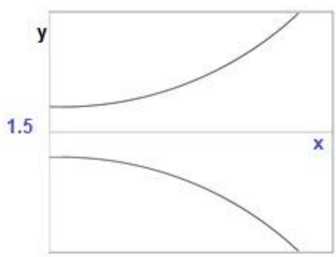

Figure 6 Using the MIRROR and MOVE commands to locate the upper and lower curve on the plane.

1.2 Extruding the up and down side curves.

To extrude the curves in 3D we should apply the 3DFACE command to join both curves to create a face. Having the face, we use the EXTRUDE command 15.5 units along the Z axis to get the wider view of the horn, that will be its mouth. As seen in Figure 5.

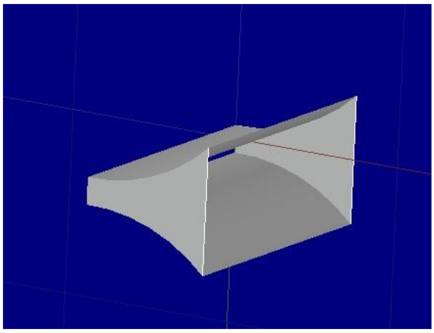

Figure 7 Extrude the side face

1.3 Cutting side planes.

Now we generate two planes, each one perpendicular to the XZ plane. Both inclined with respect to the Y axes.

These planes will be the side walls of the horn. To get their coordinates I used the only blueprint that I could find on the Internet with a top view of the model 811B. [2]. See Figure 6.

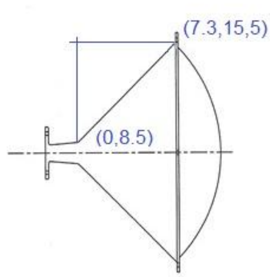

Figure 8 Top view of the 811B horn.

The coordinates of the first plane are (0.3.15,-7), (7.3,3.15,0), (7.3,-3.5,0) and (0,-3.5,-7). The coordinates of the second plane are (0, 3.5,-8.5), (7.3, 3.5,-15.5), (7.3,-3.15,-15.5) and (0,-3.5,15.5). Both boundaries were made using the 3DPOLY command. After the command 3DFACE was used to create the planes. See Figure 7.

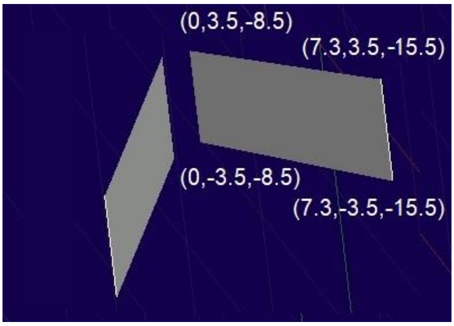

Figure 9 3D view of the two planes.

Once obtained the two planes across the solid I proceeded to use the CONVTOSURFACE command so that all the components were surfaces. See Figure 8.

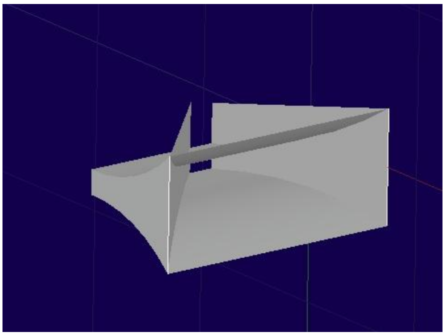

Figure 10 Inclined base of the horn walls

To proceed to remove the leftover parts of the body of the horn I used the command SLICE and its option Surface. See Figure 9.

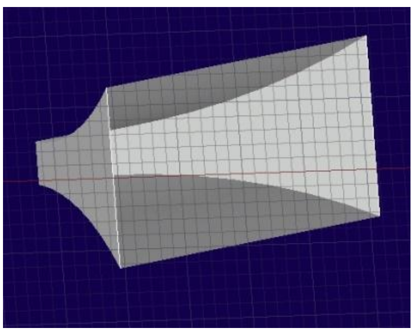

Figure 11 Getting the angle of the inclined panel

1.4 Top and bottom of the horn.

The top and the bottom of the horn are not flat, they are curved, so we need to get rid of the actual up and low surfaces and draw the suitable ones.

To create the top and bottom flat curved surfaces, the first step is to create two flat curves on the mouth using the ARC command with three points. The coordinates of the upper curve are (7.3, 3.5,0), (7.3,1.25,-7.75) and (7.3,3.5,-15.5). The coordinates of the lower curve are (7.3, -3.5, 0), (7.3, -1.25, 7.75) and (7.3,-3.5,-15.5). Because the ARC command is two dimensional, I only used the Y and Z coordinates. (See figure 10).

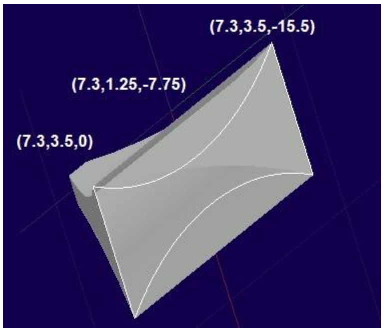

Figure 12 Curve walls sliced

Once the two flat curves of the mouth have been obtained I deleted the actual flat up and low surfaces. Now I need to create a curve region which boundaries are the flat curve of the mouth that I drew before, the two inclined side walls and a line that I draw on the back of the horn as shown in Figure 11.

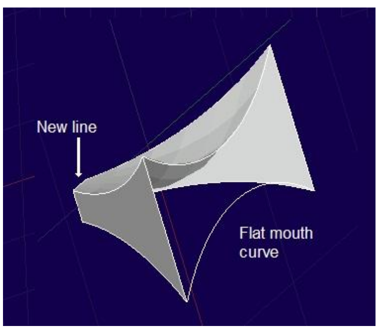

Figure 13 Line at the end of the horn to close the region

The command EDGESURF that creates a mesh (A 3D surface) between four contiguous edges or curves that form a close loop, was used to generate the region. Before using this command, I need to get the edges from the side walls to generate the four sides needed to close the region. For this purpose, I use the command XEDGES, (Extract Edges in the 3D Tools Menu/Solid Editing.). I perceived also that the command EXPLODE works well to break down a compound object into its individual components.

1.5 Drawing the brims of the mouth.

To create the extension brim of the mouth of the horn, I must draw a line between the front limits of the mouth and then use the command REGION (Menu Draw.). Selecting this last line and the flat curve that I created in the section 2.4 I generated a front surface. (See Figure 12).

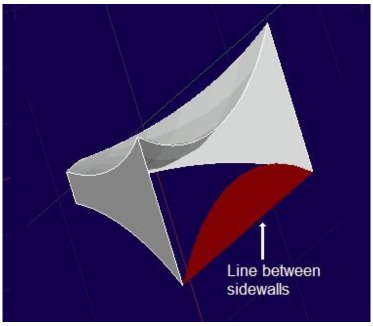

Figure 14 Front surface color in red to create the brim.

To finish the brim I rotate the front surface 90° using the command REVOLVE around the axis formed by the line that joins the side boundaries as shown in Figure 13.

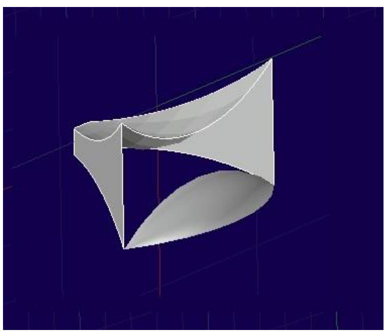

Figure 15 The first brim showed

I can draw the second brim and make visible all the sides of the horn as show in Figures 14 and 15.

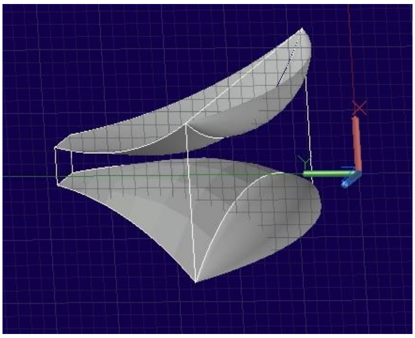

Figure 16 View of the first side wall

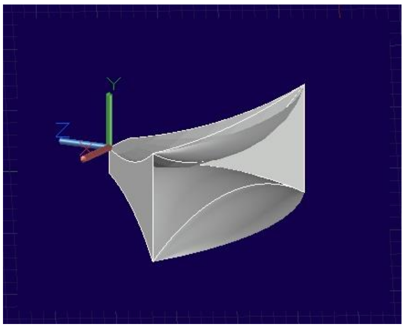

Figure 17 View of both panels with realistic visual style

1.6 Drawing the vanes of the horn.

The vanes dimension and angles were measured from my own 811B horn, showed in Figure 2. Because the scope of this work is the methodology to draw the body of the horn, I did not build any special device or tool to get the correct horn curves measurements.

With the measurements shown in Figure 16 the angle of the incline vane is 30°.

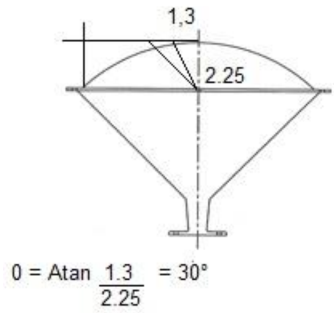

Figure 18 Angle of the inclined vanes

The vanes are symmetrically distributed, the center vane coordinates are (7.3,3.5,7.75), (9.55,3.5,7.75), (9.55,-3.5,7.75) and (7.3,-3.5,7.75) as showed in Figure 17. To draw the plane of the vane I used the 3DFACE command.

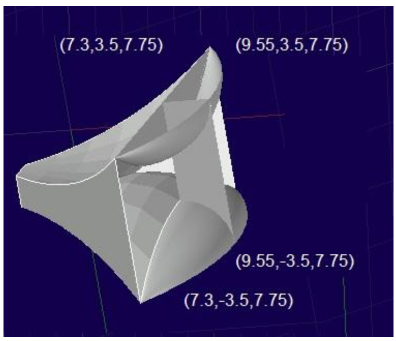

Figure 19 Coordinates of the center vane

With the generated planes it was necessary to cut off the spare over the brim using the SLIDE command as I did at the end of 2.3 section.

The coordinates of the inclined left and right vanes are as follows: Left one (7.3, 3.5,3.5.174), (9.55, 3.5, 3.875), (9.55,-3.5,3.875) and (7.3,-3.5,5.174). Right one (7.3, 3.5,10.3260), (9.55, 3.5, 11.6250), (9.55,-3.5, 11.6250) and (7.3, -3.5, 10.3260). Once the inclined vanes were drawn and the spare parts were cut off I used the SLICE command to obtain the view of Figure 18.

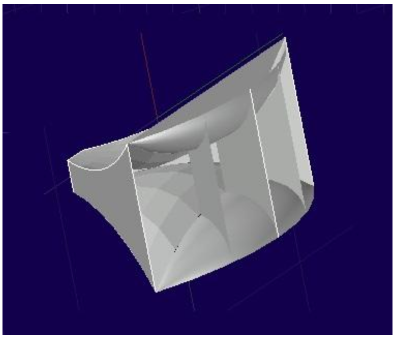

Figure 20 Body of the horn without spare parts

2. Drawing the throat

Now proceed to draw the throat with a depth of 2.95 units. I started from the end of the side curves previously obtained. The coordinates to get the additional points to create the four 3DFaces needed to build the throat are, (-2.95,0.625,-7.125), (-2.95, 0.625, -8.375), (-2.95,-0.625,-8.375) and (-2.95,-625,-7.125), as showed in the Figure 19.

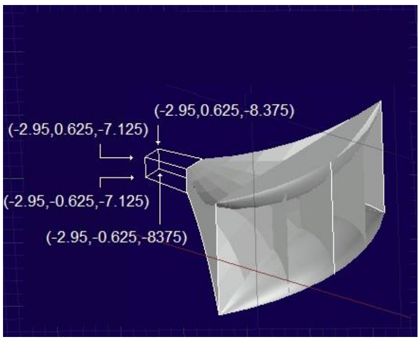

Figure 21 Building the throat

2.1 Drawing the base of the driver.

The base of the driver is a circle with the center on the axis of the horn at (-2.95,0,-7.75). Once created , I used 3DROTATE to make it perpendicular to the axis of the horn. See Figure 20.

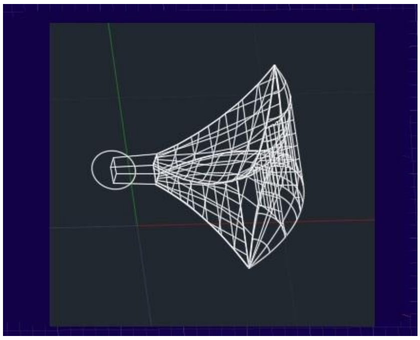

Figure 22 Circle as Driver base to rotate

Because the base of the driver is perpendicular to the axis of the horn, I used the EXTRUDE command with 0.2 depth and converted the object to solid with the CONVTOSOLID command. See Figure 21.

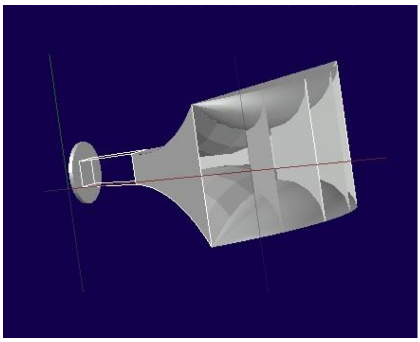

Figure 23Circular solid base

I have to repeat all the previous procedures to create a smaller circular hole at the center of the solid base. I used the CIRCULAR command with the Radius and Center coordinate options. The Radius is 0.5 units, and the center is at (-2.95,0,-7.75). After the EXTRUDE command I used the SUBTRACT command to show the empty space. Alternatively, I could have used the PRESSPULL command also to get the hollow, but this command is cumbersome to use because one has to follow one particular sequence of instructions to get the desired effect. See Figure 22.

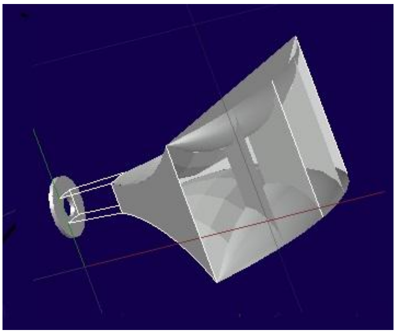

Figure 24 Driver base hollow

3. Drawing the driver

Because the main purpose of this work is to show a methodology to draw the curves of the body of the horn, I only wanted to draw the driver as a non-detailed visual reference in the final drawing. For this purpose, I only considered the contour side section view of an Altec Lansing driver specification sheet[5]. See Figure 23.

Figure 25 Specification sheet of Altec 807 and 808 drivers

From the shape of the image of Figure 23, I drew an approximation of a half of the driver using AutoCad. See Figure 24.

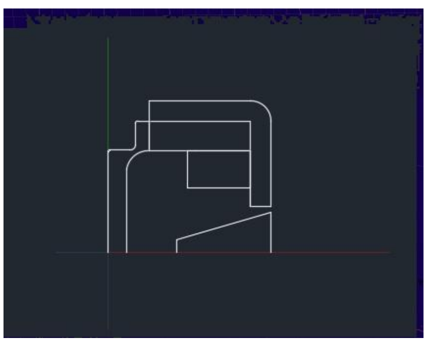

Figure 26 Approximation of a half of the Altec driver

Now I use the REVOLVE command to get the driver in 3D. See Figure 25.

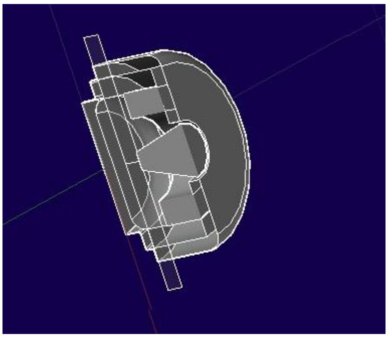

Figure 27 Driver sectional view

I created the driver scaled in a single file and used copy and paste to join with the figure in the horn file. At this step I must use the 3DROTATE and ALIGN commands to connect the driver to the horn.

4 End view of the entire horn and driver

Finally, I have the entire drawing of the horn with its driver as shown in the following Figures.

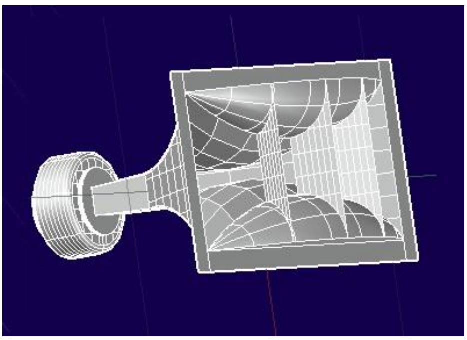

Figure 28 Full wired view of the horn

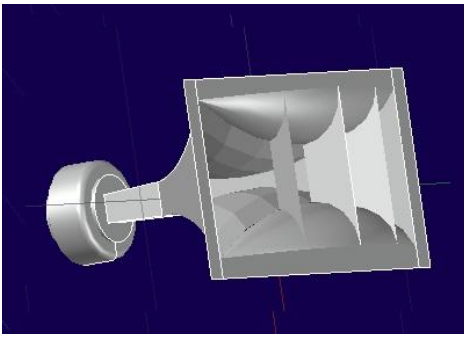

Figure 29 Full conceptual view of the horn

5 Conclusions

The view of the Altec Lansing horn 811B never cease to astonish its followers. It not only reaches the collector micro universe but also the general audiences who admire the unique characteristics of this marvelous horn.

New technologies in the midrange horns surpasses the sound quality of the Altec Lansing horn 811B but not the experience to see and hear it. You can compare this with the experience of seeing and listening to a Gramophone or a vintage vinyl record player. Therefore, Altec Lansing horn 811B followers will continue growing through the years to come. It is my hope that this paper can be used and be useful as a reference or starting point for those who in the future will attempt to get the perfect dimensions of the Altec Lansing horn 811B.

Acknowledgement

The author wishes to express his gratitude to Dr. Ramon Mata-Toledo (James Madison University) for his thorough review and constructive criticism of this work. His input, highly appreciated by the author, contributed to improve this work significantly.

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GENERATIVE PRETRAINED TRANSFORMERS FOR INVESTOR-CENTRIC PORTFOLIO CONSTRUCTION

Dimitrios Papakyriakopoulos[1]

Manolis Kritikos[2]

Abstract

The objective of this paper is to examine the application of generative artificial intelligence in personalized portfolio construction and evaluate its performance relative to traditional benchmarks. A generative AI model, specifically OpenAI's GPT-4o, was employed to construct investment portfolios for ten virtual investor profiles over a fixed three-month investment horizon. The methodology involved prompting the model to create portfolio allocations, followed by performance evaluation using financial metrics including total return, volatility, beta, Sharpe ratio, and maximum drawdown. All AI-generated portfolios outperformed the S&P 500 index over the investment period, demonstrating stronger risk-adjusted returns and lower drawdowns. These results highlight the potential of large language models to synthesize financial data and produce competitive investment strategies. The study contributes to the growing body of research on AI-driven decision-making in finance and provides a foundation for the development of generative models tailored to asset and wealth management

Keywords: Generative AI, wealth management, portfolio optimization, personalization

JEL Classification: G11 Portfolio Choice; Investment Decisions

1. Introduction

Wealth management oversees the strategic allocation of capital through portfolio construction on behalf of investors and has been a critical driver of the financial industry, due to its indispensable role in shaping economic growth, promoting financial stability and driving innovation through investment vehicles [14]. Wealth management's significance can be further highlighted by the trillions of dollars of managed capital. The overall finance industry is witnessing an unprecedented technological arms race to adapt, upgrade, and implement emerging technologies to gain a competitive edge, enhance operational efficiency, and meet the evolving needs of their clients [12]. This trend signifies the onset of a technological revolution that is reshaping the industry's competitive dynamics, driving the adoption of breakthroughs like artificial intelligence, which is setting a new trajectory towards the replacement of traditional mechanisms, by making financial institutions leaner,

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more agile and digitalized [8]. AI's potential is particularly evident in the realm of wealth management, which is traditionally characterized by human intervention, meticulous analysis, and high-touch interactions. Portfolio construction is now at the precipice of a transformation, leveraging AI's capabilities to offer a more personalized, dynamic, and innovative approach to offer tailor-made solutions and client experience.

Portfolio theory, ever since it was introduced by Harry Markowitz in 1952, has continued to remain a cornerstone in the financial investment domain and portfolio management [13]. The theory provides investors with a mathematical framework for assembling a portfolio of assets in a way that maximizes the expected return for any given level of risk [15]. The modern portfolio theory not only managed to connect the risk and the return of an asset in a quantitative function, but it further paved the way for the introduction of the efficient frontier, which highlights the most efficient portfolios an investor could possibly invest at various risk levels [11]. Despite its foundational role, the modern portfolio theory struggles to capture the intricate, non-linear interrelationships within the financial markets fully. These markets are marked by their complexity and inherent volatility, which marks as a necessity the constant adaptation and improvements to existing models. While the traditional models and methods have been critical in shaping investment strategies in the past, their ability to generate optimal portfolios under the diverse market conditions of the 21st century remains limited.

Artificial intelligence, due to its vast computational power, offers the potential to minimize errors that occur from the traditional models' inability to include multi-domain external factors that influence the financial markets and the assets' performances. AI's ability to learn from large amounts of data uncovers hidden patterns and enhances its performance over time, making it a promising tool for portfolio construction [9]. AI's potential in finance is increasingly being recognized, with advancements in machine learning and predictive analytics fundamentally altering how financial professionals manage, operate, and interact with financial systems [1]. The role of AI is not just limited to automating specific data-heavy or time-consuming tasks, but it has started to evolve into decision-making, reshaping strategies, and influencing outcomes.

In October of 2022, the launch of OpenAI's ChatGPT raised dramatically the interest around "Generative AI", which is an innovative branch of artificial intelligence that is capable of producing and creating data and outputs in various formats, such as text, images, audio and 3D models, which are highly realistic and resemble human-like content and originality [10]. GenAI's ability to generate unique, original and novel data - instead of just understanding and re-creating pre-existing datasets - is a key driver that led make generative AI models stand out from other machine learning and deep learning algorithms [7]. Generative AI utilizes generative models, such as generative adversarial networks, variational auto-encoders and generative pertained transformers to create original data with similar statistical properties and attributes with their respective training data set [10]. These groundbreaking models leverage concepts that have been around for a long time, but their efficiency and potential have reignited interest and sparked curiosity in researchers, data scientists, and the broader public alike [5]. Large language models, which serve as the foundation for generative pertained transformers, have been in use for more than 50 years [4]. The first generation of these models used "n-gram" based systems to estimate the probability of a word given the previous words [5]. However, limitations arise when the computational complexity increased dramatically with higher n-values. This obstacle was overcome with the introduction of neural networks and the advances in computational power by machines, which made it possible to calculate probabilities for longer n-grams and set the foundations for the creation of generative pertained transformers models [5]. A generative model, is trained with the purpose of understanding the joint probability distribution of the P(x, y) function of the inputs x and outputs y in a training dataset, in contrast to common machine learning and discriminative models that are trained based on the conditional probability distribution P(y | x), which is the probability of outcome y given x as input [10]. Generative AI -and Large Language Models (LLMs) in particular- are trained on vast volumes of unlabeled data by extracting and learning patterns from substantial datasets, which requires extensive resources and time [6].

In the financial industry, the potential of generative AI is particularly compelling in the realm of portfolio management [3]. In theory, GenAI has the potential to deeply analyze and generate an unlimited number of diverse and personalized portfolio solutions that are capable of accommodating the risk tolerance, investment objectives, financial conditions, and other preferences of individual investors. The central aim of this paper is to explore how this theoretical potential of Generative AI can be actualized in the real-world of financial markets through the lens of wealth management, and the increasing consumer trend for personalization. Our methodology presents a pilot experiment evaluating the use of OpenAI's GPT-4o model in personalized portfolio construction. Ten synthetic investor profiles were generated using Python to reflect diverse financial and demographic characteristics. Portfolios were created by prompting the model with each profile and restricting the investment universe to S&P 500 stocks and cash. Historical price data from October 2023 to January 15, 2025, was used to ensure no overlap with the model's training. Performance was assessed using return, volatility, beta, Sharpe ratio, and maximum drawdown, with all AI-generated portfolios outperforming the S&P 500. These results demonstrate the potential of generative AI to support efficient and adaptive wealth management.

2. Proposed Methodology

The purpose of this paper is to explore how generative artificial intelligence can be used to create personalized investment portfolios tailored to different types of investors. Python was the primary tool used throughout the process, with the Pandas library supporting data processing and analysis. Visualizations and performance charts were created using Matplotlib and Seaborn to better illustrate the results. Historical financial data for all S&P 500 companies was sourced through the Bloomberg Terminal to ensure high-quality and reliable inputs. Portfolio construction was performed by sending tailored prompts for each investor profile to OpenAI's API, leveraging the GPT-4o model to generate portfolio allocations. The results were evaluated over the specific time period between January 15, 2025, and April 15, 2025, with the use of key performance metrics such as return, volatility, beta, Sharpe ratio, and maximum drawdown. We aim to demonstrate the practical value of generative AI in asset management by showing how it can adapt to individual investor needs and generate data-driven portfolio strategies.

