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STRATEGY FOR INCLUSION OF AI ADVANCED TECHNIQUES IN FINANCE, ACCOUNTING AND BUSINESS ADMINISTRATION IN THE BIHOR–HAJDÚ-BIHAR REGION

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Executive Summary

Artificial Intelligence (AI) is increasingly becoming a crucial component in finance, accounting, and business administration. Its integration into these fields has generated significant transformative effects, enabling organizations to enhance operational efficiency, improve decision-making processes, and deliver more personalized and data-driven services to clients and stakeholders.

Strategy for Inclusion of AI Advanced Techniques in Finance, Accounting and Business Administration in the Bihor–Hajdú-Bihar Region was developed within the project "Exchange of Experience for research and usage of Artificial Intelligence' Advanced Techniques in finance, accounting and business administration in Bihor-Hajdu Bihar Region" (acronym: E2U-AI), project code ROHU00120, implemented by the University of Oradea, Faculty of Economic Sciences and the University of Debrecen, Faculty of Economics and Business, between 19.02.2025-18.02.2026, funded by the Interreg VI Romania-Hungary Programme.

The main objective of the project ROHU00120 is to strengthen the institutional cooperation between the University of Oradea and University of Debrecen in the field of usage Artificial Intelligence' Advanced Techniques in finance, accounting and business administration in Bihor-Hajdu Bihar Region through organization of 5 joints specialized courses, acquisition of AI software and laptops, 2 cross-border exchange of experience, 2 workshops, elaboration of a common strategy and an e-book of AI techniques applied in Finance, Accounting, and Business Administration.

This comprehensive strategy will serve as a guiding document to drive the successful integration of advanced AI techniques in finance, accounting, and business administration within the Bihor–Hajdú-Bihar region, fostering innovation, economic growth, and competitiveness in these sectors. This strategy aims to reduce skills gaps, address identified barriers, and encourage university–business cooperation, thereby increasing organizational readiness for AI adoption and fostering trust in the responsible use of advanced artificial intelligence techniques across the region.

Finally, the *Strategy for Inclusion of AI Advanced Techniques in Finance, Accounting and Business Administration in the Bihor–Hajdú-Bihar Region* represents a firm commitment of the academic environment in University of Oradea and University of Debrecen to become leaders of digital transformation. By operationalizing this strategy, the Bihor – Hajdú-Bihar region not only aligns itself with European standards, but also creates the premises for sustainable economic development, based on knowledge and technological innovation.

Implementing advanced AI techniques in the Bihor-Hajdú-Bihar region presents a compelling opportunity for fostering economic growth, optimizing public administration, and supporting sustainable development. By prioritizing AI's integration into various sectors, local stakeholders can improve efficiency, enhance service delivery, and lay a solid foundation for future prosperity. The successful implementation of this roadmap will transform digital challenges into concrete opportunities, ensuring the economic prosperity of the region and the professional excellence of future generations of economists.

Chapter 1. Introduction

Artificial Intelligence (AI) is increasingly becoming a crucial component in finance, accounting, and business administration. Its integration into these fields has resulted in transformative changes, enabling firms to enhance operational efficiency, improve decision-making processes, and provide personalized services. The prevalent use of AI in financial technology (FinTech) exemplifies this revolution, shaping the dynamics of the financial services sector. AI technologies facilitate a myriad of applications that improve the quality and efficiency of financial services. Algorithms powered by AI and machine learning streamline operations across various areas, including risk management, fraud detection, and customer service automation. As suggested by Wang (2023), the research into AI algorithms has led to significant advancements in practical applications in finance and accounting, marking this field as a pivotal area of interest for further research.

AI applications in FinTech have also transformed traditional theories of finance. Moreover, the use of AI in automated trading systems and predictive analytics has revolutionized how financial institutions approach investment and asset management, contributing to a more robust understanding of market behaviors. The role of AI in promoting financial inclusion cannot be overstated, particularly in augmenting the accessibility of financial services for small and medium-sized enterprises (SMEs). Innovations in FinTech harnessing AI and big data analytics have proven effective in mitigating the challenges associated with traditional lending, thereby improving financing options for SMEs. This capability is critical given that these enterprises often face significant hurdles in securing funding due to stringent credit evaluation processes that traditionally favor larger businesses.

AI also plays a vital role in risk management within financial institutions. By leveraging big data and advanced algorithms, firms can better assess credit risks and prevent fraudulent activities, making AI indispensable in managing financial security and compliance (Bao et al., 2024). These technologies not only enhance the accuracy of risk assessment but also streamline the processes involved in maintaining regulatory standards.