To generate realistic and diverse investor profiles, the Faker library was used, producing ten distinct individuals with varying backgrounds, financial goals, and risk tolerances. The profiles spanned a broad spectrum of demographics and psychographics. The profiles ranged from a 20-year-old musician, with a very low risk tolerance, to a 62-year-old interpreter, with a high-risk tolerance. The dummy investors also varied in their financial knowledge, with some having extensive investment experience, while others had no investment experience. The profiles also covered a wide range of occupations, from a civil engineer to a journalist, further diversifying the group's background. Economic factors, such as income, were also varied, with the yearly income spanning from $32,371 to $178,896. Debt, marital status, and level of education were other factors considered to create a comprehensive, nuanced picture of each investor. This diversity enabled the creation of a robust testing ground to examine the versatility and adaptability of generative AI in constructing investment portfolios based on people with different characteristics and financial needs and objectives. In Tables 1, 2 and 3, the results from the different investor profiles generated:

Investor ID	Age	Marital Status	Children
1	23	Single	No
2	62	Single	Yes
3	44	Single	Yes
4	29	Single	Yes
5	20	Married	Yes
6	49	Married	No
7	21	Single	Yes
8	34	Married	Yes
9	22	Married	Yes
10	21	Single	No

Table 1: Personal details of investors, including demographics and family information

Investor ID	Occupation	Education	Income	Debt
1	Chemist	High School	32,371	7,463
2	Interpreter	PhD	174,374	116,260
3	Veterinarian	Bachelor’s Degree	169,571	43,817
4	Artist	PhD	108,375	30,729
5	Musician	Master’s Degree	145,123	77,519
6	Chef	Master’s Degree	113,492	33,773
7	Civil Engineer	Master’s Degree	65,792	28,907
8	Journalist	High School	178,896	15,407
9	Dentist	PhD	136,034	50,551
10	Musician	PhD	120,639	52,428

Table 2: Educational background, occupation, and financial metrics for each investor

Investor ID	Risk Tolerance	Financial Knowledge	Investment Experience
1	High	Medium	None
2	Low	Low	Extensive
3	Low	Low	Extensive
4	Very High	Low	Some
5	Very Low	Low	Some
6	Moderate to High	Medium	Some
7	Moderate	High	Extensive
8	Very High	Medium	Extensive
9	Low	Low	Extensive
10	Moderate to Low	Low	Extensive

Table 3: Investors' risk profiles and experience with financial instruments

To guide the generative AI model in producing meaningful and realistic investment portfolios, a detailed set of constraints was defined and embedded within each prompt. The objective was to construct one personalized portfolio per investor, aligned with their unique financial profile and risk tolerance. Each portfolio was composed of a combination of cash and equities drawn exclusively from the S&P 500 index. To ensure sufficient diversification without overwhelming complexity, the number of stocks in each portfolio was constrained to fall between 8 and 15. Additionally, to promote broad exposure to the overall market, the total set of portfolios was required to utilize at least 100 distinct S&P 500 companies across the ten investors. The allocation for each stock was expressed in percentage terms, and the sum of all stock weights in each portfolio had to equal 100%.

A key variable in the construction was the investor's risk tolerance, which directly influenced the cash allocation. Cash weights were set to range from 15% to 80%, with more risk-averse investors receiving higher allocations to cash and fewer equity holdings. This allowed the model to adjust the aggressiveness of each portfolio according to individual investor preferences. To preserve output structure and enable automated parsing, the response format was specified in JSON, listing only the stock tickers with their respective weights (e.g., "AAPL - 10%"), followed by 2–3 concise comments explaining the investor's profile and associated risk approach. The final personalized portfolios and the comments are presented in Table 4 and 5 respectively:

Investor ID	Risk Profile	Cash Allocation(%)	Stocks
1	High	21	ADI - 12.31%; NET - 9.87%; NFLX - 10.43%; AIG - 3.49%; ZTS - 4.27%; COST - 5.99%; CRWD - 10.58%; SBUX - 10.07%; PSX - 11.99%
2	Low	63	MDT - 1.49%; PG - 2.66%; BA - 2.57%; SYK - 2.51%; USB - 2.18%; F - 1.24%; DE - 3.0%; PYPL - 1.59%; TSLA - 4.96%; PEP - 1.39%; LIN - 2.3%; JNJ - 3.72%; WBA - 4.8%; V - 2.59%
3	Low	63	ROKU - 2.45%; APD - 4.11%; BDX - 2.86%; SYK - 2.88%; KO - 2.14%; REGN - 2.4%; FDX - 5.51%; PLD - 4.17%; LYFT - 3.99%; ETN - 1.96%; NOW - 4.53%
4	Very High	15	LLY - 12.25%; NOW - 5.72%; HD - 3.37%; CI - 6.75%; ADP - 6.18%; AMAT - 5.51%; MDT - 14.24%; DE - 13.45%; AXP - 6.75%; KHC - 10.78%
5	Very Low	78	PLD - 1.01%; BAC - 2.68%; CB - 1.63%; TMO - 0.73%; COST - 0.64%; MMC - 0.77%; SHOP - 1.88%; LOW - 2.24%; LIN - 1.44%; ZM - 0.67%; INTU - 1.35%; UNH - 2.67%; AAPL - 1.67%; ABNB - 2.62%
6	Moderate to High	39	C - 6.02%; DOCU - 5.55%; AMD - 4.17%; LIN - 2.59%; ORCL - 9.93%; NET - 9.91%; KHC - 12.48%; PLD - 10.35%
7	Moderate	43	GILD - 3.02%; UBER - 8.85%; CI - 8.62%; ADBE - 8.59%; AMGN - 6.24%; PYPL - 5.43%; LIN - 2.66%; ADBE - 4.5%; WBA - 9.09%
8	Very High	15	DIS - 3.7%; CAT - 7.08%; MDT - 7.81%; PLD - 5.03%; AMGN - 10.96%; ABNB - 6.58%; XOM - 4.51%; APD - 7.7%; F - 9.57%; TXN - 4.41%; KHC - 5.48%; MA - 12.17%
9	Low	63	JPM - 1.13%; TMO - 4.19%; MA - 1.35%; IBM - 1.39%; MMC - 1.23%; ZTS - 2.54%; CRWD - 3.34%; V - 2.31%; ORCL - 3.22%; BA - 3.45%; AMD - 4.26%; KO - 4.96%; MDT - 3.63%
10	Moderate to Low	58	AIG - 6.21%; COST - 1.69%; GOOGL - 5.04%; BA - 5.0%; GOOGL - 1.73%; CB - 5.46%; V - 5.85%; COF - 2.0%; TSLA - 2.46%; AMZN - 4.38%; AVGO - 2.18%

Table 4: Personalized Portfolio Asset Allocation with Weights

Investor ID	Risk Profile	Cash Allocation(%)	GPT Model Comment
1	High	21	Investor has a high risk tolerance. Allocated 21% to cash due to risk preference. Stock weights are diversified to reflect their risk profile.
2	Low	63	Investor has a low risk tolerance. Allocated 63% to cash due to risk preference. Stock weights are diversified to reflect their risk profile.
3	Low	63	Investor has a low risk tolerance. Allocated 63% to cash due to risk preference. Stock weights are diversified to reflect their risk profile.
4	Very High	15	Investor has a very high risk tolerance. Allocated 15% to cash due to risk preference. Stock weights are diversified to reflect their risk profile.
5	Very Low	78	Investor has a very low risk tolerance. Allocated 78% to cash due to risk preference. Stock weights are diversified to reflect their risk profile.
6	Moderate to High	39	Investor has a moderate to high risk tolerance. Allocated 39% to cash due to risk preference. Stock weights are diversified to reflect their risk profile.
7	Moderate	43	Investor has a moderate risk tolerance. Allocated 43% to cash due to risk preference. Stock weights are diversified to reflect their risk profile.
8	Very High	15	Investor has a very high risk tolerance. Allocated 15% to cash due to risk preference. Stock weights are diversified to reflect their risk profile.
9	Low	63	Investor has a low risk tolerance. Allocated 63% to cash due to risk preference. Stock weights are diversified to reflect their risk profile.
10	Moderate to Low	58	Investor has a moderate to low risk tolerance. Allocated 58% to cash due to risk preference. Stock weights are diversified to reflect their risk profile.

Table 5: GPT Model Commentary for cash allocation

3. Results

The results of this study offer strong evidence of the ability of generative AI to construct personalized portfolios that align with individual investor profiles while demonstrating resilience and competitive performance in real market conditions. Table 6 presents the key performance metrics - return, risk (standard deviation), maximum drawdown, and beta versus the S&P 500 - for each of the ten portfolios generated by the generative pretrained transformer model during the investment window from January 15, 2025, to April 15, 2025. The S&P 500 served as the benchmark for performance comparison.

Investor	Return	Risk (σ)	Max Drawdown	Beta vs S&P 500
Investor 1	-0.02	0.016	-0.16	0.79
Investor 2	-0.01	0.003	-0.023	0.12
Investor 3	-0.02	0.003	-0.0353	0.1426
Investor 4	-0.004	0.011	-0.1014	0.5223
Investor 5	-0.003	0.0009	-0.0094	0.0445
Investor 6	-0.0241	0.0088	-0.0992	0.4305
Investor 7	0.0015	0.0043	-0.0337	0.1654
Investor 8	-0.0350	0.0129	-0.12	0.5898
Investor 9	-0.002	0.0028	-0.0261	0.1373
Investor 10	-0.005	0.0033	-0.0255	0.1633
S&P 500	-0.09	0.0192	-0.189	1

Table 6: Performance Metrics of Generated Portfolios and the S&P 500

Despite the S&P 500 recording a significant negative return of -9% over the three-month investment period, all ten generative AI-created portfolios demonstrated notably stronger performance, showcasing as a result the model's capacity to construct resilient and context-aware strategies. Returns for the AI portfolios ranged from -3.50% to +0.15%, with every single portfolio outperforming the benchmark by a meaningful margin. Investor 7's portfolio stood out as the only one to close with a positive return (+0.15%), despite the broader market downturn. Meanwhile, portfolios belonging to Investors 2, 4, 5, 7, 9, and 10 remained close to breaking even, reflecting the model's ability to protect capital in challenging market conditions and effectively tailor asset allocations to individual investor risk profiles. Even the most underperforming portfolio (Investor 8) managed to outperform the S&P 500 by over 5 percentage points, illustrating the model's robustness and adaptability in designing investment strategies that balance exposure and caution. This outcome is particularly noteworthy given that no forward-looking data or financial statements were fed into the model; only static investor profiles and historical price data were used to guide the allocation.

Risk metrics further highlight the defensiveness and discipline of the AI-generated portfolios. The standard deviation of portfolio returns (used here as a proxy for volatility) was significantly lower than the S&P 500 benchmark (0.0192) across all portfolios. The lowest volatility was observed in Investor 5's portfolio (0.0009), a result that aligns perfectly with the investor's low-risk tolerance and higher cash allocation. Such consistency between intended risk preferences and realized portfolio behavior demonstrates the model's capacity to interpret and execute tailored strategies effectively. Most other portfolios also maintained low volatility, with even the highest level (Investor 1 at 0.016) still coming in below the market average. In addition, Maximum drawdown, an important measure of downside protection, tells a similarly positive story. While the S&P 500 experienced a drawdown of -18.9% during the investment period, none of the AI portfolios came close to this level of loss. The smallest drawdown was once again recorded by Investor 5 at just -0.94%, while even the highest drawdown (Investor 1 at -16%) still provided better downside protection than the benchmark. Furthermore, beta values across all portfolios were substantially lower than the market (1.0), with the majority falling below 0.2. These figures reflect a consistently lower sensitivity to market fluctuations, particularly for the more conservative investor profiles. Investors 2, 3, and 5, whose risk aversion was high by design, exhibited beta values of 0.12, 0.14, and 0.04, respectively. Such insulation from systemic market risk was primarily achieved through larger cash allocations and restrained exposure to high-volatility equities. All of the above results provide a clear indication of the AI model's ability to synthesize profile information into coherent and risk-aligned investment strategies.

A visualization of the normalized returns for all portfolios relative to the S&P 500 over the investment period is presented in Figure 1. The graph reveals a stark contrast between the sharp declines experienced by the benchmark index and the smoother, more stable trajectories of the AI-generated portfolios. While the market endured periods of heightened volatility and pronounced drawdowns, the portfolios produced by the model exhibited a strong degree of capital preservation, with many displaying gradual, stable performance curves. In some cases, particularly among the moderately risk-tolerant profiles, a slow but steady positive drift was evident—an indication that the model was not only reducing risk but also identifying profitable opportunities within its constrained investment universe.

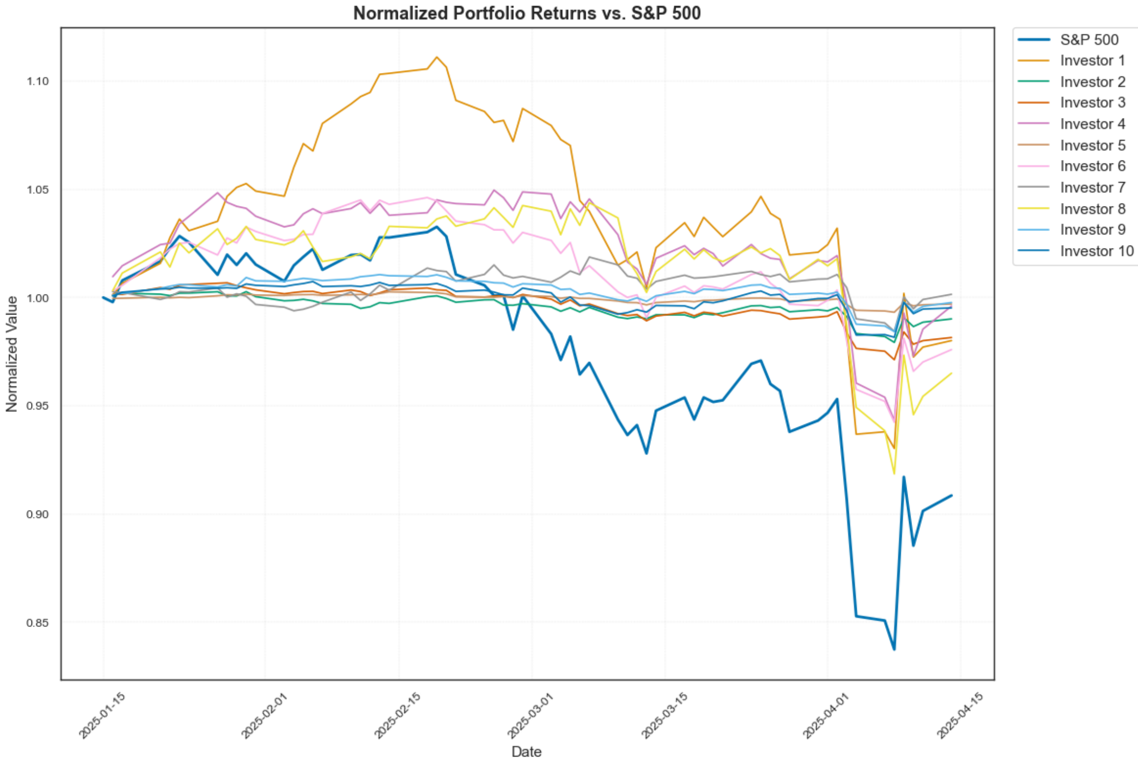

Figure 30: Normalized AI-Generated Portfolio Returns vs S&P 500

4. Discussing the Challenges and Limitations

While the AI-generated portfolios consistently outperformed the benchmark over the investment period, the methodology employed is subject to several notable limitations and operational challenges. Foremost among these is the token constraint inherent in generative pretrained transformer models, which imposes a ceiling on the amount of information that can be processed in a single prompt. This technical limitation precluded the integration of detailed historical financial data, macroeconomic metrics and predictive modeling, thereby preventing the execution of a dynamic, day-to-day simulation that could have enabled real-time portfolio rebalancing, adaptive allocation strategies, and continuous price monitoring. Consequently, the model's ability to respond to evolving market conditions was inherently restricted. In addition, the same constraint hindered the incorporation of unstructured data, such as financial news, analyst commentary, and social sentiment, which are critical inputs in contemporary investment decision-making. The inability to perform natural language-based sentiment analysis or interpret current events surrounding individual securities diminished the contextual richness of the model's outputs and restricted its scope to a purely static investment framework.

Another critical limitation originates from the opaque, "black-box" nature of the model's architecture. The rationale behind the selection of specific securities and their respective weightings remains undisclosed, as the model does not provide interpretable outputs or accompanying justification for its decisions. This lack of explainability poses significant challenges, particularly in the context of wealth management, where transparency, accountability, and traceability are foundational; not only for building and maintaining client trust but also for meeting evolving regulatory and compliance standards. Moreover, the stochastic nature of large language models like generative pretrained transformers means that results may vary across iterations, even when the same inputs and constraints are applied [2]. This intrinsic non-determinism introduces an additional layer of uncertainty, as portfolio structures and performance outcomes may diverge significantly from one generation to the next. As such, practitioners would be required to conduct multiple iterations and statistical aggregation to detect consistent patterns or gain actionable insights; an approach that adds computational complexity and raises concerns about reliability and repeatability.

Finally, the scope of this study was deliberately limited to equities listed on the S&P 500, in order to manage data complexity and maintain consistency across the experiment. While this constraint enabled a focused analysis, it also restricted the model's exposure to the broader financial universe, including international equities, fixed income instruments, commodities, and alternative investments. As a result, the study does not fully explore the model's potential to navigate multi-asset portfolio construction or handle heterogeneous financial instruments, an area warranting further investigation in future research.

5. Conclusion

Portfolio management has long stood as a cornerstone of financial research, evolving significantly over the past century. The pioneering work of Harry Markowitz in the 1950s laid the groundwork for what is now known as Modern Portfolio Theory (MPT), introducing a mathematical and statistical framework for optimal asset allocation. MPT marked a paradigm shift by formalizing the trade-off between risk and return, enabling investment professionals to construct efficient portfolios through diversification and quantitative analysis. As both technological capability and investor expectations have advanced, so too has the discipline of portfolio theory. Recent decades have witnessed the emergence of more personalized, dynamic, and risk-sensitive frameworks that account for a broader array of factors, including behavioral characteristics, time horizons, and individual financial goals. These developments reflect a broader movement within the industry toward customization and adaptability in wealth management. At the forefront of this transformation is artificial intelligence (AI), which has demonstrated immense utility across various domains of finance from algorithmic trading and fraud detection to credit scoring and risk assessment. AI's ability to process vast datasets in real time, identify complex patterns, and generate predictive insights offers substantial value to institutions seeking to gain a competitive edge. Among the most recent and disruptive innovations in this field is the emergence of generative AI models, most notably following the release of

ChatGPT in late 2022. Unlike traditional AI systems, generative models exhibit the unique capability to produce human-like content and simulate reasoning across diverse tasks. These models are not only capable of synthesizing vast amounts of structured and unstructured data but can also generate nuanced responses, narratives, and even investment strategies tailored to specific prompts. Their application to the finance industry holds significant promise—particularly in the domain of wealth management, where personalization and responsiveness are increasingly critical. This paper explores the application of generative AI in personalized portfolio construction. Utilizing OpenAI's GPT-4o model, the study generated investment portfolios for ten synthetic investor profiles over a three-month period, from January 15, 2025, to April 15, 2025. Each portfolio was tailored to reflect the investor's demographic, economic, and risk-related characteristics. Despite current limitations, such as token constraints and the inherent variability of generative outputs, the results were encouraging. All AI-generated portfolios outperformed the S&P 500 benchmark during the evaluation window and exhibited lower levels of volatility and drawdown. The findings underscore the potential for generative AI to revolutionize portfolio management by offering scalable, individualized investment strategies that replicate the work of countless human analysts. Financial institutions could leverage these models to enhance productivity, reduce operational costs, and deliver sophisticated, real-time portfolio services to clients of all types. As the AI landscape continues to evolve, it is reasonable to expect that existing technical limitations will diminish. Future iterations of generative models may be capable of ingesting and analyzing large-scale financial datasets, parsing news and sentiment data, and continuously rebalancing portfolios in response to market dynamics. The implications for the financial sector are profound: institutions that fail to adapt may risk obsolescence, while those that invest in AI capabilities stand to benefit from enhanced decision-making, client engagement, and market competitiveness. As the generative AI arms race accelerates, the financial industry stands at a pivotal moment; one where embracing technological change is not just advantageous, but essential.

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SMART HOSPITALITY: THE ROLE OF AI IN ENHANCING SUSTAINABLE GUEST EXPERIENCES

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Abstract

Emerging demands for sustainability and personalized service are fundamentally transforming the hospitality industry, with AI-driven technologies reconfiguring operational structures and advancing guest engagement methodologies. This study`s objective is to investigate the role of AI in enhancing comfort and promoting environmentally responsible practices within the hospitality sector. Based on data gathered from 150 respondents in Bucharest (Romania), the research explores how guest satisfaction, sustainability awareness, and perceived concerns shape attitudes toward AI-enabled hotels. Results show that guests who have experienced AI technologies report significantly higher levels of comfort and satisfaction. Additionally, eco-conscious travelers are more likely to prefer and be attracted to hotels that use AI for sustainable purposes, particularly when such technologies also enable personalized services. Although concerns about data privacy and reduced human interaction were widespread, their influence could not be quantitatively assessed due to sample limitations. The findings highlight AI's potential to boost efficiency and sustainability but also stress the importance of transparency and human-centric design to mitigate adoption barriers

Keywords: Artificial Intelligence (AI), smart hospitality, sustainability, guest experience, eco-conscious travelers, hotel technology adoption

JEL Classification: L83, Q01, O33

1. Introduction

The hospitality industry is undergoing a significant transformation with the integration of smart technologies and artificial intelligence (AI) in all operational facets. As travelers increasingly seek personalized and sustainable experiences, hotels are adopting AI-driven solutions to enhance guest satisfaction while reducing their environmental impact. From automated check-in processes and smart room controls to AI-powered energy management systems, these innovations are reshaping the way guests interact with hospitality services.

This study explores the role of AI in modern hospitality, with a particular focus on its impact on guest experiences and sustainability. Our research is based on survey data collected from individuals who have stayed in hotels utilizing AI-driven technologies. The findings

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provide insight into the extent of AI adoption in the hospitality sector, guest perceptions of AI-enhanced services, and the role of AI in promoting eco-friendly practices.

A key component of smart hospitality is its ability to optimize resource consumption. AI-powered thermostats, automated lighting systems, and smart water management solutions help hotels minimize waste while maintaining a high standard of comfort for guests. The survey results indicate that travelers are increasingly aware of AI's potential to contribute to sustainability, with many expressing a preference for hotels that implement green AI technologies. However, the adoption of AI in hospitality is not without challenges. While AI-driven automation can improve efficiency and enhance guest experiences, concerns such as data security, lack of human interaction, and usability issues remain prevalent among travelers. This study aims to address these concerns and provide a comprehensive analysis of how AI can be leveraged to create smarter, more sustainable hospitality experiences.

2. Literature review

Concept of sustainability in hospitality

Sustainability in the hospitality industry involves integrating eco-friendly and socially responsible practices into all aspects of operations, aiming to minimize environmental impact while enhancing economic and social benefits. This encompasses reducing waste, conserving energy and water, sourcing local and organic products, and adopting responsible tourism practices [1,2]. Implementing such measures can lead to reduced operational costs, improved brand reputation, and increased guest loyalty. Since the consumer demand for environmentally responsible accommodation has been on the rise, booking platforms specializing in green hotels have emerged. This shift has prompted many establishments to adopt green certifications, such as the Green Key or Green Globe eco-labels, to attract eco-conscious guests and differentiate themselves in a competitive market.

Smart hotels, also known as smart building systems [3], which leverage advanced technologies to enhance guest experience and operational efficiency, play a growing role in promoting sustainability. From automated energy management systems to digital check-ins and smart room controls, these innovations help reduce resource consumption and streamline service delivery. Overall, smart hotels can reduce operating costs by up to 40% compared to traditional hotels, thanks to their optimized use of space, efficient processes, and advanced technologies [4]. Moreover, guest satisfaction and loyalty in smart hotels are significantly influenced by guests' motivation and ability to use technology, highlighting the need for hotels to align technological features with user competencies while considering both internal and external factors for long-term success [5]. Smart hotels must tailor technology integration to diverse guest preferences, balancing innovation with human touch [6].

Artificial Intelligence in hospitality

Artificial Intelligence has become a transformative force in the hospitality industry, streamlining operations and enhancing guest experiences. AI-powered tools are utilized for various applications, including virtual assistants, real-time translation services, and dynamic pricing strategies. These technologies automate repetitive tasks, allowing staff to focus on personalized guest interactions. Tussyadiah (2020) explored the effects of AI-driven smart hotel technologies, including voice-activated room controls and facial recognition for streamlined check-ins. The findings indicated that while these innovations enhanced convenience and operational efficiency, they also sparked concerns regarding data privacy and ethical issues. The same concerns are present in a study conducted by Du et al. (2024), highlighting that consumers are more likely to adopt technology if they see others using and endorsing it. Sarude (2025) and M'hamed (2024) highlight in their studies that the integration of AI in the hospitality industry brings substantial advantages, such as personalized guest experiences, enhanced operational efficiency, and improved decision-making. However, both studies underscore that to fully realize these benefits, businesses must balance technological innovation with ethical considerations and a continued focus on human-centered service.

Author Gajic et al. (2024) affirms that the implementation of AI and IoT technologies offers hotel managers practical opportunities to reduce costs, and promote sustainability, ultimately leading to long-term economic and ecological benefits without compromising guest experience. In terms of personalization, AI enables hotels to analyze vast amounts of data to predict guest preferences, tailor recommendations, and manage in-house services more effectively. This leads to superior guest experience and increases operational productivity. Additionally, AI-driven energy management systems can monitor and control energy usage, contributing to sustainability efforts by optimizing resource consumption.

Smart Hospitality and Sustainable Experiences

The concept of smart hospitality involves the integration of advanced technologies, such as Artificial Intelligence (AI) and the Internet of Things (IoT), to develop intelligent, responsive hotel environments and enhance management efficiency [7]. Smart hotels leverage automated systems for functions like energy management, smart lighting, and climate control, thereby enhancing guest comfort while simultaneously reducing environmental impact [8]**.** For example, AI-driven algorithms can optimize housekeeping operations by analyzing guest check-in and check-out patterns, promoting efficient resource allocation. According to King (2024), AI serves as a strategic enabler of sustainability in the hospitality sector, allowing hotels to reduce their ecological footprint through intelligent resource management and environmentally conscious practices, while also strengthening their competitiveness and long-term viability.

By implementing AI-driven solutions, hotels can offer personalized services that cater to individual guest preferences, such as customized room settings and tailored recommendations [9]. Simultaneously, these technologies contribute to sustainability by minimizing waste and conserving energy, thereby reducing the hotel's overall carbon footprint. Chang (2024) identifies key barriers to the adoption of eco-friendly technologies in the hospitality sector, such as high implementation costs, limited staff expertise, and a perceived lack of adequate return on investment, obstacles that are similarly applicable to the adoption of AI technologies.