Through the automation of routine tasks, AI significantly enhances operational efficiency in finance and accounting. The implementation of AI-driven tools allows organizations to reduce labor costs associated with manual processes, leading to a more efficient allocation of resources toward strategic and value-added activities (Singh, 2023). Lăzăroiu et al. point out that AI optimizes financial services by providing cost-effective solutions tailored to customer requirements through personalized financial offerings (Lăzăroiu et al., 2023).

Furthermore, machine learning algorithms identify patterns and trends, enabling proactive decision-making that can enhance overall business performance (Dabija & Vătămănescu, 2023). This operational innovation not only reinforces the competitive positioning of firms but also aligns with the evolving expectations of clients for customized financial services.

While the integration of AI in finance, accounting, and business administration presents numerous benefits, it is not without challenges. Security concerns surrounding data privacy and ethical implications of AI decision-making pose significant risks that need to be managed carefully. Zetzsche et al. (2017) identify the regulatory challenges facing financial institutions as they adopt these advanced technologies,

emphasizing the need for an adaptable regulatory framework that can accommodate the fast-paced changes in FinTech.

As organizations continue to embrace AI, future research must address the evolving interplay between AI, regulation, and financial practices to ensure that the benefits of AI are maximized while mitigating associated risks. In conclusion, AI is reshaping finance, accounting, and business administration in profound ways. Its applications enhance efficiency, improve risk management, and foster inclusivity in financial services. As the technology continues to evolve, it will be essential for stakeholders to navigate the accompanying challenges while leveraging AI's full potential to drive innovation in these fields.

The Bihor-Hajdú-Bihar region, straddling the border between Romania and Hungary, is witnessing transformative socio-economic developments. Leveraging advanced Artificial Intelligence (AI) techniques has become pivotal for driving growth, optimizing public services, and enhancing the business landscape in this region. This paper outlines the rationale for implementing AI technologies, emphasizing their potential to advance sustainable regional development. In the context of Bihor-Hajdú-Bihar, the introduction of AI can optimize resource allocation and improve the efficiency of local enterprises, allowing them to compete more effectively in an increasingly globalized market. Furthermore, studies indicate that regions adopting AI technologies can experience significant improvements in productivity and operational efficiency. By automating routine tasks and leveraging data-driven analytics, businesses can focus on strategic decision-making and innovation. This is particularly relevant for the Bihor–Hajdú-Bihar region, where enhancing competitiveness in sectors like agriculture, manufacturing, and services is essential for its economic advancement.

The inception of AI in public finance and administration can streamline government operations, thereby promoting sustainable development in the Bihor-Hajdú-Bihar region. Moreover, AI can play a critical role in predictive analytics for urban planning and management. Utilizing AI algorithms to analyze demographic and economic data allows for better resource allocation, leading to improved public services such as transportation, health care, and education. The agility offered by AI in policy implementation can also foster a more adaptable approach to emerging regional challenges.

Implementing advanced AI techniques in the Bihor-Hajdú-Bihar region presents a compelling opportunity for fostering economic growth, optimizing public administration, and supporting sustainable development. By prioritizing AI's integration into various sectors, local stakeholders can improve efficiency, enhance service delivery, and lay a solid foundation for future prosperity. The strategic implementation of AI depends on addressing existing challenges and ensuring a collaborative approach between public institutions, businesses, and academia.

Chapter 2. Vision and Mission

2.1. Vision

The vision of this strategy is to position the Bihor–Hajdú-Bihar Euroregion as a cross-border model of excellence in the use of advanced artificial intelligence techniques in finance, accounting, and business administration.

By capitalizing on the academic, technological, and institutional potential of the region, the strategy aims to foster innovation, enhance regional economic competitiveness, and support sustainable development based on data-driven, digital, and future-oriented decision-making, in line with the objectives of the Interreg VI Romania–Hungary Programme.

2.2.Mission of the Strategy

The mission of this strategy is to provide a coherent and practical framework for the integration of advanced artificial intelligence techniques in finance, accounting, and business administration within the Bihor–Hajdú-Bihar Euroregion, through the strengthening of institutional cooperation between the University of Oradea and the University of Debrecen.

The strategy focuses on building institutional capacity, enhancing digital skills, facilitating the transfer of knowledge and best practices, and supporting businesses and public authorities in the adoption of AI-based solutions, thereby contributing to innovation, efficiency, and mutual trust across the border.