Enhancing Sustainable Guest Experiences through AIS

In the hospitality industry sustainability has become a critical focus, with AI playing a significant role in promoting eco-friendly practices. AI technologies facilitate energy management systems that optimize resource consumption, thereby reducing the environmental footprint of hotel operations. Arana-Landín et al. (2024) emphasize that AI and IoT technologies play a key role in promoting environmental sustainability in hospitality by optimizing energy consumption—particularly through predictive management of HVAC systems—thus reducing resource use while maintaining guest comfort.

Moreover, the ability to personalize services ensures that sustainability initiatives are seamlessly integrated into the guest experience without compromising comfort or convenience. Also, AI tools enable the collection and analysis of guest feedback on sustainability efforts, allowing hotels to continuously improve and align their initiatives with guest expectations. In a study by Çeltek (2023), it was found that smart hotels use AI and recognition technologies to personalize services, with over 75% of hotels applying these tools at key customer touchpoints like check-in and room customization.

This study addresses a gap in existing research by empirically examining how AI technologies influence guest satisfaction and sustainability preferences in the context of real-life hospitality experiences. While previous literature has largely focused on the theoretical advantages of AI and its technical implementation, there remains limited empirical evidence connecting AI-driven hotel services with specific guest behaviors and perceptions. By grounding its insights in primary data from a tech-savvy urban sample, this study advances the understanding of how smart hospitality can meet the dual demands of personalization and sustainability in a post-pandemic travel landscape.

Built on Self-Determination Theory (SDT) [10] and Green Information Systems (Green IS) [11], this study examines how AI technologies in hotels address psychological needs (autonomy, competence) while advancing sustainability goals. SDT posits that technology fulfilling intrinsic needs enhances satisfaction, while Green IS argues for AI's dual role in operational efficiency and environmental stewardship. Empirical studies corroborate these frameworks: AI-driven personalization improves guest experiences [12], and energy-saving AI systems reduce hotel carbon footprints [13].

Based on these results of previous studies, the following hypotheses are proposed:

H1: Guests who have experienced AI technologies in hotels report higher levels of satisfaction and comfort compared to those who have not. Guests exposed to AI technologies (e.g., smart check-in, voice-controlled amenities) will report higher satisfaction (H1), as these tools fulfill SDT's autonomy and competence needs [10]. Prior research shows that self-service technologies enhance perceived control [14], supporting this hypothesis.

H2: Eco-conscious travelers are more likely to prefer hotels that use AI-driven sustainability measures (e.g., smart energy management) and perceive such hotels as more attractive. Melville's (2010) Green IS framework suggests that sustainability-signaling technologies attract eco-conscious consumers. H2 extends this by proposing that travelers who prioritize environmental responsibility will prefer hotels using AI for sustainability (e.g., smart energy systems). Wiederhold and Martinez (2018) empirically validated this, showing AI reduced hotel energy use by 22%.

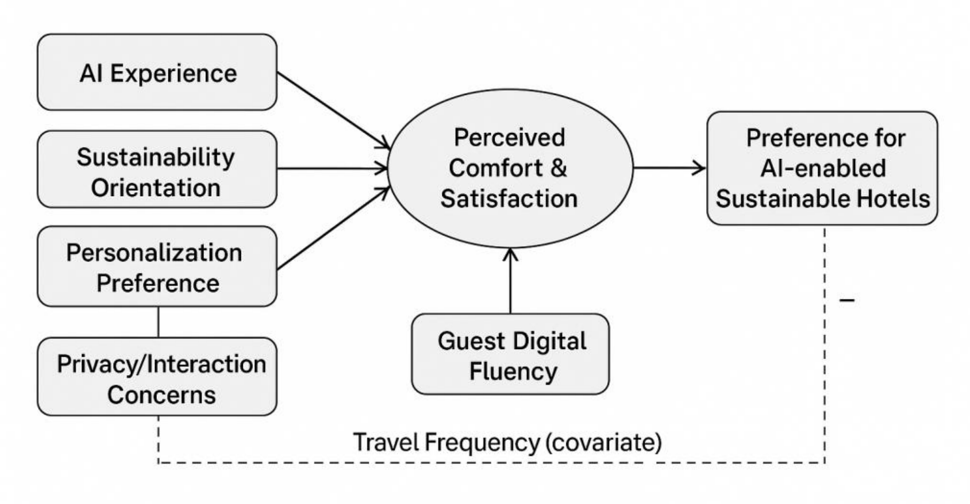

Figure 1. Conceptual framework: the role of AI in enhancing sustainable guest experience

H3: Guests who value sustainability measures are more likely to prefer hotels that integrate AI for both personalization and environmental impact reduction. Elliot's (2016) hybrid-value model demonstrates consumer preference for technologies blending convenience and sustainability. H3 hypothesizes that guests will favor hotels integrating AI for both personalized services (e.g., adaptive room settings) and environmental benefits (e.g., waste reduction), a synergy observed in smart hospitality [15].

H4: Concerns related to data privacy, lack of human interaction, or complexity of use negatively influence guests' willingness to stay in AI-enabled hotels. Despite benefits, Technology Acceptance Model (TAM; Davis, 1989) highlights adoption barriers. H4 predicts privacy concerns and human interaction deficits will reduce AI-hotel willingness, while H5 posits age as a moderator [16], given younger travelers' higher digital literacy.

Figure 1 illustrates our theoretical framework, integrating Self-Determination Theory (Ryan & Deci, 2000) and Green IS (Melville, 2010) to explain AI's dual role in hospitality.

3. Data Analysis

This research employed a quantitative approach through a questionnaire-based survey conducted in Bucharest, Romania, between February and March 2025. Bucharest was selected as the research setting due to its status as Romania's most urbanized and technologically developed city, hosting a diverse population of digitally literate travelers and a growing number of smart hospitality providers. Its robust tourism infrastructure and early adoption of AI-based hotel solutions made it an appropriate environment for examining guest perceptions of technology - enhanced experiences. However, it is important to note that the sample was obtained through a non-probability sampling method, relying on voluntary responses from individuals who had stayed in hotels within the past year. As such, the findings may not be generalizable to the broader population of travelers, particularly those from rural areas or less technologically integrated environments.

The survey aimed to capture traveler perceptions of AI-enhanced hospitality services, particularly focusing on satisfaction, sustainability awareness, and technology-related concerns. The questionnaire included items measuring experiences with smart technologies in hotels, attitudes toward sustainability, perceived comfort, and openness to AI-driven personalization.

3.1 Data screening and methodological approach

The dataset underwent a rigorous screening process to ensure analytical accuracy and methodological integrity. Missing data were minimal (<2%) and addressed using pairwise deletion, a conservative technique that preserves statistical power while minimizing bias [17]. The Shapiro-Wilk test ($p < 0.05$) indicated non-normal distributions for all Likert-scale variables, necessitating the use of non-parametric statistical methods [18].

3.2 Descriptive statistics

A total of 150 valid responses were analyzed. The demographic profile of the sample is summarized in Table 1. The majority of respondents (56%) were aged between 25 and 44, a demographic typically associated with higher digital fluency and openness to technological innovation (Venkatesh et al., 2012). Most reported traveling for leisure (86.7%) and staying in hotels three to five times annually (43.2%). Preferred accommodation types were boutique/independent hotels (30.7%) and apart-hotels (25.3%), consistent with a shift toward flexible and personalized lodging options in contemporary hospitality [19].

Table 1. Profile of the sample (n = 150).

Characteristics	N	Procentage
Age		
Under 18	-	-
18-24	24	16
25-34	28	18.7
35-44	56	37.3
45-54	38	25.3
Over 55	4	2.7
How many times have you stayed in a hotel in the past year		
1-2	34	23
3-5	64	43.2
6-10	36	24.3
Over 10	14	9.5
Reason		
Business travel	16	10.7
Vacation	130	86.7
Family/friends visit	2	1.3
Events	2	1.3
Type of hotels		
Hotel chains	36	24
Boutique/independent hotels	46	30.7
Eco-friendly/green hotels	6	4
All-inclusive resorts	18	12
Low-cost motels	6	4
Apart-hotels (Airbnb type)	38	25.3

3.3 Hypothesis Testing

H1: AI-enabled services and guest satisfaction

The first hypothesis posited that guests who have experienced AI technologies in hotels report higher levels of satisfaction and comfort compared to those who have not. To test this, a Mann–Whitney U test was conducted, comparing responses to the item "AI technologies made my hotel stay more comfortable and enjoyable" between guests with prior AI-hotel experience (n = 112, 74.7%) and those without (n = 38, 25.3%). The analysis revealed statistically significant differences between groups ($U=1,532$, $p<0.001$), with a moderate effect size ($r=0.42$) indicating higher satisfaction among AI-exposed guests. These findings provide strong empirical support for H1, indicating that AI-enabled services—such as smart check-in, intelligent room controls, and voice-activated systems—positively influence guests' perceptions of comfort and convenience. This result aligns with Self-Determination Theory [10], which suggests that such technologies fulfill intrinsic psychological needs for autonomy and competence. Moreover, it echoes prior empirical work by Tussyadiah (2020), who emphasized that AI-driven automation enhances operational efficiency and guest experience, thereby reinforcing the strategic value of smart hospitality systems in elevating service quality.

H2: Eco-Consciousness and AI sustainability appeal

A Spearman rank-order correlation analysis examined the relationship between guests' recognition of AI's environmental benefits and their perception of AI-enabled hotels' attractiveness. The results revealed a statistically significant, moderate positive correlation ($\rho = 0.45$, $p < 0.001$), providing strong support for H2. This finding indicates that travelers who value sustainability are significantly more likely to perceive hotels implementing AI-driven ecological measures (e.g., smart energy systems, predictive resource management) as attractive accommodation choices.

These results align with and extend Green IS theory [11], demonstrating that environmentally beneficial technologies enhance organizational legitimacy among eco-conscious consumers in the hospitality context. The findings further corroborate King's (2024) research on AI as a strategic enabler of sustainable tourism, particularly through intelligent resource management systems that reduce environmental impact while maintaining service quality.

The robust correlation ($\rho = 0.45$) suggests that sustainability-focused travelers not only acknowledge but actively prefer hotels that leverage AI for ecological benefits. This has important implications for hotel operators, indicating that marketing AI implementations through an environmental lens may particularly appeal to this growing demographic of eco-conscious guests.

H3: Personalization and Sustainability as Dual Drivers

To test Hypothesis 3, a non-parametric Spearman's rank-order correlation was conducted to examine the association between guests' preferences for AI-enabled personalization ("I value hotels that use AI to customize my experience") and their appreciation of sustainability initiatives ("I prefer hotels that use technology to reduce environmental impact"). Both variables were measured using five-point Likert scales. To control potential demographic and behavioral confounds, partial correlation analyses were conducted with age and travel frequency as covariates. The correlation analysis yielded a statistically significant positive relationship between AI personalization and sustainability preference ($\rho = 0.43$, $p < 0.001$, 95% CI [0.32, 0.53]), thereby providing empirical support for H3. According to Cohen's (1988) benchmarks, this represents a moderate effect size.

To further validate the robustness of the results, additional analyses were conducted. A subgroup analysis focusing on eco-conscious travelers—defined as those in the top quartile of sustainability orientation—revealed a stronger correlation between AI-enabled personalization and sustainability preference ($\rho = 0.51$, $p < 0.001$), indicating that values-driven guests are particularly responsive to technologies that serve both individual and environmental objectives. Moreover, a bootstrapping procedure with 1,000 iterations confirmed the stability of the primary correlation estimate, yielding a bias-corrected 95% confidence interval of [0.30, 0.55].

The results align with the dual-path model advanced by Gajić et al. (2024), wherein artificial intelligence functions both as a mechanism for enhancing personalized guest experiences—satisfying the competence dimension of Self-Determination Theory [10], 2000)—and as a symbolic indicator of environmental commitment, consistent with the legitimacy signaling function described in Green IS theory [11].

Preliminary diagnostics supported the appropriateness of the chosen analytical methods. Shapiro-Wilk tests confirmed non-normal distributions for both personalization ($W = 0.92$, $p < 0.001$) and sustainability ($W = 0.91$, $p < 0.001$) variables, thereby justifying the application of non-parametric techniques. In terms of scale reliability, internal consistency was deemed acceptable, with Cronbach's alpha values of 0.83 for the personalization construct and 0.79 for the sustainability construct, indicating strong measurement validity.

The strength of the observed correlation ($\rho = 0.43$) exceeds that of AI-convenience effects reported in Tussyadiah (2020) ($\rho = 0.28$) and closely matches green technology adoption patterns found in Melville (2010) ($\rho = 0.41$), underscoring the significance of the synergy between personalization and environmental values in guest decision-making.

H4: Barriers to AI Adoption

Hypothesis 4 proposed that concerns regarding data privacy, reliability, and diminished human interaction negatively affect guests' willingness to stay in AI-enabled hotels. However, due to the uniform reporting of concerns across all respondents (100% prevalence), statistical comparison techniques—such as group-based analysis—could not be applied. This limitation, while methodological in nature, also underscores an important empirical insight: skepticism toward AI in hospitality has become nearly ubiquitous, echoing trends observed in prior studies [12,20].

Discussions

This study investigated the role of AI-driven technologies in enhancing guest experiences and advancing sustainability objectives within the hospitality industry. The findings provide empirical support for the positive impact of AI adoption on guest satisfaction (H1), particularly when aligned with sustainability values (H2, H3). However, concerns surrounding data privacy and diminished human interaction (H4) were consistently reported, underscoring the need for hotels to balance technological innovation with strategies that foster guest trust. The following subsections contextualize these findings within established theoretical frameworks and recent literature, offering a multidimensional analysis of AI's role in sustainable hospitality. Our findings corroborate those of Gajić et al. (2024), who identified AI and IoT integration as critical to optimizing resource efficiency—particularly through predictive energy systems such as HVAC management—while preserving guest comfort. Their structural equation modeling (SEM) revealed operational efficiency as a mediating factor in the relationship between technological implementation and sustainability outcomes, a dynamic also observed in our confirmation of H3. Specifically, guests in our study recognized and appreciated the dual functionality of AI in enabling personalized service and reducing environmental impact. This supports the Green Information Systems (Green IS) framework [11], wherein AI functions not only as a tool for performance enhancement but also as a signal of environmental stewardship.

AI and IoT as Catalysts for Sustainable Hospitality

The association between smart energy systems and hotel attractiveness ($\rho = 0.45$) further aligns with Gajić et al.'s assertion that AI-enhanced sustainability fosters competitive advantage. However, unlike Gajić et al., who emphasized managerial and infrastructural challenges, our study foregrounds guest-centered barriers, particularly the pervasive concern with data privacy (H4). This observation resonates with the findings of Dianawati et al. (2024), who demonstrated that perceived ease of use and usefulness—mediated by user ability and motivation—strongly influence technology acceptance. Taken together, these studies suggest a paradox: while AI systems may deliver measurable operational benefits, their long-term success ultimately hinges on user trust and perceived usability.

The Role of Guest Profiles in Technology Adoption

Building on the Motivation–Opportunity–Ability (MOA) framework employed by Dianawati et al. (2024), our findings highlight the significance of demographic and psychographic variables in shaping attitudes toward AI in hospitality. Like their study, our sample was dominated by younger, digitally literate guests (56% aged 25–44), a cohort typically more receptive to AI-enabled services. Importantly, our results extend their conclusions by illustrating those environmental values—specifically, eco-consciousness—amplify the appeal of AI technologies. The observed correlation between sustainability orientation and preference for AI-driven personalization ($\rho = 0.43$) underscores the strategic value of green branding for attracting this guest segment.

Nevertheless, the inclusive challenges identified by Dianawati et al. remain pertinent. Their study noted that older or less technologically inclined guests may experience usability issues in smart hotel environments. Given the limited representation of guests over 55 in our sample (2.7%), we were unable to empirically assess this dimension. Future research should prioritize the design of adaptive interfaces (e.g., voice-activated systems or simplified user flows) to accommodate a broader range of users and ensure equitable access to AI-enhanced hospitality experiences.

Table 2. Summary of hypotheses and results

Hypothesis	Statement	Result	Statistical Support
H1	Guests who experience AI report higher satisfaction and comfort.	Supported	Mann–Whitney U test, $p < 0.001$, $r = 0.42$
H2	Eco-conscious travelers prefer AI-enabled sustainable hotels.	Supported	Spearman's $\rho = 0.45$, $p < 0.001$
H3	Guests value AI for both personalization and sustainability.	Supported	Spearman's $\rho = 0.43$, $p < 0.001$
H4	Privacy and interaction concern lower AI hotel adoption.	Not testable	100% concern prevalence – no group-based comparison possible

Nevertheless, the inclusive challenges identified by Dianawati et al. remain pertinent. Their study noted that older or less technologically inclined guests may experience usability issues in smart hotel environments. Given the limited representation of guests over 55 in our sample (2.7%), we were unable to empirically assess this dimension. Future research should prioritize the design of adaptive interfaces (e.g., voice-activated systems or simplified user flows) to accommodate a broader range of users and ensure equitable access to AI-enhanced hospitality experiences.

Ethical and Operational Trade-offs

The unanimous concern regarding data privacy reported in our study (H4) aligns with previous findings by Tussyadiah (2020) and Du et al. (2024), both of whom cautioned that AI adoption may alienate guests when perceived as intrusive or opaque. Gajić et al. (2024) offer pragmatic strategies for addressing such concerns, including the implementation of transparent data governance policies and comprehensive staff training on digital engagement. The adoption of explainable AI—systems that clearly communicate data usage and functionality—may serve as an effective countermeasure to privacy-related distrust.

The fact that our study could not statistically test H4 due to the universal prevalence of concern reflects a critical industry challenge: while the operational benefits of AI are well-documented (e.g., a 22% reduction in energy usage, as reported by Wiederhold & Martinez, 2018), the perceived risks remain widespread. This dichotomy suggests the need for a hybrid service model, wherein AI technologies manage routine, efficiency-driven tasks (e.g., check-ins, environmental controls), while human staff remain central to emotionally nuanced and high-touch interactions (e.g., concierge services). Such an approach echoes the model proposed by Wirtz et al. (2018), advocating for a complementary relationship between automation and human service to preserve hospitality's relational core.

5. Theoretical and practical implications

This study contributes to theory development in two significant ways. First, it extends the application of Self-Determination Theory (SDT) by illustrating how AI technologies in hospitality settings can support fundamental psychological needs. Specifically, AI-enabled personalization fosters a sense of autonomy, while maintaining elements of human interaction addresses the need for relatedness—thereby enhancing the guest experience in digitally mediated environments. Second, the findings advance the conceptual framework of Green Information Systems (Green IS) Theory by empirically demonstrating that AI technologies serve not only as tools for operational efficiency but also as strategic symbols of an organization's environmental commitment. In this regard, AI adoption signals sustainability-oriented values to eco-conscious consumers, reinforcing the reputational and legitimacy dimensions proposed in the Green IS literature.

As for the practical implications, the findings of this study offer actionable insights for hospitality managers aiming to implement AI technologies in a sustainable and guest-centric manner. First, it is crucial for hoteliers to prioritize high-impact AI features that directly contribute to guest comfort, such as smart check-ins and intelligent room controls. These technologies not only streamline operations but also enhance the overall experience by offering convenience and responsiveness. However, usability should remain a key design consideration to ensure inclusivity for less tech-savvy guests.

Moreover, AI's dual contribution to personalization and environmental sustainability presents a compelling marketing opportunity. Hotels can attract eco-conscious travelers by clearly communicating the environmental benefits of AI, such as energy-saving thermostats and automated lighting systems that adapt to guest preferences while minimizing waste. Framing these features as both luxurious and environmentally responsible aligns with current consumer values.

Despite its benefits, AI adoption must be balanced with transparency and trust. This is particularly relevant as the study revealed universal guest concerns regarding data privacy and the potential loss of human interaction. To mitigate these fears, hospitality providers should implement clear, user-friendly data policies and preserve the human touch in complex service interactions.

6. Limitations and future research

This study has some limitations. The sample was collected primarily from Bucharest, a technologically advanced and urbanized context, which may not reflect the experiences and perceptions of travelers from rural or less technologically integrated environments. In addition, the use of self-reported data could have introduced social desirability bias, particularly in questions related to environmental consciousness and sustainability.

Future research should aim to diversify the sample to include non-urban and demographically varied populations, particularly older or less technologically inclined guests. Longitudinal studies tracking guest perceptions and behavior over time could reveal how repeated exposure to AI influences satisfaction, trust, and brand loyalty. Additionally, incorporating behavioral metrics, such as real-time energy savings or system usage logs, could validate the effectiveness of AI-driven sustainability initiatives and complement subjective survey responses.

Although Hypothesis 4 was conceptually grounded in the Technology Acceptance Model, statistical testing could not be performed due to the uniform reporting of concerns related to data privacy and reduced human interaction. This lack of variance, while methodologically limiting, reveals a noteworthy trend: skepticism toward AI in hospitality is widespread and potentially embedded in baseline guest expectations. To explore the depth and diversity of these concerns, future research should include open-ended qualitative items or conduct semi-structured interviews, allowing for richer insights into the specific anxieties or contextual triggers underlying these attitudes. Moreover, incorporating Likert-scale questions measuring the intensity of concern (e.g., "How worried are you about data misuse in AI-enabled hotels?") would provide a more nuanced dataset, allowing for statistical comparisons even when overall concern prevalence is high.

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ARTIFICIAL SOCIAL INTELLIGENCE AND THE TRANSFORMATION OF HUMAN INTERACTION BY ARTIFICIAL INTELLIGENCE AGENTS

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Abstract

Artificial Intelligence (AI) has profoundly influenced numerous sectors, with Artificial Social Intelligence (ASI) emerging as an extremely important area focusing on AI agents' ability to understand, interpret, and engage within human social contexts. This article provides an analysis of ASI and its changing impact on human interaction. We trace the evolution of ASI from early concepts to complex computational agents capable of nuanced social behaviors, highlighting the interdisciplinary foundations spanning computer science, psychology, sociology, and ethics. The paper makes an in-depth analysis into the theoretical basis and into the key technologies that enable ASI. We explore the emergence of AI agents in diverse social settings and analyze the mechanisms through which they are reshaping communication dynamics, group interactions, social norms, empathy, and concepts of identity and authenticity. Furthermore, the article presents applications and case studies across very important domains, analyzing both the potential benefits and inherent challenges. A significant portion is dedicated to the ethical, legal, and societal implications (ELSI), addressing concerns related to transparency, privacy, bias, accountability, trust, and psychological well-being. We identify key challenges and open research questions and discuss future directions, exploring enhanced technologies, the pursuit of generalized social intelligence, and the potential for human-AI symbiosis. The conclusion emphasizes the need for a collaborative, ethically grounded, and systemic approach to guide the development and deployment of ASI, ensuring it serves to augment human flourishing and enrich the collective social experience rather than diminishing it.

Keywords: Artificial Social Intelligence, Computational Agents, Artificial Intelligence, AI Agents, Human Social Contexts, Human Interaction, Ethical Legal Societal Implications, Challenges and Open Research Questions

JEL Classification: O3, O33, O34, O35, O36, O38

1. Introduction

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Research and development in the field of AI have experienced unprecedented growth over the last several decades, influencing numerous sectors of society. Economic, political, and cultural domains have all felt the impact of increasingly complex AI systems. Nevertheless, within the emergence of AI in various industries, ranging from finance [1] and healthcare [2] to entertainment [3] and transportation [4], one of the most important and impactful aspects has been the rise of ASI. This area focuses on the ability of AI systems to control, interpret, and engage in social contexts, thereby influencing the way in which humans interact with each other and with computational agents [5]. An emphasis on social capabilities compels AI research to draw on theories and practices from psychology [6], sociology [7], linguistics [8], neuroscience [9] and cognitive science [10], among other fields, highlighting that ASI requires an inherently interdisciplinary approach.

In its most basic sense, ASI aims to replicate or approximate various dimensions of human social behaviors and interactions within artificial agents. Rather than simply performing computations or providing information, socially intelligent AI agents are designed to detect emotional expressions [11], infer intentions [12], respond empathically [13], and adapt to changing social environments [14]. While early AI research focused heavily on problem-solving, logic, and symbolic reasoning, the next generation of AI systems has shifted attention to nuanced interpersonal dynamics [15], complex communication patterns [16], and adaptive social behaviors [17]. This transformation is fueled by the growing recognition that human interaction encompasses much more than the exchange of factual content. It involves shared context, subtle emotional cues, cultural norms, relational history, and a wide range of evolving social meanings.

The significance of ASI is becoming more pronounced as AI technologies begin to mediate human communication on a large scale. Online platforms, messaging services, virtual assistants, and social media channels increasingly rely on AI algorithms that filter information, recommend content, and simulate social presence. Advancements in Natural Language Processing (NLP) [18], Machine Learning (ML) [19], and computer vision [20] have enabled the creation of conversational agents [21], social robots [22], and other AI-driven systems that can carry out tasks in ways that feel surprisingly personable and context-aware [23]. These developments prompt a recalibration of human interaction, as AI moves from an automated background function to a socially interactive presence capable of influencing interpersonal dynamics.

At the core of this progression is the fundamental question of how humans respond to, adapt to, and co-evolve with AI entities that exhibit social intelligence. The phenomenon transforms the user experience into technology-mediated settings, along with the broader landscape of social norms, ethical considerations, psychological constructs of identity and agency. It is therefore very important to investigate the interaction between AI systems with social capacities and the human communities that adopt them [24]. The transformation has potential to yield positive outcomes such as enhanced accessibility, improved social connectivity, and the facilitation of collaborative tasks across cultural and geographic distances [19]. Nevertheless, it also raises critical challenges, including privacy concerns [25], bias in AI decision-making [23], the erosion of certain human to human interaction skills [26], and a reevaluation of how authenticity is defined and maintained in the digital and physical spaces [27].

Within this broader context, the article provides an in-depth exploration of ASI and of the way in which it supports and drives a transformation of the human interaction. The introduction focuses on the historical roots, theoretical frameworks, technological advancements, ethical considerations, and future directions that comprise this complex topic. By examining the motivations, scope, and significance of developing socially aware AI agents, it becomes possible to put forward the broader implications for human society, as well as the responsibilities of designers, policymakers, and researchers involved in this cutting-edge field. The following sections describe the motivations behind the field's rapid expansion, the objectives that guide ongoing research, the significance of interaction between human beings and AI technology for social experiences.

The evolution of AI, from symbolic reasoning to data-centric methods, has led to breakthroughs in image recognition [28], NLP [29] and robotics [30]. Nevertheless, many systems lack social awareness and interaction. The development of socially aware AI aims to replicate human social intelligence, including emotional recognition and perspective-taking, to enable more natural and ethical human-machine collaborations [31].