The mission of this strategy is to respond directly to the needs and gaps identified through the survey conducted among enterprises in the Bihor–Hajdú-Bihar Euroregion regarding the use of advanced artificial intelligence techniques in finance, accounting, and business administration.

The mission directions of the strategy, which derive from identification needs, are:

Direction 1: Supporting the transition from early-stage AI adoption to structured implementation

One key direction of the mission is to support organizations in the Bihor–Hajdú-Bihar Euroregion in moving beyond early-stage awareness and limited experimentation toward the structured and effective use of advanced artificial intelligence techniques.

This direction builds on the survey finding that, although a favorable attitude toward AI and its potential benefits is widely recognized, actual adoption remains at an early stage for many organizations, particularly in financial analysis, accounting operations, and business management.

Direction 2: Addressing barriers through capacity building and guidance

A second direction of the mission is to reduce the main barriers to AI adoption identified in the survey by strengthening organizational capacities and providing practical guidance.

This includes developing specialized skills and human resources, improving practical knowledge of AI applications, clarifying cost–benefit considerations, and addressing concerns related to data security, ethical use, and regulatory and legal compliance, thereby creating a supportive environment for responsible AI integration.

Direction 3: Strengthening university–business cooperation and knowledge transfer

A third direction of the mission is to enhance cooperation between enterprises and academic institutions in order to facilitate knowledge transfer, applied research, and access to expertise.

This direction responds to the strong interest expressed by enterprises in collaborating with universities for training, consultancy, and applied research, while also addressing the current lack of sufficiently structured and systematic cooperation frameworks within the region.

In light of these findings, **the mission of the strategy** is to strengthen cross-border institutional cooperation between the University of Oradea and the University of Debrecen in order to support enterprises and public institutions through targeted training programs, knowledge transfer, applied research, and practical tools for AI implementation. The strategy aims to reduce skills gaps, address identified barriers, and encourage university–business cooperation, thereby increasing organizational readiness for AI adoption and fostering trust in the responsible use of advanced artificial intelligence techniques across the region.

Chapter 3. Context Analysis and Needs Assements

3.1. Socio-Economic and Digital Context (Romania and Hungary)

Romania and Hungary enter 2026 with equally challenging socio-economic landscapes, shaped by persistent inflationary pressures, tightening fiscal conditions, and uneven labour-market dynamics, while both countries continue to navigate slow digital transformation and structural vulnerabilities that weigh on their medium-term growth prospects (European Commission, 2025).

In short, as can be seen in Table 3.1, economic indicators show Romania and Hungary closed 2025 with weak growth, easing but still high inflation, moderate unemployment, negative real wages, fiscal deficits, and rising government debt. Social contextual indicators point to high for Romania and medium poverty risks for Hungary, labour shortages linked to emigration, demographic decline, and moderate regional inequality. Digital decade indicators highlight better basic digital skills for Hungary, limited ICT workforce growth, strong connectivity, but slow SME digital adoption.

Table 3.1. Key Economic, Social, and Digital Decade Indicators in Romania and Hungary

ECONOMIC INDICATORS (European Commission - *Economic forecast)*		
Indicator	**Romania (2025–early 2026)**	**Hungary (2025–early 2026)**
GDP Growth	0.7% (2025), 1.1% (2026)	0.4% (2025), 2.3% (2026)
Inflation	6.7% (2025) → 5.9% (2026)	4.5% (2025) → 3.6% (2026)
Labour Market	Unemployment 6.1% (2025)	Unemployment 4.5% (2025)
Wages	Real wages negative	Real wages negative
Fiscal Deficit	8.4% (2025) → 6.2% (2026)	4.6% (2025) → 5.1% (2026)
Government Debt	59.1% (2025) → 62.7% (2027)	73.7% (2025) → 74.9% (2027)
External Balance	–7.9% (2025) → –6.0% (2027)	0.1% (2025) → –0.4% (2027)
SOCIAL CONTEXTUAL INDICATORS (World Bank – *Systematic Country Diagnostic)*		
Indicator	**Romania (2025–early 2026)**	**Hungary (2025–early 2026)**
Poverty & Social Conditions	Among the highest poverty risks in the EU, especially in eastern rural communities	Lower overall poverty, but persistent exclusion among Roma communities
Labour Shortages	Construction, healthcare, IT (driven by emigration)	Manufacturing, healthcare, IT (driven by ageing and migration)
Demographics	Declining population, accelerated ageing	Ageing population and outward migration
Regional Inequality	Moderate to high: urban more developed than rural; west more developed than east	Moderate: west more developed than east