A particular interest consists in studying the field of socially aware AI, examining its theoretical foundations, technological innovations, historical developments, and ethical implications. We have analyzed how AI-based social intelligence differs from classical AI, evaluate key metrics for assessing AI performance in social contexts, and highlight the technological components enabling socially intelligent AI. The article has also analyzed current research within a historical perspective, discussing the impact of AI on human interaction by presenting applications and case studies.

The socially intelligent AI marks a significant shift in human-AI interaction [31], moving beyond traditional tool-like roles to more interactive and considerable positions. ASI introduces new forms of communication and collaboration [15], raising questions about trustworthiness [32], authenticity [27] and power dynamics in digital spaces [33]. This evolution impacts technology acceptance [34], community formation [35], and societal norms [36], prompting philosophical reflections on personhood [37] and human identity [31].

The present article is organized to provide a comprehensive examination of ASI, culminating in a full perspective that brings together various aspects. Therefore, following this introduction, the second section of the article makes an in-depth analysis into the foundations of ASI, the third one studies the theoretical and technological underlying elements, the fourth section analyses the emergence and evolution of AI agents in human social contexts, the fifth one makes an in-depth analysis into the transformation of human interaction, the sixth section highlights applications and case studies, being followed by the seventh one that analyses the ethical, legal, and societal implications, the eighth section that investigates challenges and open research questions, while the ninth one analyses future directions and opportunities, along with a detailed conclusions section.

2. Foundations of ASI

ASI is a rapidly evolving domain that seeks to provide computational systems with capabilities that go far beyond simple data processing or pattern recognition. The emphasis lies in designing AI agents that can traverse social contexts with sensitivity, adaptability, and awareness of both the emotional states and the behavioral norms of the people around them. This field addresses the question of how machines can acquire and exhibit behaviors that typically demand high levels of human-like empathy, context understanding, and interpersonal intuition. Over the years, there has been growing recognition of the necessity for AI to perform tasks efficiently and to be able to engage in dynamic, nuanced interactions that reflect a certain level of social complexity [2,36].

The present section makes an in-depth analysis into the foundational aspects of ASI by first clarifying what "social intelligence" means in the context of AI research. It then puts together AI social skills with more conventional AI approaches, highlighting what sets socially capable AI apart from standard ML or knowledge-based systems. Following this, the cognitive and psychological aspects that inspire how AI agents can model and respond to human behavior has been discussed, with an emphasis on both classical and contemporary insights from psychology and neuroscience. Finally, key metrics and benchmarks for evaluating AI's social intelligence are analyzed with a view to how the field measures progress and determines the extent to which AI agents succeed in meaningful interactions between humans and AI technology.

Social intelligence in AI aims to give machines the ability to comprehend communication, predict human behavior, and act appropriately. This involves more than just language proficiency, it requires competencies like reading emotions and reflecting empathy. The field, at the intersection of computer science, behavioral psychology, and interaction design, has evolved from simple chatbots to systems that consider multimodal communication and cultural context [38].

Conventional AI excels at well-defined tasks with labeled datasets or explicit mathematical models, such as image classification, speech recognition, or strategic decision-making in deterministic environments [39]. Nevertheless, social intelligence demands that AI agents process, classify, interpret, and respond to subtle human interaction complexities, including emotional nuances, cultural specificities, and historical patterns of behavior [14,36,38].

A socially intelligent AI must integrate empathy [5,13], trust-building [40], politeness [41], cooperation [42], or conflict resolution [43] into its decision-making process [33], considering not just immediate outcomes but also their impact on future relationships, group norms, and individual well-being. This change in perspective fundamentally alters AI model design, training, and evaluation.

Context is very important in the field of AI, especially in social interactions. Image classification models focus on visual features, while language models consider textual syntax and semantics within a domain [44]. In contrast, social interactions are dynamic, encompassing real-time emotions, past interactions, environmental cues, and cultural norms [45]. For instance, scheduling a meeting differs from persuading someone to attend, requiring social skills like communication and understanding group dynamics. Conventional AI approaches that treat communication as a simple input-output problem may fail in these nuanced contexts due to the lack of relational and emotive dimensions.

Evaluation metrics for socially intelligent AI differ from those used in typical AI systems. Accuracy, precision, recall, and F1 scores do not capture the richness of social interactions [46]. These metrics provide insights for well-defined tasks but overlook aspects like natural responses [47], trust advancement [32,40], or conflict resolution [43]. Users might value perceived authenticity or comfort in social settings over computational accuracy. An AI system could be considered socially skilled for understanding implicit social rules, even with occasional errors, while conventional AI systems usually face harsh judgment for small inaccuracies in classification, regardless of social rapport.

The initiative to develop socially skilled AI aims to make machines integrated participants in our social and organizational landscapes, rather than isolated tools. This requires rethinking system architectures [48], training paradigms [49], and design philosophies [50]. Researchers focus on interdisciplinary knowledge, including social psychology, communication studies, organizational behavior, and philosophical inquiries into intelligence, in order to create AI agents that can authentically engage with human social realities [14]. These agents handle the cognitive load of processing high-dimensional data and the emotional and relational dimensions of human communities. While conventional AI is important for technical tasks, socially intelligent AI systems carry additional complexity and responsibilities in their operations and interactions with human stakeholders.

The design of socially intelligent AI is informed by cognitive, behavioral, and neuroscience research [9,10,17]. Psychologists study how individuals perceive, interpret, and respond to others' emotions, intentions, and beliefs, focusing on uncovering details regarding empathy, theory of mind, and social reasoning. Computationally, researchers model these processes within an AI architecture, drawing parallels between human cognitive functions and computational modules for perception, memory, attention, and decision-making processes.

In contrast to humans who rely on neural mechanisms, socially intelligent AI systems use algorithmic and data-driven methods to replicate or approximate these capabilities [51].

In classic cognitive science, theory of mind refers to the ability to attribute mental states to oneself and others, enabling prediction of behavior and adaptation of actions [52]. AI systems aiming for social intelligence need theory of mind to anticipate user or group responses [53]. Computationally, this can be approached using probabilistic models tracking latent states representing others' thoughts or feelings. Over time, the AI updates assumptions based on the observed behaviors and refines their predictions, putting the basis for socially aware planning and collaboration, allowing AI agents to adapt strategies when the goals shift [31].

Empathy, the ability to understand and experience another's emotions, enables support, compassion, and meaningful relationships [5,13]. Capturing emotional signals from text, voice, or facial expressions and mapping them to internal representations guides empathic AI responses. Early attempts focus on keyword detection or sentiment analysis, while contemporary approaches use deep learning for nuanced emotional state detection [11]. Some systems integrate physiological data or contextual variables. The challenge consists in ensuring that empathic responses go beyond superficial imitations. AI should understand narrative context, user background, and social norms in specific cultures or situations.

Beyond empathy and theory of mind, other cognitive capacities like attention and memory significantly influence social interactions. Humans selectively focus attention based on popularity, relevance, and social cues to manage group settings. AI systems with social intelligence need efficient mechanisms to direct computational resources to important stimuli, like dynamic attention models that shift focus based on conversation topics, emotional tone, or new individuals [54]. Memory systems must account for long-term language or cultural knowledge and short-term contextual details. This integrated approach to attention and memory creates fluid, contextually grounded interactions. Reinforcement learning from human feedback forms the basis for adaptation and improvement. Social interactions involve trial and error, and AI can benefit from interactive learning loops that capture user feedback, either explicit or implicit. As AI refines its models, it can develop more accurate expectations about actions that encourage cooperation, trust, or positive emotions. The convergence of empathy, theory of mind, attention, memory, and adaptive learning provides a framework for AI researchers to build systems that mirror human social interaction [5,13,52].

Developers must be mindful of the potential pitfalls of anthropomorphizing AI. Humans tend to attribute agencies and intention to entities exhibiting social cues, even if they are algorithmically generated. This inclination can be exploited for engaging user experiences, but it raises ethical dilemmas about deception and emotional reliance on AI companionship. Understanding how humans process social signals is very important for crafting responsible, respectful AI systems that are transparent about their computational nature.

Aligning AI design with these cognitive insights ensures social intelligence coexists harmoniously with human emotions and psychology [38] .

As AI research advances, there is a growing need for robust metrics and benchmarks to quantify social capabilities. Traditional AI evaluations like accuracy, precision, and recall are useful for tasks like object recognition or language translation, but they fail to capture the depth of social interactions. Researchers must translate subjective human judgments about empathy, rapport, trust, and adaptability into metrics that guide algorithmic development and compare systems [32].

One approach involves using standardized role-playing scenarios or simulated environments where human participants interact with AI agents under controlled conditions. Researchers can measure variables like user satisfaction, perceived empathy, willingness to disclose personal information, or physiological signals to assess emotional impact [55]. Surveys and questionnaires collect subjective evaluations of the AI's performance, capturing elements like perceived social presence, trustworthiness, and attentiveness. While subjective measures vary, aggregating results provides insights into how well AI meets social expectations. As scenarios become more immersive, new opportunities arise to evaluate AI's capacity for nonverbal communication and spatial interaction.

Objective measures assess social intelligence. Turn-taking fidelity quantifies how an AI adapts to conversational rhythms. Metrics assess topical coherence and topic shifts without losing user engagement. Some systems use sentiment analysis or emotion detection to measure alignment between user and AI responses [56]. Consistent supportive responses indicate empathic alignment, but quantifying it is an extremely complex task. Blending objective data with subjective user feedback creates multi-dimensional performance indicators [38].

Benchmark datasets standardize evaluations. Large-scale conversation datasets test AI's ability to generate context-appropriate, empathetic, or persuasive responses. Specialized elements contain emotionally charged dialogues, negotiations, or collaborative tasks requiring strong social components. Systems are evaluated against these benchmarks to measure response alignment with human examples or social criteria. Nevertheless, a universal benchmark is elusive due to varying social norms, cultural references, and contextual cues. Efforts develop more culturally diverse benchmarks, but inherent variability makes any single resource incomplete [45,57].

Progress in AI social competence depends on external validation through competitions and challenges organized by academic conferences and research consortia. These competitions simulate complex social interactions, assessing multi-party negotiation, collaborative storytelling, and group consensus-building. Successful systems demonstrate linguistic skills and effective interpersonal dynamics. These competitive settings promote community convergence on best practices and refined metrics, leading to standardized evaluation protocols for ASI. However, the diversity of real-world social contexts emphasizes the need for adaptable AI social skills [58].

Iterative metric refinement extends beyond academic research. Standardized evaluations assess conversational agents, social robots, and AI-driven platforms for customer-facing tasks [22,23]. Regulatory bodies and stakeholders ensure compliance with transparency, safety, and fairness standards. A consensus may emerge on key indicators of social proficiency, such as emotional engagement, rapport continuity, privacy respect, and cultural sensitivity. Until then, the domain must balance objective and subjective metrics, universal standardization, and localized contextualization to measure AI's transition into genuinely social domains.

Social intelligence in AI combines ideas from computer science, cognitive psychology, neuroscience, sociology, and ethics. It reconciles human social competency with AI algorithmic methods. Distinguishing socially intelligent AI from traditional AI highlights its complexity and need for context-awareness, emotional resonance, and interpersonal nuance. Cognitive and psychological aspects like theory of mind, empathy, attention, and memory support AI architectures that mimic human interaction. In addition, measuring social intelligence in AI requires novel metrics beyond accuracy and efficiency, considering richness and sensitivity in genuine interpersonal interactions.

Building an AI system that truly integrates into human social fabrics goes beyond achieving high scores on narrowly defined tasks. It involves understanding how human relationships, cultural norms, emotional expressions, and interactive protocols influence community interactions. When AI agents learn dynamically, show empathy, respect social norms, and adapt, they approach true social intelligence [14,38]. This vision envisions AI entities seamlessly collaborating with people in various settings, enhancing the quality of human experience rather than displacing or disrupting it. One must take into account that this vision requires refining ethical, legal, and societal frameworks for socially intelligent AI [19]. The next sections explore the theoretical and technological underlying elements of such AI systems, their emergence, and their impact on human communities.

3. Theoretical and Technological Underlying Elements

This section focuses on the core theoretical and technological foundations that make ASI a reality. The interaction among ML, NLP, computer vision, reinforcement learning, and multi-agent systems provides numerous methods and frameworks for creating AI agents capable of understanding social cues, facilitating human-like communication, and adapting to dynamic group environments. Socially aware AI have to base upon fundamental principles from cognitive science and psychology, because the design of these agents cannot merely rely on standard computational approaches [6,10]. The more one advances in this direction, the clearer it becomes that effective social intelligence arises from the tight integration of algorithmic innovations with nuanced models of human interaction. These interactions involve diverse signals in the forms of language, emotion, and behavioral cues, all of which shape how AI agents perceive and respond within human environments.

The strategic significance of these aspects can be understood considering the evolving applications of AI across fields such as healthcare, education, corporate environments, and the public sector. A robust understanding of the algorithms and theories is important for steering the ongoing transformation of the interaction between humans and AI technologies. By providing more details on the mechanisms by which AI systems learn, interpret, and modify social behaviors, we obtain deeper insights into how to design AI that operates with empathy and accountability [57]. Technical breakthroughs in these domains will redefine how we conceptualize interaction in the future, from small-scale personal companionship solutions to large-scale policymaking and governance tools.

ML is the backbone of socially aware AI, enabling models to capture input-output mappings and contextual variables of human interactions [19]. While traditional supervised learning approaches can be adapted to label social cues, unsupervised and semi-supervised methods are very important for uncovering latent social patterns. Despite advancements in architecture like multi-modal transformer models and generative modelling, addressing biases and ensuring ethical deployment remain ongoing challenges [58].

NLP occupies a central role in ASI, enabling conversational agents to interpret user input and generate coherent responses. Large pre-trained language models, refined for social contexts, require additional training data and ethical guidelines to ensure polite and empathetic interactions. Future advancements in NLP aim to incorporate extralinguistic context, emotional intelligence, and potentially gesture recognition, creating more sophisticated and empathetic conversational agents [29,46,56] .

Computer vision is very important for AI systems in order to understand human communication, particularly through emotion and gesture recognition. While traditional methods rely on labelled datasets, real-world scenarios demand more nuanced approaches, including temporal modelling and robust performance across diverse conditions. Combining emotion and gesture recognition with contextual cues, such as scene understanding and multimodal fusion, enables more accurate inference of complex emotional states, creating the premises for truly socially intelligent AI systems [20].

Reinforcement Learning (RL) is a powerful framework for training socially intelligent AI agents in order to optimize sequential decisions in uncertain environments. RL enables agents to adapt their behavior based on rewards capturing socially desirable outcomes, such as user satisfaction and group consensus. One must consider that designing complex reward functions, handling partial observability, and ensuring scalability and ethical behavior remain significant challenges [55].

Multi-agent systems, combining ML, NLP, computer vision, and reinforcement learning, enable complex social interactions between AI agents and humans [59]. These systems, which can exhibit collaborative intelligence, require trust and reputation mechanisms, effective communication protocols, and game theory-based coordination strategies. As multi-agent systems become more prevalent in everyday life, rigorous theoretical foundations and robust technological implementations are very important to ensure they align with human values and social norms.

4. Emergence and Evolution of AI Agents in Human Social Contexts

Ever since the earliest days of computing, researchers and thinkers have envisioned whether machines could emulate, simulate, or augment human social interaction. This interest traces back to post-World War II efforts in computer science, where pioneers like Alan Turing questioned whether machines could exhibit behaviors indistinguishable from humans. Turing's famous test for machine intelligence, introduced in 1950 [60], invited a wide range of ethical, philosophical, and technical inquiries, many of which were directly linked to how a machine's language use could approximate or surpass human capacities in conversation. During those formative decades, there was less public focus on the social dimension of these interactions. The perception about AI at that time concentrated more acutely on reasoning, problem-solving, and symbolic logic. Attempts to explore the social potential of AI can be found in even the earliest attempts at building programs capable of dialogue [60].

The mid-1960s saw a notable departure from purely logic-based or mathematically oriented AI when Joseph Weizenbaum introduced ELIZA, a program that engaged in rudimentary conversation by rephrasing user inputs in the style of a Rogerian psychotherapist. Weizenbaum's intentions were neither to create a companion nor to replicate human empathy [60]. However, the way people reacted to ELIZA revealed something profound, namely despite the system's obvious limitations, many users attributed human-like qualities and emotional understanding to the program. This phenomenon of anthropomorphizing what was in essence a simple pattern-matching script, signaled that the social dimensions of AI could not be dismissed as an afterthought. Even then, the media latched onto the idea of speaking machines, which intrigued the broader public and created an enthusiasm for imagining a future where computers might be embedded in human social contexts [60].

In the following decades, from the 1970s through the 1990s, AI witnessed "several winters" where enthusiasm and funding took a downturn. These periods were often tied to a mismatch between grand promises and the technical realities of hardware constraints, software complexity, and the challenges of generalization beyond narrow, rule-based problem domains. Nevertheless, research in areas such as knowledge representation, expert systems, and Natural Language Understanding (NLU) continued to progress. While the focus was rarely placed on "social intelligence" directly, these advances created the foundational architecture that would later allow for more complex, context-aware, and interactive AI applications [46]. Systems like SHRDLU, which demonstrated the ability to interpret and act upon written commands about a virtual blocks world, hinted at the potential of AI to engage in conversation about shared contexts [57]. Even though these dialogues were strictly constrained, they represented a step forward in generating responses that took account of user input in a dynamically evolving situation [57].

In parallel, robotics labs around the world began to explore more physically embodied forms of AI. Machines that could move, sense their environment, and adapt to unpredictable contexts gave rise to early social robotics, though such projects were generally surpassed by more specialized or industrial applications. The notion of physical embodiment would later prove to be an important factor in how society received AI agents, as robots that could manage human spaces and physically assist people, aspects that generated enthusiasm, curiosity, and sometimes fear. By the late 1990s, humanoid robots started to appear in academic settings, often used for research on gait, balance, and automated movement. Some of these projects, while primarily technical, indicated the future integration of robots into domestic and care environments, signaling a transition from purely operational tasks to those that demanded social awareness [31].

As the 20th century gave way to the 21st, the internet and mobile devices revolutionized how people communicated, stirring fresh interest in socially oriented AI. Digital infrastructure evolved rapidly, with high-speed connectivity enabling large-scale data collection from user interactions. These data-rich environments became suitable for ML approaches, opening the door for systems that could learn from static databases and also from continuous streams of human behavior in real-world contexts. By this point, a historical pattern was beginning to manifest progress in AI's social capabilities followed closely behind by innovations in computational power, data availability, and fundamental algorithmic improvements. While the earliest conceptual explorations might have been rooted in philosophical questions about conversation, by the early 2000s, it was clear that the social dimension of AI was not a marginal or speculative curiosity. It was moving into the mainstream of research and, increasingly, into public awareness [25].

Interactive AI has evolved from early chatterbots like ELIZA to sophisticated systems capable of NLP [56,61] and generation [62]. Advancements in neural networks [63], computer vision [20], and robotics [30] have enabled AI to interpret visual signals and engage in social interactions [45,64]. The widespread adoption of deep learning techniques in the early 2010s further improved AI capabilities, leading to the development of more advanced chatbots and virtual assistants [65].

Advancements in AI have led to the development of advanced social robots, chatbots, and virtual assistants [46]. These agents, equipped with advanced sensors and computational frameworks, can interpret and respond to human cues, engage in dynamic dialogues, and adapt to user emotions and contexts. The integration of large language models and multi-modal interaction further enhances their capabilities, enabling them to simulate social presence and seamlessly blend into daily life.

Public perception of AI agents in social contexts is shaped by cultural accounts, media portrayals, and historical experiences. While some regions, like Japan and South Korea, embrace AI due to positive cultural perceptions, others are concerned about job displacement, privacy, and ethical implications. The acceptance and integration of AI into society vary widely across demographics, nations, and historical contexts, influenced by factors like trust, cultural values, and technological advancements.

5. Transformation of Human Interaction

The advent of ASI has created an extremely important change in human activities, in which conversations, social gatherings, organizational meetings, and even personal relationships are being fundamentally changed by the presence of AI agents [11–14] . These agents, with capabilities ranging from NLP to emotion recognition, assist human beings in completing tasks and also actively participate in communicative settings that have historically been the exclusive domain of human-to-human interaction. Such participation leads to a profound reconfiguration of the ways in which people convey information, interpret social cues, form judgments, and develop empathy. Over time, the integration of AI agents into everyday communication holds the potential to transform cultural values, ethical norms, and conceptions of identity [15–17]. The following sections explore these developments by examining the specific impacts of AI agents on communication dynamics, the mediation of group interactions, the evolution of social norms and etiquette, the facilitation or hindrance of human empathy, and the larger implications for personal identity and authenticity in environments that blend human and AIs.

The integration of AI agents into communication channels is changing social and organizational ecosystems. AI agents, with their contextual awareness and real-time response capabilities, influence communication styles, pacing, and even non-verbal cues. As individuals adapt to the AI's presence, new norms of "AI etiquette" emerge, blurring the lines between human and machine input in communication.

The integration of AI agents into group settings, from small teams to large social networks, is changing collaboration, conflict resolution, and resource sharing. AI mediators, often acting as facilitators or leaders, can detect conflicts and propose data-driven solutions, potentially leading to more impartial decisions. Nonetheless, this raises concerns about autonomy, creativity, and the potential perpetuation of biases, highlighting the need for transparency and oversight in AI-mediated group interactions [31,45] .

The integration of AI agents into personal and professional spheres is leading to the emergence of new social norms and etiquette. These new conventions, which often develop naturally, address the challenge of interacting with machines that mimic social behaviors [17]. As AI systems become more complex, etiquette rules will continue to evolve, reflecting the hybrid nature of modern interactions and potentially leading to numerous localized "AI etiquette" traditions [66].

The impact of AI on human empathy has a high degree of complexity. While AI can facilitate empathetic engagement through tools for emotional analysis and conflict resolution, it can also create dependencies and artificial simulations that weaken human-to-human emotional bonds. The net impact of AI on empathy depends heavily on design decisions, cultural interpretations, and user choices [5,13].

The introduction of artificial intelligence into social interactions prompts deep reflection on concepts like human identity and authenticity. AI-driven agents, capable of producing coherent and contextually relevant interactions, increasingly model our digital and social environments. Such involvement significantly influences the way individuals form and perceive identity across personal, community, and professional contexts, impacting factors such as creativity, interpersonal networks, and individual autonomy. Consequently, the distinction between identities constructed by humans and those influenced or created by AI becomes progressively ambiguous.

6. Applications and Case Studies

ASI, capable of interpreting, responding to, and anticipating social cues, has rapidly moved beyond theoretical constructions and laboratory experiments to become a significant force in various human-centered domains. Social Artificial Intelligence (AI) agents are becoming increasingly integrated into important societal sectors, including healthcare, education, corporate settings, and governmental institutions, thereby changing the operational practices, communication norms, and individual user experiences. The incorporation of socially capable AI is evolving from an optional enhancement to an important component for improving service quality, enhancing user satisfaction, and broadening access to resources. Nevertheless, the global proliferation of these technologies is uneven, presenting substantial ethical and structural complexities contingent upon variations in technological infrastructure, regulatory directives, and established societal values. Despite these impediments, an analysis of existent use cases and case studies highlights both the significant potential, and the inherent challenges associated with deploying social AI across diverse domains [62].

The functionality of socially aware AI relies upon several core technologies, namely Machine Learning (ML) which enables personalization, Natural Language Processing (NLP) that facilitates conversational capabilities, and Computer Vision which allows for the recognition and interpretation of human behavior. Furthermore, Reinforcement Learning techniques permit continuous adaptation, particularly within dynamic social environments. Successful deployment requires rigorous methodologies for data collection and interpretation, along with ethically guided AI outputs. Domain-specific ethical considerations are very important, healthcare and education need strict privacy and security protocols due to the handling of sensitive personal data [30,40], while corporate and governmental applications emphasize the importance of fairness, accountability, and inclusivity [15].

The changing impact of AI is manifested in specific applications. Within healthcare, social AI agents contribute to mental health therapeutic interventions and help mitigate communication barriers [2,46,61]. In education, adaptive tutoring systems provide personalized learning experiences and support the development of social competencies [63]. Corporate environments leverage AI for enhanced coordination, although this raises concurrent concerns regarding employee privacy and the potential devaluation of human tasks [57]. In the situations of social media and personal digital life, AI-driven content recommendation presents an ethical dilemma, balancing beneficial personalization against the risk of promoting manipulative echo chambers [35]. Public administration applications highlight AI's role in changing civic engagement, policy decisions, and citizen trust [57]. Exploring these domains reveals AI's profound impact on human connections, cooperation, and agency in an automated world.

In the following there are depicted the applications of socially capable AI across five major areas: healthcare, education, corporate environments, social media and personal life, along with governance and public administration. There are also explored operational mechanisms, challenges, and opportunities in these rapidly evolving fields.

AI-driven companions and therapeutic interfaces in healthcare offer personalized support, medication reminders, and emotional assistance. These tools, powered by NLP and context-aware reasoning, improve communication between patients and professionals, potentially reducing misdiagnoses and enhancing treatment compliance.

AI-driven mental health companions, equipped with NLP algorithms, offer constant, stigma-free support. While promising in reducing mild to moderate depressive symptoms, challenges include data privacy, recognizing high-risk scenarios, and avoiding over-reliance on AI. Despite these concerns, AI companions show potential as scalable mental health support [13,67].

Socially aware AI systems enhance patient-clinician communication by gathering patient data, adapting to emotional states, and providing real-time translation. These systems offer decision-support functions during consultations, augmenting clinician expertise with data-driven insights. Nevertheless, challenges remain in trust, regulatory compliance, system interoperability, and cultural sensitivity [11,68].

Education presents another area where ASI's power grows rapidly. AI-driven platforms support students' intellectual, emotional, and social development. These systems provide personalized learning, real-time feedback, and inclusivity. Social intelligence in AI tutors or collaborative learning agents interprets the learners' emotional states and adapts content delivery. This aims to impart knowledge and develop socio-emotional competencies which are extremely important in modern life. AI reimagines education as an instructional assistant and promoter for empathy, cooperation, and broader social skills [69].