DIGITAL DECADE INDICATORS (European Commission - *Digital Decade Scoreboard*)		
Digital Decade Indicator	**Romania (2025–early 2026)**	**Hungary (2025–early 2026)**
Basic Digital Skills (DDPP)	~30% of adults (well below EU average)	~50% of adults (close to EU average)
ICT Specialists in the Workforce	Moderate growth; smaller to medium shortage	Moderate growth; smaller shortage
Connectivity (gigabit readiness)	Strong 5G coverage; existing fiber expansion	Strong 5G coverage; rapid fiber expansion
Cloud/AI/Big Data Adoption in SMEs	Higher in big companies; SMEs still lag	Higher in industry; SMEs still lag
Digitalisation of Public Services	Modest level; limited interoperability	Medium level; higher e-government usage
Digital Identity / eID	Partial implementation, medium usage	More advanced implementation, wider usage
Cybersecurity (national capacity)	Improving, but below EU average	Aligned with EU standards

In economic terms, Romania faces weak growth, high inflation, and persistent fiscal and external imbalances, while Hungary shows a modest recovery supported by stronger wages and a tighter labour market but remains constrained by rising debt and fiscal pressures, highlighting two distinct yet challenging macroeconomic trajectories that reflect differing short-term dynamics but shared medium-term vulnerabilities.

From a social perspective, Romania continues to grapple with some of the highest poverty risks in the EU, deepened by labour shortages in construction, healthcare, and IT, largely driven by emigration, alongside a rapidly declining and ageing population and stark regional divides between the capital region and the rest of the country, as well as between urban and rural areas. Hungary faces lower overall poverty but persistent exclusion among Roma communities, labour shortages concentrated in manufacturing, healthcare, and IT due to ageing and migration pressures, and more moderate regional disparities, with the western regions outperforming the east, which continue to lag behind.

From the perspective of Digital Decade indicators, the data reveal two distinct digital development trajectories. Romania enters 2025–early 2026 with major gaps in basic digital skills, small-to-medium ICT-specialist shortages, and modest public-sector digitalisation, despite strong 5G and fibre infrastructure; SMEs also lag in adopting cloud, AI, and big data, and cybersecurity capacity remains below EU standards. Hungary displays a more advanced profile, with higher basic digital skills, a smaller ICT shortage, strong and expanding connectivity, more mature e-government services, wider eID use, and cybersecurity aligned with EU norms. Overall, Romania is infrastructure-ready but limited by skills and institutional weaknesses, while Hungary shows a more balanced and advanced digital trajectory.

What should be mentioned at this point is that, across economic, social, and digital indicators, Bihor County (Romania) and Hajdú-Bihar County (Hungary) display broadly similar development profiles, as Bihor consistently performs above Romania's national average while Hajdú-Bihar tends to fall below Hungary's national average. This alignment creates a comparable regional landscape on both sides of the

border, despite the wider differences between the two countries at national level (European Commission 2022, 2023; Eurostat, 2023).

3.2. AI Readiness and Digital Maturity Assessment

AI, understood as a set of applications and techniques that enable economic agents to act intelligently, does not simply integrate itself into organizational processes; it demands a substantial level of structural, managerial, cultural, technological, and human preparedness. This requirement is captured by the concept of readiness, which reflects the extent to which an organization possesses the internal conditions necessary to adopt and operationalize AI effectively (Jöhnk, Weißert and Wyrtki, 2021).

AI readiness is not limited to having technological tools in place; it entails mobilizing adequate resources, developing relevant competences, and cultivating organizational capabilities. In essence, it means having the means to act, knowing how to act, and being able to act in ways that allow AI to generate meaningful business value by creating measurable improvements in productivity, profitability, customer experience, and long-term strategic positioning. Thus, AI readiness emerges as a prerequisite for AI adoption, understood as the outcome of the interaction between the firm's main subsystems and the dimensions that define AI readiness, as identified by Jöhnk, Weißert and Wyrtki (2021) (see Table 3.2).