Personalized AI tutors in education adapt instruction based on individual student performance and emotional states, promoting collaborative learning through AI-facilitated study groups. While offering advantages, this approach raises concerns about over-personalization, data privacy, and the balance between immediate fulfillment and long-term cognitive development.

Socially aware AI systems are increasingly used in education to facilitate social skills training through real-time feedback on interpersonal interactions. These systems that use techniques like sentiment analysis and facial expression detection offer custom support to students, particularly to those with special needs, in mastering social cues and peer interactions. Nevertheless, challenges persist in scalability, contextual nuance, and potential biases, necessitating ongoing research in order to improve AI systems and develop blended learning models [58].

Social AI can streamline various operations in corporate environments, from team communication and project management to customer service and marketing [70]. In inherently social workplaces, individuals must collaborate, manage hierarchies, and handle external client interactions. AI agents with social intelligence can facilitate these processes, boosting productivity, employee satisfaction, and customer engagement. Nevertheless, businesses deploying such agents must address transparency, privacy, job displacement concerns, and societal implications of delegating human-facing roles to AI.

Social AI tools, analyzing team communication and interpersonal dynamics, can enhance project management by identifying miscommunications, optimizing resource allocation, and improving team morale. However, concerns about surveillance, data consent, and algorithmic bias must be addressed to ensure ethical implementation [31,71,72].

Socially adept AI, particularly in customer service, can enhance operational efficiency and brand perception. Advanced virtual agents, equipped with real-time emotion detection and context-aware decision-making, offer personalized solutions and are able to escalate complex cases to human representatives. While this hybrid model improves customer satisfaction and reduces costs, concerns about depersonalization, skill erosion, data security, and cultural differences persist.

Social AI, particularly recommender systems and digital companions, significantly impacts daily life through social media and personal interactions. While offering personalized experiences, it can be both empowering and corrosive, amplifying voices while promoting echo chambers and enabling manipulative behaviors [35].

Recommender systems, while beneficial for personalization, can create echo chambers and societal polarization by reinforcing existing beliefs. Regulatory efforts and platform reforms aim to mitigate these effects, but commercial incentives for high engagement pose a challenge. Social AI extends into personal life through applications that facilitate relationships and virtual companionship platforms. These platforms use NLP models to engage users in conversations, offering advice and support, but raise concerns about authenticity, emotional dependency, and data handling. Despite these challenges, they will continue to evolve and broaden the perspectives [18,29,61].

As social AI gains traction, its implications for governance and public administration become more noticeable. Digital platforms and AI-assisted policy making processes change aspects such as power structures, civic engagement, and accountability. Governments seek efficiency, transparency, and citizen participation, but these benefits raise fairness, bias, and democratic norm concerns. Social AI streamlines policy-making and public services, but it must balance human oversight and community respect [57].

Socially aware citizen engagement platforms, powered by social AI, analyze user submissions to identify urgent issues and facilitate more inclusive civic dialogues. Nonetheless, concerns about algorithmic biases, data privacy, and surveillance must be addressed through careful dataset curation, transparent model design, and robust data protection protocols [23].

Socially intelligent AI is increasingly used in policymaking, analyzing data to evaluate public opinion and simulate policy outcomes. While this allows for real-time feedback and adaptive policymaking, it also raises concerns about policy automation, bias, and lack of transparency. Addressing these challenges through ethical considerations and democratic oversight is very important for the responsible use of AI in governance [1,73].

7. Ethical, Legal, and Societal Implications

The rise of ASI has highlighted its ethical, legal, and societal impacts. As AI mimics human behavior, addressing transparency, privacy, bias, and accountability becomes very important. While improving technology is important, designing, regulating, and reassessing the AI ecosystem responsibly is an extremely important necessary step. This section explores very important questions regarding the integration of AI within modern society. It emphasizes the need for transparency and explainability in social AI, privacy, data protection challenges, bias, fairness, inclusivity issues, accountability, legal frameworks, building trust and ensuring well-being. By understanding these dimensions, AI-driven transformations can uphold human dignity, autonomy, and progress.

Social AI's urgency is given by its intimacy with individuals and communities. Unlike abstract computational tasks, social AI agents engage in fluid dialogues, interpret emotions, and influence relationships. This depth of engagement offers support and enrichment but also creates risks of manipulation, exploitation, and human value erosion. Ethical dilemmas intensify when systems replicate empathy or demonstrate emotional responsiveness, distorting genuine human connection with simulation. Ethical mandates must extend beyond data management and efficiency to include trust, authenticity, and emotional safety [11,67,68].

Legal questions arise when AI is embedded in social contexts. AI agents' nuanced conversations, apparent empathy, and adaptability to social norms suggest they may participate in social networks rather than being only static tools. This active role presents novel legal challenges, such as determining if an AI's decision or recommendation carries the same weight as a human actor's does, establishing liability among developers, data providers, deployers, and end users, and ensuring alignment with international human rights standards. Legislators and regulators must balance innovation with potential harms [5,68,74] .

Societal implications of AI-mediated interaction include transformations in social structures, cultural norms, and personal identity. Social AI agents can act as companions, advisors, educators, and intermediaries, potentially redefining family dynamics, reshaping workplace communication, and changing relationship formation. Some changes may be positive, encouraging inclusivity and bridging social barriers. Nevertheless, certain social skills and cultural expressions could erode or be distorted under continuous AI intervention. Sustained, multidisciplinary research and iterative policy development are needed to understand these shifts. Addressing the ethical, legal, and societal dimensions of ASI involves technical design, institutional oversight, and public awareness and engagement [62].

Transparency and explainability are very important for the responsible use of social AI systems. While transparency ensures clarity about AI decision-making processes and data sources, explainability allows AI systems to provide reasoning for their decisions. Achieving this balance is complex, involving technical solutions, ethical guidelines, and legal frameworks to ensure accountability and user trust [40].

The adoption of AI agents in social contexts raises privacy concerns due to the collection and storage of sensitive personal data [57]. While regulatory frameworks like the GDPR provide legal constraints, the rapid evolution of social AI outpaces legislative processes, creating ambiguities around compliance. A multi-layered approach involving industry, government, civil society, and academia is necessary to ensure robust privacy protections, including transparent communication with users and continuous monitoring of AI systems.

Bias in AI systems, particularly in social AI, arises from unrepresentative or skewed training data, potentially leading to discrimination and reinforcing harmful social hierarchies. Addressing these issues requires a complex approach, including data augmentation, algorithmic fairness, and continuous monitoring. Ensuring inclusivity involves considering diverse user needs, cultural adaptability, and accessibility, while strong governance structures and societal conversations are very important for accountability and informed policymaking [66].

As AI agents become more complex and autonomous, questions of accountability and liability arise. Determining responsibility for AI-related harm is complex, involving multiple stakeholders and potentially challenging traditional legal frameworks. Collaborative efforts among lawmakers, technologists, ethicists, and civil society are needed to establish robust accountability measures for social AI [66].

Societal acceptance of social AI agents depends on their technical capabilities and users' trust in their interactions. Trust is linked to AI agents' perceived intentions, reliability, competence, and morality. As AI integrates into communication, domestic, and professional settings, people rely on it for support, companionship, decision-making, and social facilitation. These shifts in behavior and emotions are significant, but concerns about manipulation, loss of genuine human connection, and psychological dependency arise. Balancing AI benefits against mental health and social well-being challenges require public discussions, ethical oversight, and cross-sector collaboration.

Trust is not built solely based on assurances or compliance, it builds through cumulative interactions and experiences. When an AI assistant consistently offers sound guidance, accurately interprets emotions, and shows empathy, trust forms. Conversely, unpredictability, mishandling sensitive information, or expressing biases can erode trust quickly. In emotionally charged contexts like mental health counseling or grief support, any breach of privacy or feeling of judgment can cause emotional harm. Once broken, trust is challenging to rebuild. Rigorous testing, ongoing user feedback, and ethical design principles are very important [32,40,73].

Psychological well-being and social AI intersect in multiple ways. AI companions and chatbots can alleviate loneliness, especially for socially isolated individuals. Studies show potential improvements in mood and perceived social support among older adults using AI-powered robotic companions [36]. AI systems in education can boost self-esteem with personalized feedback. Chatbots serve as accessible first-line support in mental health applications, bridging healthcare gaps. These positive outcomes suggest social AI can enhance psychological welfare, complementing traditional human interventions [75].

Nevertheless, the pervasive presence of social AI agents may lead to dependencies and subtle social manipulation. Users might over-rely on AI-generated validation or emotional support, neglecting human relationships. AI systems gathering psychological profiles might influence users' behaviors or opinions, raising concerns about autonomy and free will. Subtle manipulations could be difficult to resist or identify, especially in contexts where commercial or political interests exploit AI for targeted advertising, information control, or ideological persuasion. Without clear boundaries and transparent mechanisms, social AI could inadvertently or deliberately create echo chambers, polarize communities, or undermine critical thinking [68].

Advancing digital literacy and emotional intelligence among users is very important in mitigating the risks associated with social AI. Educational initiatives that teach users about AI's learning, data interpretation, and outcomes empower critical engagement and self-reflection. Recognizing when AI-driven advice or support should be supplemented by professionals helps users avoid unhealthy dependencies. Emotional intelligence training for both users and developers ensures respectful and supportive interactions, minimizing the risk of harmful manipulation. Robust oversight mechanisms, including independent audits, ethics review boards, and user advocacy committees, monitor the deployment of AI systems at scale. Public reporting of key metrics provides insights into how well these systems align with societal values and psychological needs. Policymakers can mandate reporting, set transparency requirements, and impose penalties to ensure trust is achieved through institutional processes and accountability.

Cultural factors shape how communities perceive and integrate social AI. In certain societies, AI agents facilitating communal problem-solving may be accepted more readily while more individualist cultures might be cautious about data-sharing and potential psychological influences. Developers must be sensitive to these cultural dimensions to design AI that resonates across societies. For instance, language patterns and norms of polite speech vary widely, and an AI agent's inability to conform can slow down trust and give rise to misunderstandings [19,50].

Psychological well-being depends on authenticity and genuine connection. Critics argue that advanced AI companionship can never replicate human emotion and empathy, potentially diminishing people's motivation and ability to connect with others. Social AI should serve as a supplement rather than a substitute for human interaction. Proponents argue that these technologies can fill care and communication gaps when human resources are insufficient or inaccessible. The debate is ongoing as AI advances to being capable of nuanced emotional engagement [5,13,68].

A balanced approach is needed to manage social AI's complexities, acknowledging its potential and risks to trust and psychological health. This includes proactive governance, user education, rigorous research on long-term impacts, and dialogue between technologists and the public. Societal trust is built when social AI acts consistently in people's best interests, respects autonomy, and is governed ethically and legally. Psychological well-being must remain a priority, ensuring technology contributes to human flourishing rather than replacing or distorting social connections [19,40].

This exploration of transparency, privacy, bias, accountability, and trust highlights the depth of ethical, legal, and societal challenges posed by social AI. Integrating AI into human communication and interaction requires reevaluating norms like data protection and human agency. Multiple stakeholders must collaborate to control these changes. Responsibility spans design decisions, policy principles, cultural adaptations, and moral commitments. Thoughtfully approached, social AI can enrich interaction with empathetic support, inclusive communication, and complex social understanding. Nevertheless, misuse and harm highlight the urgency of robust governance and transparent design. In the following, we explore challenges, research questions, and future opportunities, guiding AI's evolution towards a more human-centered and socially beneficial paradigm.

8. Challenges and Open Research Questions

The rapid transformation of human interaction by AI agents with varying degrees of ASI has raised unresolved questions and technical obstacles. Researchers across multiple disciplines face challenges in conceptualizing, developing, deploying, and governing AI systems that engage effectively and ethically in complex social environments.

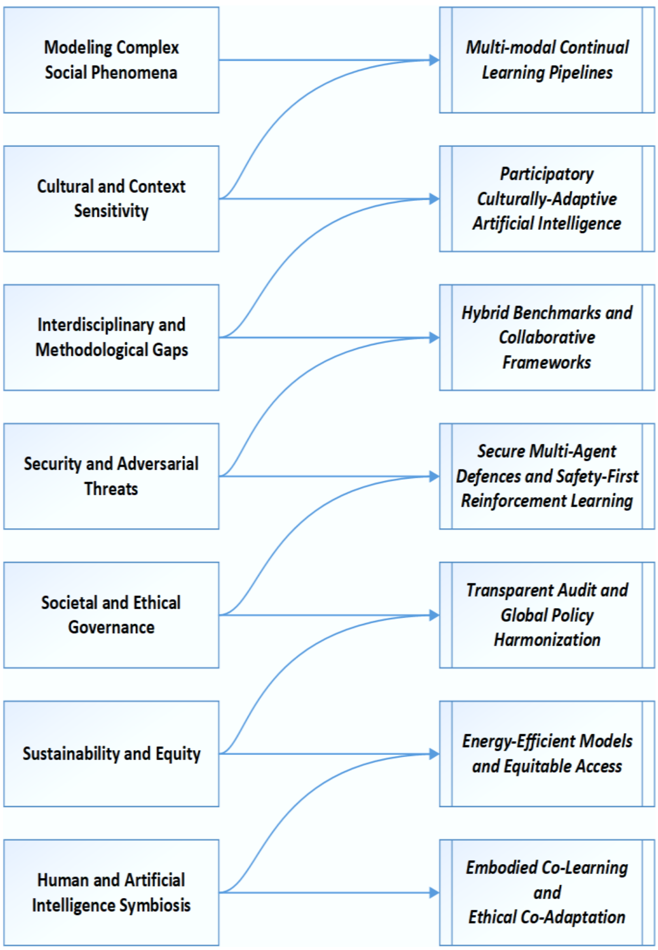

Figure 1. The proposed roadmap highlights a systemic continuity approach rather than an isolated paired one

This section examines the main challenges and open research questions, including technical limitations in modeling social phenomena, cultural sensitivity requirements, interdisciplinary collaboration, security threats from adversarial behavior, and societal integration. Each dimension poses distinct problems and highlights the inseparability of technical, social, and ethical considerations in ASI. The proposed roadmap highlights a systemic continuity approach rather than an isolated paired one, being depicted in **Figure 1** above.

Capturing the complexities of real-world social interactions in computational models remains a persistent challenge for ASI. While progress has been made, many forms of sociality, such as context-dependent schemas and dynamic group dynamics, remain elusive. Addressing these challenges requires interdisciplinary collaborations and the development of advanced computational frameworks that can handle multimodal data, subjectivity, and uncertainty in real time.

As AI systems become more prevalent, cultural sensitivity becomes very important. This involves understanding subtle nuances in communication styles, gestures, and social norms across different cultures. While some aspects of social intelligence may appear universal, culturally specific adaptations are necessary in order to avoid misinterpretations and ensure ethical behavior.

ASI requires interdisciplinary collaboration between computer scientists and social scientists in order to develop meaningful social capabilities. Nevertheless, this collaboration is hindered by methodological gaps, terminology differences, and institutional structures. Overcoming these challenges demands proactive strategies, including the creation of multi-disciplinary teams and the promotion of open dialogue about technical and social scientific frameworks.

As AI agents become more integrated into human life, security vulnerabilities and adversarial attacks become more urgent challenges. Adversarial attacks can manipulate data inputs, exploit trust in AI agents, weaponize generative models, and breach privacy. Adversarial resilience must be a priority in designing socially intelligent AI systems, integrating cryptographic safeguards, anomaly detection, robust ML paradigms, and user education.

Beyond immediate challenges, the long-term trajectory of AI agents in human societies is profound. As AI matures, it can transform interactions and the broader social, economic, and political aspects. Nevertheless, the direction and desirability of these transformations are debated and uncertain. Researchers must address fundamental questions about how AI will shape norms, structures, and human concepts.

An extremely important area involves the shifting nature of social bonds and interpersonal relationships. Early evidence suggests users derive emotional support from AI interactions. These relationships may deepen, raising issues about dependency, authenticity, and emotional well-being. AI companions could mitigate loneliness, provide empathy, and encourage personal growth. Nevertheless, they might displace or erode genuine human connections, especially if AI agents become so compelling that they outcompete human interaction. The ethical implications of promoting AI-human emotional attachments are complex, as they can be unilateral, algorithmically mediated, and lacking reciprocity. Researchers must design AI systems that complement human bonds, supporting socially beneficial outcomes without undermining communities.

AI's integration into the workplace will have significant consequences. AI systems with nuanced social interaction may take on roles like recruitment, team management, negotiation, and customer service. While automation has been discussed in terms of its economic impact, the social dimension adds complexity. Intelligent agents may perform emotional labor tasks, such as comforting customers or resolving conflicts, redefining human skill sets and altering organizational hierarchies. Industries like healthcare, education, and hospitality may heavily rely on compassionate, empathetic, and culturally sensitive AI agents. The question is whether these agents will enhance human capabilities or lead to job displacement and to professional expertise erosion. Policy interventions, including retraining, labor regulations, and ethical guidelines, will determine how these technologies coexist with human labor.

The normalization of AI agents in daily life necessitates a deeper exploration of their impact on social norms and values. Societies evolve through interactions between individuals, institutions, and traditions. AI integration could accelerate shifts in norms around privacy, autonomy, and communication. For instance, as people rely on AI assistants for social interactions, expectations of responsiveness, politeness, and emotional availability may change. This could lead to new etiquette frameworks for the interactions between human beings and AI agents. Alternatively, it could exacerbate social inequalities as those with advanced AI tools better manage complex social networks. The trajectory depends on various factors, including technological innovation, market forces, cultural receptivity, legal frameworks, and public preferences.

AI's role in shaping collective decision-making processes is a significant open question. Some envision AI as a facilitator of "deliberative democracy", providing data-driven insights and moderating debates. This could reduce polarization by highlighting areas of agreement. Nevertheless, critics argue that ceding control of civic positions to algorithmic mediators risks undermining democratic values, especially if models are controlled by vested interests. Biases in training data or manipulations in information presentation can steer public opinion and amplify divisions. Rigorous research is needed to evaluate how AI systems might inadvertently institutionalize biases or marginalize certain voices. Developing transparent, accountable frameworks for deploying socially intelligent agents in public decision-making is very important.

Long-term integration hinges on the AI's ability to adapt ethically over time. Human societies continually redefine ethical boundaries. AI agents must have mechanisms for ethical self-reflection, guided by human oversight or normative frameworks. This raises the possibility of designing "moral machines" with dynamic ethical reasoning. Nevertheless, philosophical and technical hurdles remain. Determining ethical standards and resolving conflicts among competing moral systems are unresolved questions with global implications. Ensuring transparency and democratic oversight is necessary for maintaining trust.

Ecological sustainability and social stratification are very important aspects of evaluating the long-term role of socially intelligent AI. Training and deploying large-scale AI systems consumes significant computational resources and non-renewable energy, potentially exacerbating environmental costs and colliding with international emissions reduction commitments. If AI integration into daily life increases, energy demand could soar. Researchers must design energy-efficient models, explore decentralized computing, and integrate sustainability into AI ethics. Failing to do so risks accelerating the climate crisis.

Technological adoption also leads to social stratification, with wealthier communities benefiting sooner. If socially intelligent AI determines social and professional success, existing inequalities may worsen. Targeted interventions like subsidized or open-source AI solutions can mitigate disparities, but their effectiveness is uncertain. An integrative unifying perspective considering race, gender, age, and socioeconomic status is needed for equitable long-term strategies.

The future trajectory of AI in human societies requires sustained, globally inclusive discussions. Research should extend beyond laboratories to longitudinal field studies, pilot projects, and continuous feedback from diverse user groups. Cross-cultural collaboration involving global tech companies, local innovators, and community leaders is very important in order to ensure that AI integration does not exacerbate historical injustices or undermine cultural autonomy. The interaction of technology, policy, business interests, and civic values will determine whether AI evolves into a tool of liberation or social control.

The proposed roadmap comprising the identified challenges in ASI along with key insights towards solutions proposals is synthetized in **Table 1** below.

Challenge	The Reason for its Importance	Key Insights Towards Solutions Proposals
Modeling Complex Social Phenomena	Current approaches struggle with high-dimensional, sequential and culture-laden behavior	Multi-modal sensors, richer sequential models and continual-learning pipelines

Cultural and Context Sensitivity	Risk of mishandling idioms, norms or under-represented groups	Transfer/meta-learning plus genuinely participatory data-collection to "learn with" local communities
Interdisciplinary and Methodological Gaps	Social science insight rarely reaches model design or evaluation metrics	Shared vocabularies, hybrid qualitative-quantitative benchmarks, new collaboratory funding models
Security and Adversarial Threats	Social bots are attractive targets, adversarial inputs can hijack narratives	Secure multi-agent protocols, game-theoretic defenses and "safety-first" reward shaping
Societal and Ethical Governance	Fragmented regulation, opacity erodes trust and accountability	Global policy road-maps, transparent auditing, user-centric consent flows
Sustainability and Equity	Carbon cost of large models and the "digital divide" threaten inclusive progress	Energy-efficient architectures, open-source subsidies, intersectional impact audits
Human and Artificial Intelligence Symbiosis	Long-term vision where AI augments rather than supplants human agency	Embodied co-learning systems, mixed-reality collaboration, continual ethical co-adaptation

Table 1. Proposed Roadmap Comprising the Identified Challenges in ASI along with Key Insights Towards Solutions Proposals

The long-term integration of AI agents in human societies presents a defining challenge, encompassing technical, ethical, economic, and existential considerations. The ultimate shape and impact of these systems remain uncertain, and research plans must adapt to AI's connection with human needs and aspirations. Societies' evolution towards benevolent AI partners enhancing human flourishing or dystopian scenarios involving pervasive surveillance and social fragmentation depends on current decisions. The task's complexity emphasizes the urgency of robust, ethically grounded research, transparent policymaking, and inclusive societal debates.

The challenges and open research questions surrounding ASI and its impact on human interaction are vast and complex. Technical hurdles in modeling social phenomena, the need for cultural sensitivity, interdisciplinary collaboration, adversarial attacks, and long-term integration implications demand sustained attention from various stakeholders. Only comprehensive, ethically informed, and collaborative efforts can harness the potential of socially intelligent AI for the collective well-being while respecting human social complexities.

9. Future Directions and Opportunities

ASI, a dynamic research area, bases on knowledge from diverse disciplines like computer science, cognitive psychology, and ethics. As AI integrates into human social spaces, its impact expands. Controlling the design, development, and deployment of AI with technical complexity and sensitivity to human emotions and cultures is very important. Ongoing research, policy-making, and cross-disciplinary engagement ensure responsible evolution and unlock novel possibilities. Emerging technologies for enhanced social cognition, ethical frameworks, and policy roadmaps, generalized social intelligence, human-AI symbiosis, along with a vision for the coming decades and beyond are explored.

The development of ASI relies on advanced technologies that enhance AI agents' social perception, interpretation, and responsiveness. These technologies include complex sensors, mixed reality interfaces, edge computing, quantum computing, neuromorphic computing, and brain-computer interfaces. By leveraging these technologies, ASI aims to create AI agents capable of near-human levels of social interaction and understanding in complex environments.

Ethical considerations and regulatory initiatives are very important as AI agents gain social responsibilities and decision-making capacities. Explainability, data privacy, bias, and fairness are dimensions that demand rigorous analysis. Policymaking must be adaptive, incorporating multi-stakeholder collaboration and global discussions in order to maximize the potential of social AI while safeguarding public welfare and individual rights.

Achieving generalized social intelligence in AI involves creating agents capable of adapting to diverse tasks and contexts. This requires multi-modal and multi-cultural competence, integrating language understanding, cultural anthropology, and advanced ML architectures. The approach involves interdisciplinary efforts, flexible architectures, and ethical considerations in order to develop AI agents that can enhance human communication and cross-cultural collaboration.

As AI integrates into society, a key question arises about genuine symbiosis between humans and artificial entities. Symbiosis goes beyond cooperation, it is a relationship where humans and AI enhance each other's capabilities and well-being, leading to new forms of collective intelligence and creativity. Advances in personalization, adaptive learning, trust-building, along with merging physical and digital realities are important prerequisites.

Personalized interaction is very important for symbiosis. AI systems that accurately model individual preferences and cognitive patterns can tailor assistance and companionship. In education, symbiotic AI tutors collaborate with teachers and students, providing just-in-time support that augments skills or emotional resilience. Over time, these adaptive tutors co-create educational content, refining lessons based on student feedback, while teachers maintain oversight. This collaborative learning system combines human intuition and empathy with the AI's data-driven insights.

Trust is very important for symbiosis, but humans may be hesitant to trust AI partners due to concerns about data misuse, opaque decision-making, or hidden programs. Socially intelligent AI designed for symbiotic relationships should prioritize transparency, consistency, and reliability. These systems should acknowledge their limitations, clarify uncertainty, and provide users with additional resources or expert opinions. Continuous user feedback loops reinforce trust by granting humans agency in shaping the AI's role. "Explainable symbiosis" may emerge, where AI provides correct or contextually relevant outputs to deepen mutual understanding by specifying core reasoning or data patterns.

Symbiosis implies growth and transformation for both humans and AI. For instance, AI-driven brainstorming assistants in creative industries can propose diverse concepts, enabling artists and designers to explore new aesthetic territories. Over time, this symbiotic relationship can shape human perception of creative processes, leading to emergent forms of expression. Similarly, AI can serve as a partner for hypothesis generation, data synthesis, or strategic planning in knowledge work, freeing human collaborators to focus on higher-level decision-making or ethical considerations. In these scenarios, AI becomes a valued co-contributor whose inputs and insights are integrated into the human mental model.

Physical embodiments of AI, like social robots, exoskeletons, or prosthetics, augment human physical capabilities. Socially intelligent exoskeletons could aid rehabilitation by dynamically adjusting support levels based on progress and factors like terrain or fatigue. These robotic aids, integrated with the user's body schema, could become extensions of their sense of agency. Over time, human intention and AI-driven movement can lead to augmented embodiment, diminishing the biological and technological boundaries.

Organizational structures and social norms will also change. AI-enabled group decision-making platforms collect inputs, identify consensus, and suggest compromise solutions. Socially aware AI in boardrooms, strategic planning, or public policy forums can make use of collaborative intelligence by integrating multiple perspectives. These AI systems manage conflict, recognize agreement or dissent, and adapt communication styles to de-escalate tension or build rapport. This leads to more inclusive and transparent processes that empower marginalized voices. Human–AI symbiosis amplifies collective intelligence, but it also raises questions about responsibility and leadership when AI insights are the ones shaping the outcomes.

Achieving true symbiosis between humans and AI faces challenges. Over-reliance on AI may diminish essential skills and critical thinking. AI agents with cultural or social biases could reinforce those biases, creating a symbiotic loop. Power imbalances in AI access may lead to stratified symbiosis, benefiting some while others lag. Addressing these pitfalls requires thoughtful design, oversight, resource distribution, and public debates on AI boundaries.

Despite complexities, the symbiosis between humans and AI technology remains a powerful motivator for social AI research. Focusing on personalization, trust, co-creation, augmented embodiment, and organizational transformation can lead to AI as a genuine partner, not just a tool or competitor. Mutual respect, aligning AI with human values, and refining collaborative processes are key to success. Symbiosis is not an unattainable ideal but a practical, human-machine evolving partnership.

The future of social AI, driven by advancements in machine learning and the interaction between human and computer technology, promises to integrate seamlessly into daily life, healthcare, education, and beyond. While this integration offers opportunities for personalized care, adaptive learning, and enhanced community engagement, it also raises concerns about privacy, bias, and significant changes in social interactions. Ultimately, the responsible development and deployment of social AI will be very important in creating a future where technology amplifies human creativity, empathy, and problem-solving capacity.

10. Conclusions

ASI, rapidly impacting human interaction, is a complex domain where computational systems replicate, simulate, and reconfigure social dynamics. Unlike just processing information or solving logical tasks, true ASI arises from integrating psychological, cognitive, and sociocultural insights into ML architectures, NLP, computer vision, multi-agent systems, and reinforcement learning. These advancements enable AI agents, from chatbots to advanced social robots, to interpret, predict, and shape human behavior in real-time.

The conducted analysis highlighted the interaction between AI theoretical constructs and practical implementations. Traditional AI relied on rigid rule-based systems or specialized ML models for limited interaction. Recent advances in deep learning, transfer learning, and multi-modal processing expanded the AI's operational domain, enabling new forms of interaction. Conversational agents understand contextual shifts, computer vision systems detect facial expressions, and reinforcement learning agents adapt in dynamic settings. Examining these technological aspects shows that AI is evolving from technical problem-solvers to social participants, reinforcing the need for social intelligence combining reasoning, perception, adaptability, and cultural sensitivity.

AI's deployment in social contexts spans decades, starting with primitive chatbots like ELIZA, progressing to interactive robots, and culminating in contemporary virtual assistants managing personalized services. These historical aspects highlight the tension between aspirations and realizations, where early visions faced limitations in sustaining natural dialogues or interpreting emotions. Recent improvements in GPU computing, large-scale NNs, and datasets have addressed these limitations. Today, AI-driven systems are integrated into daily life, from digital customer service to healthcare companionship. These developments change our perception of AI agents from static tools to dynamic interactants in the human social existence.

Throughout the article, transformations in communication and group dynamics were highlighted. AI-mediated interactions reconfigure social exchange patterns, altering conversational flow and agency distribution. AI agents can facilitate group interactions as neutral mediators, but they can also introduce biases, reinforce echo chambers, or undermine privacy. These shifts in social norms and etiquette necessitate recalibrating social protocols in AI-coexistent environments. Boundaries between private conversations and AI-stored data tend to dissipate therefore challenging autonomy, disclosure, and intimacy assumptions. The role of AI in empathy adoption or hindrance is a concern, as mechanized empathy can extend care or lead to manipulation.

Socially aware AI has proven beneficial in diverse domains, from education and healthcare to corporate and governmental settings. In education, personalized tutoring systems improve engagement, while group-based AI facilitates collaborative learning. In healthcare, social robots and AI companions support mental health, covering the needs of isolated populations. Corporates use AI for project management and team communication, sometimes replacing traditional management tasks. Governments and public administration employ AI to engage citizens, reflecting an effort to integrate intelligent platforms into governance. Nevertheless, accountability, data security, and the potential erosion of direct human oversight remain pertinent concerns.

AI's ethical, legal, and societal implications are very important aspects, especially when it influences mental health, political stance, or group decision-making. Bias in AI-driven interactions arises from skewed training data or flawed algorithms, emphasizing the importance of inclusive design processes. Privacy and data protection concerns grow as social AI collects sensitive data. Accountability mechanisms, from legal frameworks to public oversight, are emerging but lag behind innovation. Societal acceptance depends on ethical behavior, privacy protection, fairness, and security against manipulation.

AI is evolving into a social actor that supports, augments, or supplants human interaction. Interdisciplinary integration between computer science, psychology, sociology, ethics, and law is very important for constructing general models that are capturing human communication and group behavior. While remarkable milestones have been reached, fundamental challenges remain, including modeling context, culture, and emotion, and societal questions about autonomy, identity, and authenticity in AI-augmented spaces.

The article emphasizes the need for critical engagement with AI systems that assume social roles. AI's evolving complexity holds significant potential to change the way in which individuals and societies construct meaning, form relationships, and organize collective activities. The pursuit of artificial social intelligence is no longer a peripheral research question but a central concern requiring robust theoretical models, empirical validation, ethical scrutiny, and inclusive design practices. An integrative approach is needed to ensure that AI's growing presence in human social life serves as a technical milestone, a channel for human flourishing, and an opportunity to enrich, rather than diminish, the collective social experience.

ASI's implications extend to various stakeholders, shaping how individuals, communities, institutions, and global networks interact with AI-augmented realities. In the case of users, socially aware AI offers personalization, convenience, and accessibility, addressing emotional states, interpersonal nuances, and contextual cues. Mental health support is accessible through empathetic AI companions, while adaptive tutoring and therapy cater to social and cognitive impairments. In consumer contexts, AI assistants enhance daily tasks with nuanced social understanding, from scheduling to domestic management.

Nevertheless, AI's implications for individuals are mixed. While convenience is appealing, AI systems trained on proprietary data continuously gather insights into personal habits, emotions, and social networks, potentially eroding privacy and autonomy. Surveillance demonstrates how data can be harvested and leveraged for targeted advertising, potentially harming users' interests. Psychologically, relying on AI for social needs raises questions about how human empathy and emotional intelligence might decline if AI mediates more interpersonal contact. AI's subtle influence on self-expression, self-awareness, and social development must be carefully considered in order to avoid offloading human capacities to machines.

At the community and societal levels, socially adept AI offers opportunities for collective problem-solving, inclusive group dynamics, and enhanced public discussions. Social robots in eldercare facilitate group activities and reduce isolation, while AI-based platforms in education provide broader and more equitable access to specialized knowledge and collaborative learning experiences. AI-driven interfaces can simplify bureaucratic processes, promote digital town halls, deliver multilingual support, increase civic participation and lower barriers to engagement. These improvements can be significant in under-resourced or remote settings where access to human experts or specialized infrastructure is scarce.

Society-wide implications reveal complex aspects. AI-mediated social systems can systematically manipulate public sentiment through content curation, targeted persuasion, or synthetic media, making institutions susceptible to algorithmic influence. Socially oriented AI can either promote civic renewal or exacerbate political polarization. When AI becomes a cultural gatekeeper, limiting public discourse to automated curation, modelling social norms, values, and discussions become very important aspects to analyze. AI's proliferation in social media, news aggregation, and interpersonal communication emphasizes this significance.

In the case of corporate stakeholders, AI-driven social environments and processes promise efficiency, insights, and innovative service delivery. Customer service deploys conversational agents for routine inquiries and data collection. Decisional factors analyze internal communication for collaboration bottlenecks and team dynamics improvements. Cost savings, faster decision-making, and a cohesive culture entice integration. Nevertheless, ethical dilemmas arise from employee surveillance, data ownership, and job displacement. The modern workplace's change to AI-driven decision-making raises labor questions about error responsibility, inclusive workforce development, and preserving human qualities like trust and empathy in professional contexts.

Policymakers face unique challenges in responding to AI's profound social transformations. Drafting and implementing regulations that balance innovation, and public welfare requires forward-looking legal frameworks for rapid technological changes. Social intelligence in AI diminishes the user and subject separation, raising questions of liability, data governance, and ethical accountability. Explainability is very important in public administration, where citizens must trust resource distribution, service administration, and policy recommendations. Transparency, oversight, and cross-sectoral partnerships maintain democratic accountability when AI reshapes public opinion, participation, and resource allocation. Governments risk widening social disparities, enabling discrimination, or authoritarian surveillance.

Collaborative, interdisciplinary engagement is important for socially aware AI systems with ethical principles, robust design, and cultural sensitivity. Societal transformations will vary based on resources, infrastructure, norms, and regulations, magnifying global inequities. Stakeholders responsible for fairness, explainability, and inclusivity can harness the AI's positive potential while mitigating adverse outcomes. Open dialogue between technologists, ethicists, user communities, corporations, and public institutions is very important, in situations where each sector contributes expertise to shape AI attuned to human values and social well-being.

Despite significant progress in developing AI systems with social intelligence, intrinsic limitations persist due to technical, methodological, and conceptual challenges. Capturing the contextual richness of human social interaction is particularly difficult. Human communication involves various signals, and while AI excels at language parsing, facial expression recognition, and context-awareness, it struggles to adapt to rapidly shifting environments with subtle contextual cues, power dynamics, historical relationships, and cultural norms. The high variability of social scenarios means that impressive capabilities in a well-defined domain can be inadequate in novel or cross-cultural interactions. Models trained in one language or cultural context often fail to generalize, highlighting the challenge of building truly universal social intelligence.

Modern AI's data-driven foundations face limitations. Deep learning systems require large, high-quality training datasets representing real-world interactions. Nevertheless, these datasets often suffer from biases, inconsistencies, or insufficient coverage, leading to harmful stereotypes and misinterpretations of underrepresented groups. Mitigating bias through specialized algorithms or representative datasets is partial and addressing how societal inequities are encoded in data and replicated by AI is challenging. Quantitative measures like accuracy do not capture qualitative dimensions of social intelligence like trust-building, empathy, or moral discernment.

Methodologically, there is a significant need for integrating theoretical models from psychology, sociology, anthropology, and related fields into AI architectures. While some research attempts to import concepts like theory of mind, self-awareness, or moral reasoning into algorithmic frameworks, these are nascent and often fragmented. Reinforcement learning, for instance, trains agents to optimize rewards for cooperative behavior but fails to grasp ethical dimensions or long-term social implications. Multi-agent systems that cooperate or compete in dynamic environments are hindered by modeling emergent social phenomena like complex group behaviors, hierarchical roles, and intricate relationship networks. Achieving a rigorous, interdisciplinary methodology that unites social science insights with computational efficiency remains an open research frontier.

Technical limitations in explainability, interpretability, and real-time adaptation affect black-box models, especially large NNs. These models can produce socially compelling responses but lack transparency in their decision-making processes. This opacity is problematic in high-stakes contexts like healthcare diagnosis or criminal justice risk assessments, undermining user trust. While explainable AI research advances, reconciling interpretability with complex neural architectures still remains challenging. Real-time adaptation requires continuous context updates, potentially leading to re-training or catastrophic forgetting. Achieving adaptability and stability is very important, especially in multi-party interactions where trust, timing, and rapport building are of extreme importance.

The ethical and regulatory frameworks remain fragmented. Existing guidelines, like responsible AI, highlight broad principles but lack granularity to address socially capable AI deployment. Issues of consent, data ownership, and user autonomy are challenging when AI integrates into daily life, capturing sensitive social data. Without cohesive legal frameworks, the risk of misuse can become large. Normative debates on AI integration in domains like childcare, therapy, eldercare, and education remain unresolved. Preserving human agency and ensuring AI advances human dignity rather than infringing on it is both technical and philosophical.

Adversarial behavior and security vulnerabilities pose challenges for AI systems operating in open social contexts. Malicious actors can manipulate outputs, disseminate misinformation, or exploit system weaknesses. Adversarial examples, specially crafted inputs that deceive AI models, demonstrate that advanced models remain susceptible to tampering. Targeting social AI systems with adversarial methods can spread disinformation and undermine public trust. Safeguarding AI from these threats requires specialized countermeasures, but few comprehensive frameworks exist to robustly defend socially oriented AI applications.

These limitations highlight the challenges of achieving genuine ASI. While progress has been made, the envisioned environment where AI seamlessly manages human social life is still far from realized. This aspect emphasizes the need for patient, thorough research that integrates engineering ingenuity with humanistic insight to design AI that aligns with social reality. Only through sustained effort can the field move closer to producing AI systems that truly enrich human life, rather than merely replicating social interaction.

Artificial social intelligence holds immense potential. AI agents' integration into human society through language comprehension, emotional attune, adaptive behavior, and collaborative intelligence suggests a new era of human-machine interactions. These developments promise enhanced efficiency, improved access to services, amplified creativity, and societal benefits in education, healthcare, governance, and personal well-being. Nevertheless, they also raise concerns about privacy erosion, social divisions, manipulation, and displacement of empathy, trust, and mutual understanding.

Technologists, policymakers, ethicists, psychologists, and diverse voices from marginalized communities, industry leaders, government agencies, and academic researchers must collaborate to develop socially responsible AI. This collaboration should establish shared principles, including clear regulations protecting individuals' rights, incentives for ethical AI design, and public engagement campaigns to clarify the AI's societal impact. Participatory processes ensure a genuine alignment with global societies' pluralistic values.

Incorporating interdisciplinary research methodologies from the humanities and social sciences into technological design is another very important aspect. Engineering solutions to social interaction challenges should be tested against psychological theories of emotion, cognition, and interpersonal dynamics. Anthropology can guide AI system development by understanding cultural variation in communication styles and normative behaviors. Sociology and political science can reveal macro-level implications of AI deployment, such as power changes, identity formation, and civic participation. By integrating social science theories, AI developers can move beyond superficial human interaction emulations and create systems that engage with and replicate human social complexity.

Initiatives to adopt transparency, explainability, and accountability must continue and expand. While explainable AI research makes progress, further transparency around data usage, decision-making, and system limitations is very important for building user trust and responsible AI deployment. Governments and international bodies must collaborate to create enforceable standards for comprehensible AI system reporting. Accountability is urgent as AI systems operate semi-autonomously in sensitive domains. Deciding where responsibility lies, with developers, data sources, deployers, or users, is a complex problem. Legal frameworks must evolve to address responsibility distribution when AI becomes a participant in human social ecosystems.

Robust ethical oversight and governance are strategic for sustaining societal trust. Ethical review boards or cross-disciplinary committees can integrate into AI research pipelines to systematically identify and mitigate potential risks. Oversight mechanisms must adapt to AI technology evolution, reflecting real-time updates in capabilities, data collection, and usage. Civic organizations and public play a very important role in scrutinizing AI deployments, supporting user rights, and ensuring equitable AI adoption.

Improving public literacy in AI is very important as social interactions with AI become commonplace. Educational programs can empower citizens to make informed decisions about data sharing, chatbot engagement, and cautious use of AI. Encouraging digital skepticism helps inoculate society against AI manipulation. Improvements in user interface design and consent processes make interactions more transparent, preserving individual agency.

A broader vision of the symbiosis between humans and AI technology emerges, envisioning collaborative, mutually beneficial relationships that enhance human capacities while preserving autonomy, dignity, and sociability. This symbiosis requires ongoing negotiation involving technical breakthroughs, policy changes, and cultural discussions about human social bonds. Ensuring that AI augments human potential rather than subjugating it is fundamental. The AI's role as a social actor should complement human emotional intelligence, ethical reasoning, and creative expression, recognizing the depth of human lived experience while contributing computational insights to solve the society's problems.

Without a doubt, ASI requires a multi-layered approach. Researchers and developers should integrate cross-disciplinary wisdom, refine computational models for cultural and ethical sensitivity, and strive for new forms of transparency and user engagement. Policymakers and regulatory agencies should collaborate internationally to establish frameworks that safeguard public interests and encourage responsible innovation. Corporate stakeholders should view ethical, social, and cultural considerations as strategic requirements, investing in comprehensive risk assessments and community engagement. Civil society groups, educators, and media organizations should raise public awareness about the AI's impact on society. Finally, individual users should remain vigilant, recognizing that every interaction with AI shapes the norms and values of technologically mediated social life. The future trajectory of AI depends on collective efforts to design, deploy, regulate, and use AI ethically and responsibly. By promoting collaboration, ethical rigor, and human sociality, we can steer AI toward outcomes that enhance societal flourishing and promote human identity. The path forward requires vigilance, imagination, and a commitment to shaping technology for humanity's best interests.

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GENERATING JAVA CODE WITH AI TOOLS. USAGE AND IMPLICATIONS

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Abstract

Java programming, a high-level, general-purpose language renowned for its "Write Once, Run Anywhere" (WORA) capability, has (re)gained notable traction as developers increasingly integrate artificial intelligence (AI) generative tools into their workflows. Java's platform independence, robust security features, and extensive libraries have made it a preferred choice for a wide range of applications, from mobile apps to large-scale enterprise systems. The advent of AI generative tools, such as ChatGPT, GitHub Copilot or Amazon CodeWhisperer, has further enhanced Java programming by automating mundane tasks, improving code quality, and fostering creativity in the development process. In today's world, solid knowledge related to AI code generation tools is a must for all developers and software engineers. AI tools for generating Java code have also started an entire new set of debates related to copyright issues. Currently, the relevant legal frameworks, at international level, are not harmonized and in some cases even antagonistic.

Keywords: ai code generation; java ai tools; java; ai code legal issues; ai copyright issues

JEL Classification: C8, O31, O33, O34, O39

1. Introduction

Java programming, a high-level, general-purpose language renowned for its "Write Once, Run Anywhere" (WORA) capability, has gained notable traction as developers increasingly integrate artificial intelligence (AI) generative tools into their workflows. Java's platform independence, its' very robust security features, as well as the extensive libraries have made it an excellent and preferred choice for a very wide range of different applications, starting with mobile apps and going to large-scale enterprise systems. The advent of AI generative tools, such as GitHub Copilot and Amazon CodeWhisperer, has further enhanced Java

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programming by automating mundane tasks, improving (usually) the quality of code, and increasing creativity within the entire software development process [1][2][3][4]. The integration of AI generative tools is reshaping the software development landscape, promoting efficiency and enabling developers to focus on complex problem-solving. These tools assist in various capacities, including code generation, debugging, and project documentation, thereby streamlining workflows and enhancing productivity [5][6][7]. Moreover, studies have shown a positive correlation between the use of these AI tools and perceived productivity among developers, as they consolidate multiple functions into a single application and provide quick access to critical information [5][8]. However, the incorporation of AI into Java programming is not without its challenges. Developers face issues related to the reliability of generated outputs, the need for precise prompting, and concerns regarding data security and governance. Ethical considerations, such as algorithmic bias and intellectual property rights, further complicate the landscape as the technology matures [9][10][11]. As the Java community continues to embrace AI solutions, it is imperative to address these challenges through transparency, ethical guidelines, and best practices to ensure that the advantages of AI can be fully realized without compromising quality or security [12][13][14]. Looking to the future, the collaboration between AI and developers is expected to deepen, with increasing use cases for AI in Java development, particularly in specialized areas such as natural language processing and dynamic pricing systems. As developers adapt to these evolving technologies, ongoing education and a commitment to ethical standards will be crucial in harnessing the full potential of AI while mitigating associated risks [15][16][14].

2. Java Programming Paradigm

Java is a high-level, general-purpose programming language that is both memory-safe and object-oriented, making it a prominent choice among software developers. Designed with the principle of "Write Once, Run Anywhere" (WORA), Java allows compiled code to run on any platform that supports Java without needing recompilation. This is achieved through the use of the Java Virtual Machine (JVM), which interprets Java bytecode across different operating systems and hardware architectures [1][2].

2.1. Features of Java

Object-Oriented Principles

Java is fundamentally an object-oriented programming (OOP) language, supporting core OOP concepts such as classes, objects, inheritance, encapsulation, and polymorphism. Unlike some other programming languages, all code in Java is encapsulated within classes, and every data item is treated as an object, except for the primitive data types which are optimized for performance [3][2]. The syntax of Java is influenced heavily by C and C++, yet it avoids complex features like pointers and multiple inheritance, promoting simplicity and enhancing its usability for beginners [4][17].

Platform Independence

One of Java's most significant advantages is its platform independence. Java programs are first compiled into bytecode, a platform-neutral intermediate representation. This bytecode can run on any system equipped with a JVM, making Java applications remarkably versatile across different environments [3][2][17].

Performance and Scalability

Despite being an interpreted language, Java's performance is impressive, thanks in part to its Just-In-Time (JIT) compiler, which optimizes bytecode execution. Additionally, Java supports multithreading, allowing concurrent execution of code, which improves efficiency and resource management [17][18]. These features, combined with Java's inherent scalability, make it suitable for a wide range of applications from mobile devices to enterprise-level systems [4][17].

Security and Robustness

Java is designed with security in mind, incorporating features that protect against common programming errors, such as memory leaks and buffer overflows. Its strong type-checking at compile time and runtime contributes to its reliability and robustness, ensuring that Java applications are both secure and stable [3][2]. The Java ecosystem includes a rich set of libraries for various tasks, including internationalization, database connectivity, and remote method invocation, further enhancing its utility for developers [1][4].

Development Environment

The Java development environment is extensive, comprising several frameworks and libraries. The Java Standard Edition (Java SE) provides the core functionality, while Java Enterprise Edition (Java EE) extends this with capabilities for building large-scale, distributed applications [1]. Various tools and integrated development environments (IDEs) facilitate coding in Java, allowing developers to leverage the language's features effectively in their projects [30].

3. AI Generative Tools for Java Programming

AI generative tools have become instrumental in enhancing the efficiency and effectiveness of Java programming. These tools leverage artificial intelligence to assist developers in various capacities, streamlining workflows and improving code quality.

The adoption (more or less generalized at this time) of AI in code generation offers several benefits, including faster development cycles, improved productivity, and the ability to automate mundane tasks. Nevertheless, challenges persist, particularly concerning the quality of the generated code and potential security risks. Developers must remain vigilant against issues such as security vulnerabilities that may arise from AI-generated outputs, which can lead to exploitable weaknesses in software systems [45][31]. Moreover, the copyright implications of using AI-generated code are under scrutiny. As AI tools produce outputs based on their training datasets—which may include copyrighted material - the legal status of the code generated raises questions about ownership and intellectual property rights [46][43]. The intersection of AI-generated content and copyright law continues to evolve, necessitating further examination of how these technologies interact with existing legal frameworks. The advent of artificial intelligence (AI) tools for code generation has prompted significant legal discourse surrounding copyright protections. Two primary issues stand out: the risk of copyright infringement and the difficulty in obtaining copyright protection for AI-generated content [35].

At the USA level, the U.S. Copyright Office maintains a firm stance that copyright law protects only works created with human authorship. This principle was emphasized in the 2025 Report on Copyright and Artificial Intelligence, which clarifies that works generated entirely by AI, devoid of meaningful human intervention, do not qualify for copyright protection [40][47]. Consequently, code produced solely by AI cannot be registered for copyright, placing it in a category that may be freely used by anyone unless protected under another legal framework, such as trade secrets [32][47]. However, when human developers engage in structuring, selecting, and refining AI-assisted outputs, they can establish sufficient human authorship to secure copyright for those contributions [40][47]. This distinction is critical for businesses that integrate AI tools into their development processes, as it underscores the importance of human involvement in obtaining copyright protections.

Uses of Generative AI Tools

Generative AI tools are utilized in multiple ways within the realm of software development.

- Generating and Reviewing Artifacts: AI tools facilitate the creation and refinement of project documents, including requirements specifications and design documents, ensuring accuracy and completeness in project deliverables [5].
- Supporting Ideation Processes: AI assists in brainstorming sessions and design thinking by generating novel ideas and concepts, thereby fostering creativity during the development phase [5].
- Resolving Doubts in Code Construction: Developers can leverage AI to troubleshoot and resolve technical issues encountered during programming, enhancing problem-solving capabilities [5].

Key Features of Generative AI Tools

Generative AI tools are equipped with advanced functionalities designed to aid developers in their coding tasks.

- Code Completion and Generation: Tools like GitHub Copilot, ChatGPT and Amazon CodeWhisperer enable developers to write code more efficiently by suggesting code completions and even entire functions based on their coding style and intent [19].
- Language Understanding: These tools utilize sophisticated natural language processing algorithms to interpret the intent behind code, allowing developers to work across various programming languages without hindrance [19].
- Integration with IDEs: Many generative AI tools seamlessly integrate with popular integrated development environments (IDEs) such as Visual Studio Code and IntelliJ, providing developers with immediate access to AI capabilities without disrupting their workflow [19].

Challenges of Generative AI Tools

Despite the advantages, the integration of generative AI tools in software development also presents several challenges. These include issues related to explainability and interpretability of AI decisions, as well as concerns regarding data governance and the quality of training data used in these models [9][20]. Addressing these challenges requires a comprehensive approach that emphasizes transparency and ethical guidelines in the use of generative AI technologies [12].

3.1 Integration of AI Generative Tools with Java

Overview of AI in Java Development

The integration of AI generative tools in Java programming is reshaping the software development landscape, enhancing productivity, and enabling developers to focus on more complex tasks. Generative AI tools such as Co-Pilot and Codex can generate Java code from natural language descriptions, significantly reducing the time developers spend on producing boilerplate code, thus improving overall efficiency and output quality [6][21]. As Java remains a leading platform for AI projects due to its flexibility, comprehensive libraries, and large-scale data processing capabilities, the collaboration between AI and Java is becoming increasingly vital [7][22].

At this moment, we can conclude that AI tools for code generation have significantly transformed the software development landscape, offering a new approach to writing and optimizing code. These intelligent systems leverage advanced technologies such as Artificial Intelligence (AI) and Machine Learning (ML) to assist developers by generating code based on natural language descriptions and existing code contexts.

Enhancements in Developer Productivity

Participants in studies have reported a positive correlation between the use of generative AI tools and their perceived productivity. These tools not only streamline workflows by consolidating multiple functions into a single application but also provide quick access to information that enhances team communication and collaboration [5]. Despite challenges related to reliability and the need for refinement of generated outputs, developers noted that generative AI tools facilitate gains in efficiency and flow, allowing them to produce relevant content such as code, reports, and design models more effectively [5][8].