Table 3.2. Organizational Subsystems and the Dimensions of AI Readiness

AI Readiness dimensions / **Subsystems**	**Strategic alignment**	**Resources**	**Knowledge**	**Culture**	**Data**
Technical	Alignment of technical processes with AI	IT infrastructure	Technical AI skills	Technological innovation	Operational data
Economic	Assessing AI's economic potential	Budget for AI	Training for efficiency	Performance-oriented mindset	Financial data
Managerial	Strategic direction and support	Resource allocation	AI awareness and ethics	Leading change	Coordination of data flows
Human	Employee acceptance of AI	Qualified personnel	Upskilling and ethics	Collaboration and openness	HR data
Informational	Information processes aligned with AI	IT and information resources	Data management skills	Collaboration through IT systems	Data quality and accessibility

Commercial/ Marketing	AI potential for market and customers	Resources for AI solutions	AI knowledge in marketing	Commercial innovation	Customer data
Research & Development	Identifying AI opportunities	Resources for experimentation	Advanced AI expertise	Culture of experimentation	Data for development

In practice, at the organizational level, AI readiness is simultaneously shaped by the way each subsystem contributes to strategic alignment, available resources, internal knowledge, organizational culture, and data management.

Strategic alignment represents the starting point, as AI adoption must be coherent with the firm's strategic direction, its operational processes, and its value-creation potential. The managerial, economic, and commercial subsystems play a central role in this dimension through their ability to identify opportunities, assess customer impact, and support data-driven decision-making. The technical and informational subsystems contribute by ensuring that processes and infrastructures are compatible with AI requirements, while the human subsystem influences the degree of acceptance and adaptation to new technologies.

The **resources** required for AI adoption, including financial budget, personnel, and IT infrastructure, are distributed and managed differently across each subsystem. The economic subsystem provides the necessary funding, the managerial subsystem determines how resources are allocated, while the technical and informational subsystems supply the required infrastructure. The human subsystem contributes through the availability of relevant skills, and the research-and-development subsystem through its capacity to experiment with AI solutions.

Knowledge related to AI, such as awareness, skills, and ethics, is developed primarily within human, managerial, and research-and-development subsystems. These shape the organization's ability to understand the technical, operational, and ethical implications of AI. The technical and informational subsystems complement this dimension by providing the expertise required for the effective implementation of AI technologies.

Organizational culture, defined by innovation, collaboration, and the capacity to manage change, cuts across all the firm's subsystems. The managerial subsystem shapes the cultural direction, the human subsystem expresses it through behaviors and practices, while the technical, informational, and research-and-development subsystems operationalize it through the ways they support experimentation and interdisciplinary collaboration. Culture directly influences the organization's openness to adopting AI and the pace of its digital transformation.

Data, meaning its availability, quality, accessibility, and flows, is generated and managed primarily by the informational, technical, and commercial subsystems, but it is used by all other subsystems. The quality and circulation of data determine the organization's ability to develop effective AI models and to make informed decisions.

In conclusion, AI readiness is not the outcome of a single subsystem but of a complex interdependence among all components of the organization. Each subsystem contributes in different yet

complementary ways to the five dimensions of AI readiness, and the final level of readiness reflects the coherence and maturity of these interactions (Mikalef, Fjørtoft and Torvatn, 2019).

After AI implementation, the organization undergoes a process of learning, adjustment, and development, as the implementation itself enhances IT infrastructure, increases employee competencies, strengthens data-driven culture, stimulates innovation, refines managerial processes, and generates new types of data and data-governance practice. In other words, AI adoption raises the level of readiness by making the organization more mature, more capable, and better equipped for future AI use. AI readiness therefore plays a dual role in the dynamics of digital transformation: it is both a prerequisite for AI adoption and a result of it. These two facets do not exclude one another but reinforce each other, forming an evolutionary cycle of organizational maturation. Thus, AI readiness appears as a continuous process that intensifies as the organization gains experience in using AI.

Digital maturity follows a similar evolutionary logic, but at a broader organizational scale. While AI readiness focuses on the specific capabilities required to adopt and leverage artificial intelligence, digital maturity reflects the organization's overall ability to integrate digital technologies, redesign processes, and transform its operating model. As firms advance in their AI initiatives, they inevitably strengthen the foundational elements of digital maturity, such as strategic clarity, agile structures, data-driven decision-making, and a culture that embraces experimentation and continuous improvement. In this sense, AI readiness acts as both a catalyst and an accelerator of digital maturity, pushing the organization toward more sophisticated forms of digital value creation and long-term competitiveness (Schneider et al., 2022; Dey and Ghose, 2025).