Challenges in Integration

While generative AI tools present numerous advantages, developers also face challenges such as ensuring the reliability of generated outputs and the need for precise prompting to achieve accurate results. The absence of sources to validate the information provided by these tools further complicates their integration into sensitive projects [5][21]. Moreover, there are security concerns that can restrict the use of generative AI tools when dealing with sensitive data in software development contexts [5].

Future Directions and Best Practices

Looking ahead, the Java community is actively embracing AI-driven solutions, with a high percentage of developers expressing interest in building AI-powered applications using Java [22]. As Java developers prepare for the future, they emphasize the importance of essential elements like Retrieval-Augmented Generation (RAG) and embeddings for advanced knowledge retrieval [23][22]. These approaches will be crucial in developing practical, enterprise-ready features that are reliable and secure, enabling developers to navigate complex decision-making scenarios effectively.

How AI Code Generation Works

At its core, AI code generation involves using sophisticated algorithms that are trained on extensive datasets sourced from publicly available code repositories. Large Language Models (LLMs) employ Deep Learning (DL) techniques to understand programming patterns and best practices, enabling them to suggest or create code snippets that meet user-defined functionalities [42][43]. Developers input plain text prompts that outline their coding requirements, and the AI tools respond with relevant code suggestions or full functions, streamlining the development process and reducing manual effort [44][45].

Current AI code generation tools are capable of producing code in various programming languages based on natural language input. Developers can articulate the desired functionality, and the AI translates these instructions into contextually appropriate code, enhancing productivity and accessibility for programmers of all skill levels [42][44]. As already mentioned, notable tools in this domain include GitHub Copilot, Amazon Code

Whisperer or ChatGPT, which offer features such as code completion, snippets, and even entire functions to assist in the coding workflow [45][31].

In addition to generating code, AI tools also conduct automatic reviews of existing codebases to identify security vulnerabilities, bugs, and common coding errors. This process not only helps maintain code quality but also allows developers to save time by automating repetitive tasks that would otherwise require significant manual intervention [42][43]. However, it is important to note that the code generated by these tools should still undergo rigorous review by human developers to mitigate the risks associated with inaccuracies and security vulnerabilities [44][45].

4. Case Studies and Examples

Pilot Case Study on Generative AI in Software Development

A pilot case study was conducted to investigate the impact of generative AI tools on software development productivity. The study focused on a single company and involved various software development roles, including developers, quality assurance (QA) professionals, and designers. The primary objectives were to explore how different professionals utilize generative AI tools in their tasks and to understand the tools' perceived effects on productivity across diverse project configurations and methodologies [5].

Methodology and Data Collection

The research utilized a case study methodology that involved questionnaires with open-ended questions and observations. The questionnaires aimed to gather insights from participants who volunteered to use generative AI tools, ensuring minimal disruption to their work routines [5]. Observational data from company communication channels, such as Slack, were also collected to identify potential participants and assess discussions surrounding generative AI [5].

Findings on Perceived Productivity

Participants reported a positive effect of generative AI tools on their perceived productivity, particularly in terms of efficiency gains across their software development activities. The tools facilitated time optimization by consolidating multiple individual tools into a single streamlined workflow. Despite facing some challenges, such as concerns over reliability, most software professionals acknowledged improvements in their ability to create relevant and insightful outputs, including code, design models, and documentation [5].

Indirect Impacts on Communication and Collaboration

While not explicitly stated by the participants, the use of generative AI tools appeared to indirectly enhance communication and collaboration within development teams. By providing quick access to information and facilitating knowledge sharing, these tools allowed team members to align their understanding and work towards common goals more effectively [5].

Broader Implications and Applications of Generative AI Tools

Generative AI tools offer a variety of applications that can significantly aid software developers. These applications include refactoring and code improvement, documentation generation, learning assistance, prototype development, and data transformation and analysis [24]. For example, developers can use AI to automate data cleansing tasks or rapidly develop proof-of-concept applications, thereby reducing the upfront investment of time and resources [24]. Bogdan Mykhaylovych, Technical Director at Softjourn, emphasized the importance of integrating tailored AI models into specific business domains to further enhance productivity for developers and product owners [24]. This integration highlights the adaptability of generative AI tools across various aspects of the software development lifecycle, reinforcing their potential to redefine traditional programming methodologies.

Ethical Considerations

The integration of AI generative tools into Java programming raises several ethical concerns, particularly regarding ownership and originality in AI-generated code. Issues related to intellectual property rights and copyright are increasingly becoming significant in discussions about the ethical use of such technologies [11].

Algorithmic Bias

One of the most pressing ethical considerations in machine learning and AI is algorithmic bias, which refers to systematic errors that lead to discrimination against certain groups based on the outputs of a program [10][25]. This bias can arise when training datasets are unrepresentative, leading the AI to produce results that favor specific demographics over others [26]. For instance, algorithms may exhibit racial bias in healthcare risk assessments or show discrimination in hiring practices, as evidenced by cases involving biased recruitment tools [27].

Mitigating Bias

To address algorithmic bias, developers and operators of AI algorithms are urged to implement best practices at various stages of the AI system's lifecycle [28]. This includes examining the training data for representation and ensuring that the model does not perpetuate existing inequalities. Additionally, efforts such as using AI Fairness 360, Fairlearn, and other fairness tools can help identify and reduce bias in AI systems [27].

The Role of Policymakers

Policymakers also play a critical role in addressing these issues. The establishment of regulatory sandboxes could provide a framework for testing AI technologies while developing appropriate regulations to curb biases [13]. Such environments allow for innovation in technology alongside regulatory evolution, helping ensure that ethical standards are upheld without stifling technological advancement.

Broader Ethical Implications

Beyond technical concerns, the ethical implications of AI-generated tools extend to their societal impacts. Developers must consider how their models may influence individuals and communities, particularly in high-stakes areas like job applicant suitability assessments [11]. Discussions surrounding the ethical framework of machine learning emphasize the need for guardrails to prevent the amplification of systemic discrimination and other negative consequences [13].

5. Copyright Issues for Java Code Generated with AI Tools

The copyright implications of Java code generated by artificial intelligence (AI) tools have sparked significant legal debate as the integration of these technologies into software development raises questions about authorship and intellectual property rights. Historically, U.S. copyright law mandates that only works created by human beings are eligible for protection, a principle reaffirmed by the U.S. Copyright Office and recent court rulings such as Thaler v. Perlmutter, which ruled that AI-generated works without meaningful human involvement cannot be copyrighted [31][32][33].

As a result, developers and companies face considerable risks when utilizing AI-generated code, as such outputs may not only be unprotected by copyright but could also infringe on existing copyrighted works. The uniqueness of the situation is compounded by the nature of AI code generation tools, which rely on vast datasets that may include copyrighted material. This raises the potential for legal conflicts when companies modify or deploy AI-generated code, as they could inadvertently violate the rights of original copyright holders [34][32].

Legal experts emphasize that businesses must navigate these complexities carefully, documenting their creative processes and consulting with legal professionals to mitigate infringement risks and ensure compliance with copyright law [35][36]. Moreover, the evolving legal landscape surrounding AI-generated content necessitates ongoing discourse on the definition of authorship and the applicability of copyright in the digital age. Current legislative efforts and high-profile lawsuits are beginning to address these challenges, but many uncertainties remain. The juxtaposition of rapid technological advancement with existing copyright frameworks highlights the need for reform to address the implications of generative AI on intellectual property rights, particularly in the realm of software development [37][38][39].

The use of AI in generating code also introduces substantial copyright infringement risks. As copyright automatically applies to original source code, modifying existing works with AI could infringe on the exclusive rights held by the original copyright owner [34]. Businesses must seek permission from copyright holders when using AI to modify protected works, much like any traditional method of content alteration. Additionally, the landscape of copyright law necessitates that organizations document their independent creation processes and consult legal professionals about copyright risks before reusing code. This proactive approach is essential given the complex nature of fair use determinations and the legal ramifications of infringement claims [36]. The current legal framework, in all countries, requires businesses to critically assess their reliance on AI in creative fields and to navigate the copyright landscape with very much care. While the US Copyright Office and other similar bodies worldwide have yet to provide definitive guidance on the future of copyright in relation to AI-generated works, it has been made clear that human authorship remains a cornerstone of copyright protection [32].

The legal landscape regarding the copyright of AI-generated works, particularly Java code, is evolving as courts address the implications of artificial intelligence on existing copyright law. As of now, the legality of using copyrighted content to train AI models remains unsettled, with outcomes heavily reliant on jurisdiction and specific case circumstances [37][48]. This uncertainty has led to a growing demand for legislative or regulatory solutions to clarify when training on copyrighted content is permissible [37]. This places an added responsibility on developers and companies to ensure that their use of AI tools complies with copyright law to mitigate potential legal and financial repercussions. The U.S. Copyright Office has released reports addressing the copyrightability of outputs created using generative AI, affirming that existing copyright principles can accommodate these new technologies. The Office maintains that AI outputs may be copyrightable when a human author contributes significant creative elements, such as perceptible modifications or creative arrangements, rather than merely providing prompts [41][50]. This stance sets a high bar for the recognition of AI-generated works under copyright law, leaving many boundaries regarding protectable and unprotectable works still undefined [50]. Courts have also pointed out that AI-generated outputs could infringe copyright if they closely resemble existing works, raising significant legal questions regarding originality and authorship [49][50].

As AI tools continue to transform coding practices, their legal and ethical ramifications warrant thorough examination. The lack of a clear path to copyright protection for AI-generated Java code emphasizes the importance of human involvement in the creative process to secure intellectual property rights. The outcome of ongoing legal battles and potential legislative changes will be pivotal in shaping the future of copyright in relation to AI technologies, ultimately influencing how developers and businesses engage with these innovative tools [40][37][41].

5.1 The Impact of Generative AI on Copyright

The advent of generative artificial intelligence (AI) technologies has raised new challenges for traditional notions of authorship in copyright law. Current interpretations of copyright require that an original work of authorship must be created by a human being, a stance upheld by the U.S. Copyright Office [32]. Recent court rulings in the USA, such as Thaler v. Perlmutter, have reinforced this position, stating that works generated by AI without human intervention do not qualify for copyright protection [33]. This limitation has significant implications for the use of AI in creative domains, particularly when businesses aim to utilize AI-generated content, as they may not enjoy the typical intellectual property protections if such content is challenged by rivals [33].

5.2 Current Legislative Landscape and Ongoing Legal Battles

The legislative landscape concerning copyright and AI-generated Java code is rapidly evolving as governments worldwide grapple with the implications of generative AI technologies. In March 2024, the European Parliament approved the EU AI Act, which mandates that providers of general-purpose AI models comply with existing copyright laws, particularly regarding the reservation of rights for training data [39]. This act signifies a proactive approach by the EU in addressing copyright concerns related to AI, emphasizing the need for transparency and compliance with copyright norms. In the USA, various states have introduced their own legislation targeting generative AI, with notable bills emerging in Colorado and California in 2024. These state-level initiatives reflect a recognition of the need to establish a regulatory framework that balances innovation with the protection of intellectual property rights [39]. However, the U.S. federal stance remains somewhat ambiguous, with courts and legislators still deliberating on the copyrightability of AI-generated content [53].

The approaches to copyright for AI-generated works differ significantly among jurisdictions. In the U.S., the Copyright Office maintains a stringent requirement for human authorship, stating that copyright entitlement can only be established if the work originates from a human agent [33]. This is particularly relevant to Java code generated by AI tools, as the lack of a human author would preclude such code from receiving copyright protection under current U.S. law [34]. Conversely, the EU has initiated frameworks that could potentially allow for broader interpretations of AI-generated works. The recent introduction of exceptions for text and data mining (TDM) indicates a willingness to adapt existing laws to facilitate AI development while safeguarding creator rights [37]. This distinction highlights a significant divergence from U.S. legislation, where the fair use doctrine provides a more flexible, albeit less clear-cut, framework for utilizing copyrighted material for AI training.

Experts advocate for international harmonization of copyright laws concerning AI, proposing common principles that could facilitate a global approach to managing AI-generated content [37]. Such harmonization could involve agreements that permit the use of works for AI training under specific conditions, thereby balancing the interests of creators with the need to foster innovation in AI technologies. One suggestion includes establishing a global data licensing framework that allows AI firms to contribute to a fund distributing payments to content creators in exchange for licenses to train on published content [37]. The ongoing discussions around AI and copyright reflect a critical juncture for policymakers. Achieving a consensus that aligns with technological advancements while protecting the rights of creators will likely require extensive international dialogue, possibly facilitated through organizations like the World Intellectual Property Organization (WIPO) or within trade agreements. The outcome of these discussions will be pivotal in shaping the future of copyright as it relates to AI-generated Java code and other creative works.

As AI continues to advance, high-profile lawsuits have emerged against companies like OpenAI and Stability AI, with plaintiffs alleging unauthorized use of copyrighted material to train AI models. The ongoing case of *New York Times Co. v. Microsoft* serves as a critical example of how courts are grappling with these issues, setting a precedent for the intersection of copyright law and AI technology. These cases could have far-reaching implications for the future of copyright and AI-generated content, as the outcomes may influence both the interpretation of fair use and the rights of creators in the digital age [38][51][52].

5.3 Implications for Java Code Generated with AI

When considering Java code generated by AI tools, the existing legal framework suggests that if the code lacks direct human authorship, it may not be eligible for copyright protection. This situation necessitates that developers and businesses exercise caution, as using or modifying AI-generated code could potentially infringe upon the copyright rights of existing works, unless proper permissions are obtained from the original copyright holders [34]. As the legal landscape continues to evolve alongside advancements in AI technologies, ongoing discourse regarding the definitions of authorship and the applicability of copyright law will be crucial in shaping the future of intellectual property rights in the realm of software development and beyond.

Looking ahead, it is anticipated that a more settled equilibrium will emerge between AI developers, content creators, and consumers. This will likely involve clearer guidelines on permissible data usage for AI training, ensuring that creators can benefit from AI utilization without facing undue harm. Additionally, it is crucial to foster an environment where diverse creative content continues to thrive, balancing innovation with the protection of human authorship [37]. Ultimately, while challenges exist, the potential for AI to enhance programming and creativity remains substantial, provided that stakeholders actively engage with the legal and ethical implications [19].

6. Conclusions and Future Trends

The landscape of Java programming with AI generative tools is poised for significant evolution in the coming years. As the integration of AI technologies into software development becomes more prevalent, we can expect several transformative trends to emerge.

Enhanced Collaboration Between AI and Developers

Rather than viewing AI as a competitor, the future of programming will increasingly focus on collaboration. Developers will leverage AI tools to automate mundane tasks such as code generation, debugging, and testing, allowing them to concentrate on more complex problem-solving aspects of software development [15][29]. This symbiotic relationship is anticipated to boost productivity, with AI tools offering developers real-time information and support during coding [8].

Expanding Use Cases for AI in Java Development

AI's capabilities will likely extend into more specialized areas of Java development. Use cases such as natural language processing (NLP) and dynamic pricing systems will benefit from advanced AI models embedded in Java applications, enhancing their functionality and efficiency [22]. The integration of AI frameworks into existing systems will also enable developers to implement machine learning models more effectively, addressing complex challenges like customer churn prediction and recommendation systems.

Addressing Ethical and Security Challenges

As AI becomes integral to coding practices, addressing ethical and security concerns will be paramount. Developers will need to navigate potential pitfalls related to security vulnerabilities, intellectual property issues, and code quality management [14]. Robust risk management strategies will be essential as organizations seek to balance the advantages of AI tools with the associated risks.

Continuous Learning and Adaptation

The rapid pace of AI development necessitates continuous learning and adaptability among programmers. Professionals will need to stay updated on evolving AI technologies and methodologies to maximize their effectiveness in collaboration with AI tools [16][29]. Educational institutions and training programs are likely to adapt their curricula to incorporate AI literacy, equipping future developers with the necessary skills to thrive in this changing environment.

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FINANCIAL ACCOUNTING INFORMATION IN THE CONTEXT OF SCORE-BASED SUSTAINABILITY REPORTING ESG (ENVIRONMENTAL, SOCIAL, GOVERNANCE)

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Abstract

Reliability, accuracy, relevance, and compliance with current accounting regulations are all necessary for reporting financial and accounting data responsibly from a sustainability standpoint.

Sustainability refers to an organization's ability to meet long-term goals, which include economic, social, and environmental aspects (ESG). *Sustainable accounting* is becoming increasingly significant in today's world, as businesses are becoming more aware of their environmental and societal impact and are more actively participating in sustainable development initiatives. Reflecting accurate and relevant financial and accounting information entails having a clear understanding of an organization's financial condition, performance, and social and environmental impacts. Enterprises that have invested more in social and environmental initiatives and have considered corporate governance have reported increased profits. ESG activities benefit businesses at every stage of the value chain, from cost reduction to maintaining a competitive advantage.

Keywords: sustainability, sustainability reporting, corporate social responsibility (CSR), ESG scores

JEL Classification: M41

1. Introduction

Sustainable development is a big scientific field with untapped potential. Many academic disciplines can contribute to the study of this topic, and accounting processes and actors in the accounting business connect with many of these disciplines. Reality shows the importance of analysing the function and impact of accounting methods within the

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framework of sustainable development, using an interdisciplinary approach. This approach may help us better understand how accounting might help promote sustainable development and address environmental, public health, and poverty challenges. The application of the idea of sustainable development necessitates adjustments in accounting practice to fulfil the needs of users of financial and accounting data [1]. Although sustainable development is becoming more prevalent in accounting and management literature, it is critical to define this idea in the many contexts in which it is used [2]. According to research, the specialized literature lacks empirical evidence supporting the existence of a direct causal link between accounting and economic progress [3]. The International Federation of Accountants (IFAC) emphasizes accounting and the accounting profession's critical role in achieving at least 8 of the 17 United Nations goals, such as improving educational quality, promoting gender equality, improving working conditions, stimulating economic growth, supporting innovation and infrastructure development, and promoting responsible resource consumption.

2. Literature review

CSR (corporate social responsibility) reporting has been successively referred to as 'sustainability reporting', 'CSR reporting' (notably by the Global Reporting Initiative), 'extra-financial reporting' (the current official name), 'non-financial reporting' (the 2017 European name), 'extra-financial or non-financial disclosure', 'social or societal reporting', etc. Behind this diversity nowadays is all the information that companies publish on the social, societal and environmental aspects of their activities and their performance [4]. But there may be other components in the future, as the gap will be widening between financial information and non-financial. There is nothing to prevent, for example, the New Economic Regulations (NER) information mentioned above. It should be noted that the 'governance' aspect is sometimes included in extra-financial reporting and sometimes not because it has been considered that it can be linked to accounting and financial information.

The regulatory process for sustainability reporting has evolved significantly in recent years. According to the Financial Times, there are more than 230 initiatives on corporate sustainability standards in more than 80 business sectors. According to a study [4] by Albu N, the most widely used sustainability reporting frameworks are the Global Reporting Initiatives (GRI) and the United Nations Global Compact (UNGC). GRI is mainly preferred by multinational companies, while UNGC is preferred by small and medium-sized enterprises due to its simpler nature. According to International Financial Reporting Standards (IFRS), information is considered relevant when it can be used to make predictions or estimates about an entity's future financial position and performance. In this context, predictability is essential and relevant financial and accounting information can be used to support decision making. Directive (EU) 2022/2464 is based on the premise that information is performative, with the ability to create reality and influence behavior. This distinguishes between constative and performative statements, requiring large, small and medium-sized enterprises to include in their management reports information on their sustainability impact and how it affects their development, performance and position. By adopting this policy, companies make a commitment and promise, creating an obligation. However, performance cannot be realized without a collective commitment between the authors and receivers of the statements. Through its meaning, value, content and status, Directive (EU) 2022/2464 encourages sustainability information to become more performative, generating significant changes in the representation of actors and individuals.

3. Research methodology

The research methodology was based on a careful analysis of the function and influence of accounting procedures in sustainable development, using an interdisciplinary approach. This investigation sought to gain a better understanding of how accounting can help to promote sustainable development and address difficulties linked to conveying business performance in the social, environmental, and governance domains.

To obtain solid and complete conclusions, a hybrid strategy was used, integrating quantitative and qualitative studies. To acquire a thorough knowledge of the complex relationship between sustainability reporting and financial success in a set of companies in the Reuters Eikon database, statistical data were supplemented with detailed field observations. This combined research strategy enabled the identification of significant elements impacting financial performance while also providing a comprehensive view of the impact of non-financial information on the activities of the organizations under consideration.

By evaluating the environmental impact and sustainability of enterprises (the application of ESG standards) in the context of resource optimization, performance enhancement, and decision-making, the focus was on quantifying sustainable value and sustainable added value.

We list the following methods and techniques as part of the study's development: 1. Documentary analysis and systematic review of specialized literature, as evidenced by bibliographic and bibliographic references: theoretical documentation (books, national and international articles, studies), as well as documentation pertaining to the applied part, processing, and interpretation of information gleaned from the documentation; Classification, synthesis, factor analysis, variation and correlation analysis, trend analysis, average rate of variation, analysis of central tendency, average representativeness, and graphic representation of the events and phenomena under investigation are examples of mathematical and statistical techniques; 3. Interdisciplinary research approach: the study draws on expertise from computer science, statistics, and finance and accounting. The inquiry entails collecting, systematizing, analyzing, and interpreting data, studying specific financial reports and publications, and formulating conclusions and suggestions.

4. Sustainability reporting - premises of enterprise performance

Sustainability reporting communicates a company's performance in the social, environmental, and governance domains. This technique has been increasingly crucial for businesses in recent years, as worries about their environmental and social impact have grown. Sustainability reporting is regarded as a must-have for businesses seeking to demonstrate their commitment to social responsibility while also attracting investors, partners, and customers interested in sustainability (Table 1).

Table 1. Sustainability reporting requirements in relation to entity performance

Requirements	Description
Transparency and responsibility	Sustainability reporting promotes transparency in business activities. Publishing information about environmental impact and social contribution helps build trust among stakeholders, including customers, investors and employees.
Risk management	By assessing and reporting sustainable performance, organizations can identify environmental and social risks that could affect their business operations. This enables them to develop strategies to manage these risks and minimize potential damage.
Innovation and competitiveness	Adopting sustainability practices can stimulate business innovation. For example, the development of environmentally friendly products and efficient production processes can provide a competitive advantage in the marketplace.
Access to financing	By reporting performance in this field, businesses can more easily attract investment and benefit from more advantageous financing conditions.
Employee involvement	Organizations that have well-defined and effectively communicated sustainability practices can attract and retain talented employees. An organizational culture based on sustainable values can raise team motivation and engagement.
Regulations and compliance	Many countries are adopting stringent environmental and social reporting regulations. Companies that comply not only avoid penalties but also improve their business reputation.
Contribution to global objectives	Sustainability reporting can help businesses contribute to global goals such as those of the United Nations 2030 Agenda for Sustainable Development. It enables them to position their activities in the context of global issues.

Source: authors conception and processing

4.1. The influence of corporate social responsibility on the community and the environment

The concept of corporate social responsibility (CSR) is a very modern conception, being almost in the "embryonic stage”.[6] The definitions offered by different authors differ significantly: some focus solely on the social dimension, while others highlight the philanthropic and ethical aspects of commercial activity (particularly among American authors). Some European authors emphasize the interconnectedness of the three pillars of sustainable development: economics, society, and the environment.[7] Modern businesses are encouraged to contribute to the common good by the growth of consumer and environmental movements as well as rising interest group pressure. As a result, corporate social responsibility (CSR) has emerged as a strategic problem for managers and a research area for marketing and management science scholars in recent years. Peloza and Shang claim that because of its influence on employee and customer behaviour, corporate social responsibility, or CSR, is a subject of increasing managerial and scholarly attention.[8] It also includes an opportunity to consider the company's relationship with society in a broader context, as well as an environmental component. It can be defined as the managerial process by which the company's strategic orientations toward sustainable development are expressed. Under institutional and social pressure, most multinational corporations have now launched a variety of social responsibility initiatives, originally with the goal of addressing an image problem and enhancing commercial performance. For some businesses, taking social responsibility into account becomes a means of distinguishing themselves from the competition; as a result, their innovation is focused on the development of new goods and approaches that are more environmentally friendly. Investing in corporate social responsibility becomes vital for businesses since it becomes a competitive aspect that affects performance. The interaction with the new information and reporting requirements in the field of corporate social responsibility (CSR) defines the need for significant improvement/revision, or possibly a complete overhaul of the current accounting model. This entails developing an accounting model tailored to the concept of "green capitalism". Several recommendations have been made in this area, and extra-financial reporting is becoming more regulated by legislative frameworks. According to Postel et al., CSR appears to be an attempt to balance economic efficiency with ethical considerations. The European Commission defines corporate social responsibility as the voluntary incorporation of social and environmental issues into a company's commercial activities and interactions with stakeholders. It is critical to consider the voluntary nature of this behaviour. A lot of businesses aggressively highlight the ethical components of their business practices. It is important to remember that many businesses are frequently under pressure from stakeholders to adhere to these standards, even though responsible commitments can be made voluntarily. The three essential elements of extra-financial analysis are ESG criteria, which relate to the environment (such as conservation of biodiversity), society (such as working conditions), and governance (such as business ethics). These criteria enable the evaluation of how businesses incorporate the concepts of sustainable development. For instance, AccountAbility bureau and its founder, J. Elkington, spearheaded the adoption of the Triple Bottom Line strategy by numerous multinational firms in the late 1990s. In order to supplement the evaluation of economic success with an estimate of social consequences and an evaluation of how well the company's operations correspond with the preservation of the planet's ecosystems, this expression refers to the net result from the traditional profit and loss statement. As a result, a metric that takes into account the enterprise's social and environmental effects in addition to its financial performance is suggested. The "triple P"—which stands for "Profit, People, Planet"—is another name for the approach. [9] In 1996, a consortium of multinational corporations launched the Global Reporting organization (GRI), the oldest commercial organization devoted to harmonizing social and environmental reporting, which utilized the tertiary method. The social and environmental externalities—both positive and negative—caused by economic activity are addressed by the GRI reference frameworks, which are increasingly acknowledged as essential guidelines for non-financial reporting. The purpose of the suggested non-financial indicators is to help with a better understanding and management of enterprises. This does not mean arguing against the conventional accounting model; rather, it means putting up an alternative framework that incorporates non-financial data. The World Council for Sustainable Development's (WBCSD) affiliated organizations seek to emphasize the private sector's pivotal role in promoting sustainable development, a notion that has its origins in the political and macroeconomic domains.

The primary objective of these companies' experiments with different valuation methods is to establish a price for natural capital so that externalities may be minimized, and it can be managed. Therefore, expressing the value of natural capital is crucial to current discussions on the evolution of social-environmental accounting models.

4.2. Integration of non-financial reporting in Europe and Romania

As early as 2001, when Article 116 of the law on New Economic Regulations (NRE) was implemented in France, and in 2014, when Directive 2014/95/EU on non-financial reporting (also known as the Non-Financial Reporting Directive, or NFRD) was implemented in Europe, a legal framework started to take shape, and the dissemination of social and environmental information became mandatory. This directive was implemented into French law by the decree of August 9, 2017, which requires major firms, both listed and unlisted, to prepare an Annual Non-Financial Performance Statement (DPEF) and include it in their annual management report. The information they must provide in this statement relates to the measures they have taken to adapt to the consequences of climate change, the voluntary objectives they have set themselves in the medium and long term to reduce greenhouse gas emissions and the means they have implemented to this end, as well as their actions aimed at combating discrimination and promoting diversity; listed companies must also provide information on the protection of human rights and the fight against corruption and tax evasion. However, this DPEF requirement is relatively vague and lacks a formal framework; in essence, it does not link financial and non-financial elements.

Non-financial reporting has grown in popularity among Romanian businesses as European legislation evolves and investors and consumers seek greater openness. This type of reporting involves the disclosure of information about a company's environmental, social, and governance (ESG) performance, which supplements standard financial statistics and provides a more comprehensive picture of sustainability and accountability. The implementation of non-financial reporting has been considerably influenced by the European Directive 2014/95/EU, which requires certain types of large enterprises to publish non-financial information.

According to current legislation (OMFP no. 85/2024, issued in the Official Gazette no. 75 on January 26, 2024), enterprises with more than 250 workers, a net turnover of more than 50 million euros, or total assets of more than 43 million euros must submit these reports. Some of the important features of non-financial reporting in Romania are:

➔ *Transparency and responsibility*: Non-financial reporting contributes to increasing transparency within companies, providing stakeholders with relevant information about their impact on the environment and society.

➔ *Research and innovation*: By reporting on needs and actions taken in ESG areas, businesses can identify areas that require improvement, thus being encouraged to invest in research and innovation to develop more sustainable practices.

➔ *Attracting investment*: More and more investors are looking for investment opportunities in companies that demonstrate their commitment to sustainability. Non-financial reporting provides an assessment of the risks and opportunities associated with a company's business practices.

Although the importance of non-financial reporting is clear, Romanian companies face various challenges in implementing this process. These include:

➔*Lack of Unified Standards*: Variability in reporting standards and frameworks can create confusion and difficulties in assessing information. Businesses must decide which standards to adopt, and the absence of a clear national framework can lead to inconsistencies.

➔*Administrative capacity*: Many small and medium-sized enterprises lack the resources to collect, analyse and publish non-financial information in a coherent and efficient manner.

➔*Organizational culture*: The implementation of non-financial reporting necessitates a shift of thinking inside companies, which can be a challenge, particularly in traditional businesses or those that have not previously been exposed to transparency standards.

➔*Public perception*: There is little consumer awareness or interest in non-financial data. This might make it challenging to persuade businesses to engage in non-financial reporting because the benefits are not always evident or understood.

➔*Limited resources*: Many businesses may not have the financial or human resources to create a successful non-financial reporting system. They may believe that the costs connected with creating these reports outweigh the purported benefits.

➔*Lack of expertise*: Companies may lack knowledge and skills in the area of non-financial reporting. Training employees and developing proper internal processes for gathering and analysing non-financial data can be difficult.

➔*transparency*: Some companies are concerned that having a clear position on non-financial reporting may put them at a competitive disadvantage. This can lead to reluctance to implement such a method, which is viewed as risky.

4.3. The role of non-financial information in presenting the performance of the enterprise

The 2008 financial crisis exposed the risks associated with an overemphasis on short-term financial performance, emphasizing the necessity for a different perspective on entity performance. This should encompass financial stability, long-term success, and sustainability. Numerous worldwide and national initiatives emphasize the relevance of large firms' involvement in society, in addition to the traditional goal of generating shareholder income. [10] One pertinent example is the United Nations Global Compact, which was established in 2000 and supports 10 globally agreed principles in the areas of human rights, labour, the environment, and anti-corruption. Another notable endeavour is the ISO 26000 standard, which was adopted in 2010. It provides recommendations on how corporations can be socially responsible. Furthermore, national initiatives, such as the German Sustainability Code, established in 2011, coexist with international standards, demonstrating a global trend toward corporate social responsibility. These projects demonstrate the necessity for management to give information about the enterprise's social, environmental, and intangible activities and performance.

In addition, they clearly address the information needs of stakeholders other than shareholders. While financial information is subject to well-established accounting standards such as Generally Accepted Accounting Principles and other securities-specific laws, non-financial information (NFI) is less governed by a consistent regulatory framework. However, in recent decades, a number of projects have emerged that offer guidance on how to effectively communicate NFI in financial markets. One such response comes from the Global Reporting Initiative, a non-profit organization in the United States founded in 1997 to provide guidelines for sustainability reporting, which is defined as a report published by a company or organization on the economic, environmental, and social impacts of its activities. Another example is the International Integrated Reporting Council (IIRC), which was established in 2010 with the goal of encouraging companies to transform their reporting by incorporating various information on value generation. In 2013, the IIRC published the Integrated Reporting Framework, which makes it easier to create integrated reports by providing a concise presentation of how an entity's strategy, governance, performance, and prospects contribute to value creation in the short, medium, and long term, within the context of its operating environment.

In 2013, the European Commission responded to the need for non-financial reporting (NFR) by amending accounting legislation to require large corporations to boost transparency about their social and environmental performance. As investors and other stakeholders grow more conscious of the social and environmental consequences of economic operations, non-financial data becomes increasingly important in providing a complete picture of a company's success.

In this light, a substantial shift has occurred in the way investors evaluate companies. Instead of concentrating just on short-term financial metrics, they are shifting their focus to larger factors that can affect long-term performance. As a result, investment evaluation and selection are becoming more sophisticated processes that incorporate environmental, social, and governance (ESG) variables into traditional analysis, contributing to a more holistic view of firm performance. As a result, the concept of firm performance is broadening beyond traditional financial indicators, incorporating non-financial characteristics that reflect a more comprehensive and responsible vision of long-term success.

This development emphasizes the importance of investors and corporate managers rethinking their performance perspectives and adopting a comprehensive approach that balances financial interest, social responsibility, and sustainability.

4.4. Representation of financial and accounting data in environmental accounting

Environmental accounting is a technique that allows organizations to quantify the outcomes of their efforts to transform the economic system in accordance with the principles of sustainable development [11]. *Environment accounting also known as green accounting* [12], is an extension of the System of National Accounts that includes the usage and depletion of natural resources. This type of accounting is critical for controlling the environmental and operational costs of natural resources. Natural resource valuation is important in analysing social costs and benefits, as well as in certain parts of environmental accounting. Environmental accounting has several categories, each concentrating on a different aspect of an entity's contact with the environment. There are several major types:

- Accounting of physical or natural resources

This type entails accounting for the quantity and quality of natural resources used by a company. Physical resource accounting aids to sustainable development planning by including environmental issues into economic studies, thereby balancing economic growth and environmental conservation. It aids in tracking the depletion or enhancement of natural resources, providing data on their availability and sustainability.

- Environmental costs accounting

Accounting is the process of identifying, measuring, and analyzing the expenses connected with a company's environmental actions. It comprises both internal and external costs associated with environmental issues such as pollution, resource depletion, and waste management. It enables firms to assess the financial implications of their environmental activities, such as the costs of pollution control, waste management, and compliance.

- Analysing eco-efficiency

It evaluates the efficacy of resource utilization in manufacturing processes and identifies possibilities to improve environmental performance. This methodology seeks to create sustainable development by optimizing resource utilization, reducing environmental impact, and enhancing economic value. It assists organizations in optimizing their operations to reduce resource consumption, waste generation, and environmental impact.

- Greenhouse gas accounting

It is the sort of accounting that involves monitoring and reporting greenhouse gas (GHG) emissions from a company's operations. GHG accounting is critical for an organization's sustainability, regulatory compliance, and worldwide efforts to prevent climate change. It tackles climate change concerns by enabling organizations to measure and manage their carbon footprint.

- Environmental performance indicators

They are quantitative measures for evaluating and communicating a company's environmental performance. These indicators give vital information about environmental impacts and sustainability practices, allowing stakeholders to evaluate progress, set goals, and make educated decisions. They include energy usage, water use, trash generation, and emissions, which provide an overview of environmental effect.

- Reporting stable development

The disclosure of an organization's social, environmental, and economic performance is known as sustainability reporting. In order to better understand how the organization incorporates sustainability into its operations and decision-making, pertinent information, statistics, and initiatives must be disclosed as part of this reporting process. It offers a comprehensive perspective on how a business operates, accounting for the triple bottom line—economic, environmental, and social factors.

- Full cost accounting

It considers both direct and indirect expenses connected with an entity's operations, including environmental and social costs. Full Cost Accounting aims to provide a thorough awareness of the true economic and environmental costs associated with decision-making. It seeks to provide a more thorough knowledge of production costs, including externalities that may affect the environment.

- Biodiversity accounting

It entails evaluating how an entity's operations affect ecosystems and biodiversity. This accounting approach measures and evaluates the diversity of species, their relationships, and their ecological responsibilities in a way that goes beyond conventional financial reporting. It aids organizations in comprehending and controlling their roles in biodiversity conservation or loss.

- Corporate environmental reporting

It entails sharing environmental performance statistics and related information with stakeholders. It necessitates open communication of a company's environmental actions, practices, and accomplishments to all stakeholders, including investors, customers, employees, regulators, and the general public. It promotes transparency and accountability, allowing stakeholders to make informed judgments about a company's environmental practices.

Romania, as a member of the European Union, has begun to place a greater emphasis on sustainability reporting, considering the considerable impact of economic operations on the environment and society. In light of climate change and more stringent international regulations, Romanian businesses and organizations are encouraged to develop open sustainability strategies. As a result, a number of regulations aimed at sustainability reporting have been implemented at the national and European levels, including the European Union Non-Financial Reporting Directive (NFRD), which requires certain entities to disclose information about their environmental, human rights, and corruption impacts. This law was updated in 2021 and renamed the Corporate Sustainability Reporting law (CSRD), which expanded reporting requirements even further. Many Romanian companies are already structuring their sustainability reports using international standards such as GRI (Global Reporting Initiative) or SASB (Sustainability Accounting Standards Board). These guidelines provide a systematic framework for organizations to convey their economic, social, and environmental impacts. However, sustainability reporting in Romania faces a number of obstacles. Some small and medium-sized businesses lack the resources and skills required to create an efficient reporting system, and they have a limited understanding of the idea of sustainability.

4.5. ESG effects on performance in terms of added value

The notion of ESG (Environmental, Social, Governance) is becoming increasingly important in evaluating the performance of companies. Its emergence is attributed to a growing awareness of the impact of economic operations on the environment, society, and corporate governance. Implementing ESG standards improves organizations' financial and non-financial performance, demonstrating the impact of sustainable values on economic outcomes. *Sustainable value* is a notion that considers economic, social, and environmental outcomes when evaluating a company's long-term success.

It is described as an entity's potential to earn money while also positively contributing to society and the environment. ESG standards are used to assess performance in these three areas and serve as an analytical framework for investors and management. *Sustainable value* added is defined as the additional value gained while keeping the total level of environmental and social consequences constant [13]. According to studies, there is a good association between ESG (Environmental, Social, and Governance) practices and financial performance of entities. Friede's research, which evaluated over 2000 empirical studies, found that 63% of them indicated a positive relationship between ESG and financial performance. Financial information created by businesses that apply effective ESG initiatives, such as enhancing energy efficiency or cooperating with local communities, can help cut operational costs and boost consumer loyalty, according to the McKinsey analysis [14]. Companies with strong ESG scores experienced 3%-5% better sales growth than those with poor scores. Entities that incorporate environmental, social, and governance (ESG) concepts into their business strategy can dramatically minimize operational and reputational risk. Effective governance management may prevent concerns like information leakage, corruption, and fraud, while implementing sound environmental policies can lower the chance of future penalties or litigation. According to a Harvard Business School report published in 2021 [15], organizations that demonstrate appropriate

ESG risk management are better prepared to deal with economic catastrophes, such as the COVID-19 outbreak.

5. Discussion and findings of a study on the use of financial and accounting information in generating ESG scores

An effective and quick evaluation of the non-financial performance of businesses has been made possible by access to a variety of databases, including ASSET4, EIKON, Sustainalytics, MSCI ESG (KLD), and Bloomberg. These databases also provide the ability to compare organizations, sectors, or nations. As a result, it is anticipated that the need for ESG data will only increase, and these databases will aid investors in making investment decisions. The number of entities whose data will be available from these ESG databases will surely increase as a result of the European Union's legislative amendments pertaining to the disclosure of non-financial information. The Thomson Reuters EIKON database gives access to trustworthy, current, and accurate data from over 400 capital markets and over-the-counter markets. The database contains a wide range of financial indicators and information (both current and archived), including stocks and bonds, investment and trust funds, exchange rates, interest rates, financial derivatives, and commodities (raw materials), as well as international macroeconomic data and forecasts for the world's largest economies and developing countries. The Thomson Reuters EIKON database contains:
• ESG data and results for over 6000 companies,
• over 400 partial data reported during the sustainable development,
• over 70 KPIs (key performance indicators),
• data from the year 2002,
• ESG data collected in real time from 75 000 sources,
• solutions that allow monitoring and reporting CO2 emissions to fulfil legal requirements.
In this context, the Thomson Reuters EIKON database allows you to access ESG data on a company and, eventually, an ESG rating for that business.

The calculation of the indicator value that classifies a company into an appropriate score is based on three factors:

➔ ➔ indicator for the score ESG = $\frac{a+b/2}{c}$

where: a - the number of underperforming companies,
b - the number of companies with the same results as the one evaluated,
c - total number of companies with results.

Based on the calculated result, the company is assigned a specific ESG score on a scale from D- to A+.
There are three categories of ESG indicators in the Thomson Reuters EIKON database:
- ESG Score,
- ESG Controversy Score (ESGC Score),
- ESG Combined Score.

The ESG score evaluates organizations' ESG performance using publicly available data from 10 subject categories. Thomson Reuters compiles and analyses over 400 ESG data points about a company, selecting 178 essential data elements for the final ESG score. The data obtained is based on criteria such as materiality, data availability, and sector significance. The data analysis allows us to state that the following categories can be

included in the group of five important categories (taking the relevance of each category as a criterion) that have the biggest impact on the company's ESG score:
• management (importance– 19%) – pillar: governance,
• labour (importance – 16%) – pillar: social,
• emissions (importance– 12%) – pillar: environment,
• use of resources (importance – 11%) – pillar: environment,
• innovation (importance– 11%) – pillar: environment.

The five categories stated above have a total relevance of 69%. It is also worth noting that the major categories contain all of the environmental pillar's areas. It is also worth noting that a company's CSR strategy (together with human rights) is the least important factor in the ESG score, accounting for only 4.5%. The ESG Controversy Score (ESGC Score) assesses a company's exposure to environmental, social, and governance issues, as well as negative news coverage in the worldwide media. The Reuters Eikon database includes 3107 firms from advanced and emerging nations that operate in a variety of industry categories (table 2).

Table 2. Descriptive statistics

	Mean	Median	Stdev	Min	Max
ESG_score	51,99	53,58	20,40	0,47	95,06
ESG_Combined_Score	49,89	50,85	19,38	0,47	94,59
Environmental_Pillar_Score	47,70	50,32	27,79	0,00	99,18
Social_Pillar_Score	52,55	53,88	23,99	0,26	98,63
Governance_Pillar_Score	54,87	56,96	22,04	0,29	99,51
Size (ln_assets)	22,13	22,42	2,84	0,00	28,70
ROA	4,60%	3,34%	7,44%	-113,99%	249,32%
ROE	12,17%	10,07%	72,30%	-5332,55%	2604,97%
Debt_to_Equity	209,69%	58,15%	10043,60%	-0,55%	1460694,54%

Source: own editing

The table depicts the ESG (Environmental, Social, and Governance) performance, size, and financial performance of a sample businesses from the Reuters Eikon database. The calculations yield an average ESG score of 51.99, indicating moderate ESG performance overall. The median, which is somewhat higher than the average, is 53.58, indicating a slightly better-scoring dispersion. ESG scores vary significantly, with a standard deviation of 20.40, indicating a large disparity between companies. The extreme numbers, 0.47 to 95.06, demonstrate significant disparities in ESG performance, ranging from very poor to very high. The combined ESG score averages 49.89, which is slightly lower than the average of the individual ESG scores. This could indicate a tiny discrepancy in how the performances are aggregated or reported. The median total ESG score of 50.85, which is close to the average, indicates a fairly balanced distribution.

The environmental pillar scores have a mean of 47.70 and a median of 50.32, indicating a slightly centred upper end with a larger variation (standard deviation of 27.79). The mean for the social pillar is 52.55 and the median is 53.88, indicating that social performance is stronger on average than environmental performance, but there is also significant variability, as evidenced by the standard deviation of 23.99. The governance pillar has the best relative performance, with a mean of 54.87 and a median of 56.96, indicating that most entities effectively handle these components, albeit significant variation.

The average size of the entities, as measured by the logarithm of assets (ln_assets), is 22.13, with a median of 22.42 and a standard deviation of 2.84. This suggests a more consistent size for these entities. Financial performance, as measured by return on assets (ROA) and return on equity (ROE), demonstrates a diverse position. The ROA has a mean of 4.60% and a median of 3.34%, indicating modest financial performance for most organisations. However, the standard deviation of 7.44% and extreme values (minimum -113.99% and maximum 249.32%) show significant variations amongst entities. The average return on equity (ROE) is 12.17%, with a median of 10.07%. However, there is significant variance with a standard deviation of 72.30% and extreme values ranging from -5332.55% to 2604.97%.

The debt-to-equity ratio varies the most, with an average of 209.69% and a median of 58.15%. The large standard deviation of 10043.60%, combined with extreme values (ranging from -0.55% to 1460694.54%), indicates a significant difference in capital structure between firms. This could indicate severe financial risk for some or strong capitalisation for others. This research captures the complexity and diversity of the entities' ESG and financial performance.

By analysing ESG ratings in relation to ROA and ROE, an increasing trend can be noticed, indicating that companies with sustainable and socially and environmentally responsible policies perform better financially. However, the substantial variability in both data sets implies that this is not a general rule, and that each company has unique factors that influence both ESG score and financial viability. It is critical that investors and stakeholders continue to analyse these relationships in order to make sound decisions. Table 3 shows the evolution of the average ESG score for the analysed organisations from 2018 to 2024.

Table 3. ESG score values, 2018-2024

Years	ESG score	ESG_Combined_Score	Environmental_Pillar_Score	Social_Pillar_Score	Governance_Pillar_Score	Size (ln_assets)	ROA	ROE	Debt_to_Equity
2024	58,48	54,96	54,63	60,00	58,80	22,27	4,51%	12,50%	205,84%
2023	56,60	54,11	52,24	57,94	57,59	22,15	3,82%	8,45%	125,02%
2022	54,24	52,32	48,82	55,39	56,16	22,14	4,79%	10,56%	137,95%
2021	52,24	50,43	46,26	53,28	54,73	22,10	5,10%	13,58%	603,25%
2020	49,75	48,08	46,69	50,02	53,35	22,21	4,77%	13,47%	102,65%
2019	47,57	46,28	43,98	47,18	52,61	22,05	4,66%	12,86%	137,72%
2018	45,05	43,04	41,26	44,06	50,82	21,99	4,55%	13,74%	155,40%

Source: own editing

The overall ESG score has steadily increased from 45.05 in 2018 to 58.48 in 2024. This trend shows that corporations' environmental, social, and governance performance is continuing to improve, potentially due to increased pressure from investors, regulators, or public awareness of the relevance of these issues. The combined ESG score follows a similar trend, but its values are significantly lower than the overall ESG score. This may indicate that the combined company-level performance is slightly poorer than the separate ones on different dimensions.

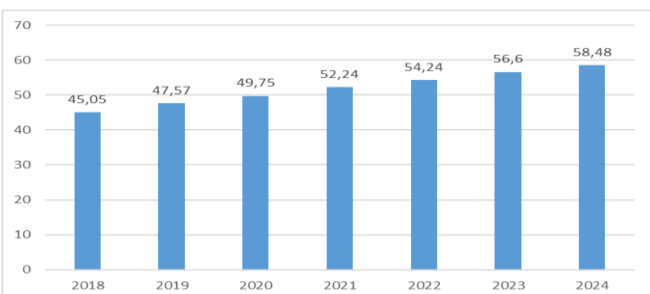
Looking more closely at the ESG pillars, it is clear that all three components (environmental, social, and governance scores) have improved over the years. The environmental pillar, for example, has risen from 41.26 in 2018 to 54.63 in 2024, indicating a more widespread adoption of sustainable methods in business operations. Similarly, the social and governance pillars have grown significantly, reflecting an increased interest in social responsibility and corporate governance excellence.

The company size, as assessed by the logarithm of assets (ln_assets), remained largely consistent during the analysed period, with only minor changes between 21.99 and 22.27. This constancy shows that firm size did not play a significant role in the variances in ESG rankings and financial performance.

ROA (return on assets) and ROE (return on equity) indicate little volatility, with ROA values ranging from 3.82% to 5.10%. This indicates a relatively consistent operational efficiency. On the other hand, ROE changes more, from 8.45% in 2019 to 13.74% in 2014, demonstrating greater variability in return on equity, which can be influenced by both capital structure and net income swings.

The evolution of the Debt-to-Equity ratio, which demonstrates significant volatility, is one of the analysis's highlights. Although the average of this indicator shows a high level of indebtedness, substantial swings, such as the sudden increase to 603.25% in 2017, signal periods of financial instability or significant changes in a company's capital structure. This could indicate different financing tactics used by businesses in response to economic opportunities or problems throughout the relevant time. Overall, the data given show an improvement in ESG performance over time, which is associated with a rather moderate variation in financial success. The rise in ESG scores indicates that companies are becoming more committed to sustainable and responsible practices, though the stability of company size and the volatility of financial indicators suggest that these improvements are not necessarily the result of company growth or stable financial performance, but rather of increased awareness and external pressure for better corporate governance and social responsibility (graph 1).

Graph 1. ESG score values, 2018-2024



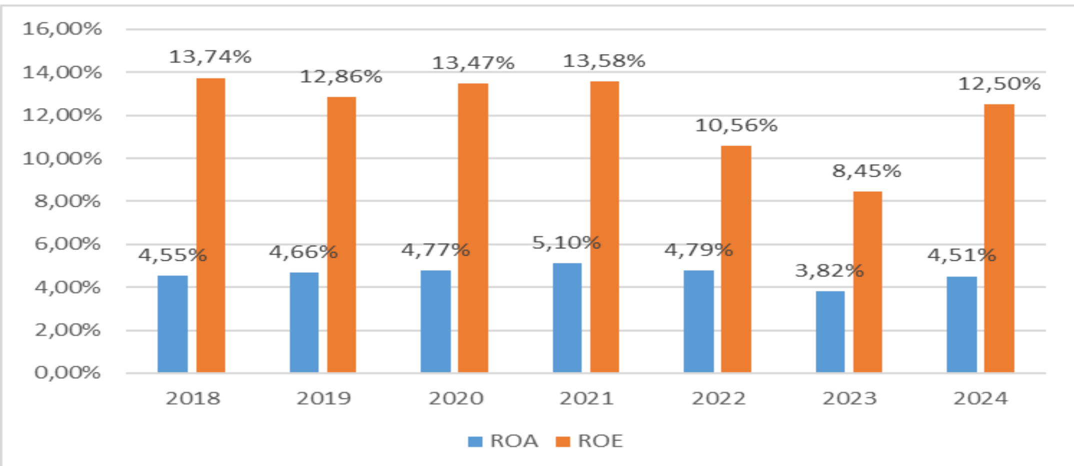
Source: authors editing

The graph shows the evolution of the ESG score from 2018 to 2024. A definite rising trend can be seen, indicating a consistent improvement in organisations' ESG performance over the period studied. Starting in 2018, the ESG score was 45.05, but by 2024 it had risen dramatically to 58.48. This constant increase reflects firms' growing commitment to incorporating environmental, social, and governance policies into their daily operations. The fact that each year sees an increase over the previous year indicates a stable and persistent tendency, rather than a transitory reaction to specific external or internal circumstances. This trend could be attributed to a variety of factors, including stronger regulation of ESG reporting and performance, a rise in investor demand for openness and accountability, or firms' improved understanding of their influence on society and the environment.

The rise can also be ascribed to the continual improvement of corporate governance, as well as the policies and procedures put in place to promote sustainability. The data shows a positive and significant evolution of ESG scores, demonstrating a gradual but consistent shift by corporations towards more sustainable and responsible practices over the period studied. This evolution shows that ESG factors have grown more incorporated into business planning, possibly becoming vital for long-term success.

The average profitability of businesses has evolved in the sense of those described in graph 2. We see a correlation between ROA and ROE in the sense that assets used in business and capital invested are stable, with net profit influencing enterprise success.

Graph 2. ROA and ROE evolution, 2018-2024



Source: authors editing

6. Conclusions

Sustainable development has been defined as meeting current needs without jeopardising future generations' ability to meet their own, with the goal of striking a balance between economic growth, social inclusion, and environmental protection, and serving as the foundation for all EU policies and initiatives. Under Article 3(3) of the Treaty on European Union, the EU officially recognises sustainable development as a long-term goal.

Sustainability reporting is more than simply a legal requirement; it is also a strategic opportunity for businesses to improve their performance and provide value in the long term. Businesses can help to create a more sustainable future by incorporating the principles of sustainability reporting into their operating plans.

Companies that invested more in social, environmental, and corporate governance initiatives saw higher returns. In summary, despite the additional costs associated with these measures, their revenues climbed, leading to the conclusion that organisations engaging in ESG actions will benefit in the short and medium term. ESG activities benefit businesses at every stage of the value chain, from cost reduction to maintaining a competitive advantage. ESG encourages investors and publicly traded companies to consider sustainability, resulting in a more robust green stock market.

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