In their analysis of EU enterprises, Becker, Becker and Zdziebko (2025), as can be seen in Table 3.3, show that Romania and Hungary occupy the lower and intermediate tiers of digital maturity, respectively, within the broader European landscape. Romanian firms are predominantly situated in the least mature cluster, characterized by low to moderate digital infrastructure, moderate data governance, and low strategic AI use. Hungarian enterprises, while still below the EU average, more frequently appear in mid-level clusters, reflecting comparatively stronger IT capabilities and a more structured approach to digitalization.

Table 3.3 Digital Maturity of Romanian and Hungarian Enterprises in the Context of AI Implementation

Dimension	Romania	Hungary
Digital maturity cluster	Mostly in the lowest maturity cluster	More often in intermediate clusters
IT infrastructure	Low to moderately developed, more consistent across big firms	Moderately developed, more consistent across firms
Data management & governance	Moderate-structured data practices, though still developing	Better-structured data practices, though still developing
AI adoption level	Early to medium-stage; low strategic use yet	Medium-stage; closer to scaling
Managerial support for digitalization	Moderate managerial commitment to digital initiatives	More stable managerial commitment to digital initiatives

Digital & AI skills	Significant skill shortages; limited internal expertise	Slightly stronger skill base, though still insufficient
Organizational culture	Cautious, risk-averse, low experimentation	More open to digital change, but still conservative
Structural gaps vs. Western EU	Large gaps in cloud, cybersecurity, and automation	Noticeable gaps, but smaller than Romania's
High-potential segments	Young tech firms, export-oriented SMEs	Multinational-integrated firms, innovative SMEs
Overall trajectory	Moderate progress but with pockets of rapid progress	Moderate progress with clearer potential for advancement

Recent studies revealed that in both countries, AI adoption remains modest and fragmented, constrained by skill shortages, managerial hesitancy, and underdeveloped organizational cultures that limit experimentation. Structural gaps, particularly in data quality, cloud adoption, and cybersecurity, further widen the distance from digitally advanced Western EU firms. Nonetheless, the study identifies pockets of rapid progress in both economies, especially among younger, export-oriented, or multinational-integrated firms, suggesting potential for upward mobility in digital maturity as AI capabilities evolve (Endrődi-Kovács & Stukovszky, 2022; Abrudan et al., 2025; Apostoaie et al., 2025; Bogdán & Popovics, 2025).

3.3. Stakeholder Mapping

Stakeholder Mapping is the process of identifying individuals or groups that can influence, or be influenced by an organization, then analyzing their interests, power, expectations, and relationships to determine how they should be engaged. It helps companies understand who matters most, where risks or opportunities lie, and how to allocate attention and resources strategically. As AI becomes more deeply embedded in business operations, it offers powerful new ways to enhance this mapping process. Powered by AI logic, intelligent systems can process large volumes of data, detect patterns in stakeholder behavior, and continuously update profiles as conditions change. By applying machine-learning models and adaptive reasoning, these systems refine their understanding over time and improve the accuracy of their predictions. This allows organizations to identify stakeholders more accurately, analyze their influence with greater precision, and prioritize them based on real-time insights rather than static assumptions. In a fast-moving and interconnected environment, AI-supported stakeholder mapping enables companies to anticipate shifts, uncover emerging stakeholders, and respond to opportunities or risks far more effectively than traditional manual methods.

Organizations still depend heavily on manual processes to gather and analyze stakeholder information, but research indicates that the gradual integration of AI will support a shift toward automated, data-driven stakeholder mapping (Kallina & Singh, 2025). This transition is especially valuable in departments where stakeholder relationships are fundamental.

Departments that stand to benefit the most include:

- Customer Relations / Client Service (often merged with sales support in SMEs)
- Marketing & Communications (frequently combined into a single unit in smaller companies)

- Procurement & Supplier Relations (sometimes part of Operations in SMEs)
- Human Resources / Personnel Management (typically a small administrative unit in SMEs, but more specialized in large firms)
- Sales & Business Development (a core function in both SMEs and large enterprises).

Intelligent systems generated by AI create value for stakeholders through four essential characteristics, namely autonomy, learning capacity, opacity and materiality as can be seen in Table 3.4 (Chandra & Rahman, 2024).

Table 3.4. AI Characteristics and Stakeholder Value Creation

AI Characteristic	Description	How It Creates Value for Stakeholders
Autonomy	The ability of AI to operate without direct human intervention.	Enables task automation, reduces response time, and increases operational efficiency.
Learning Capability	AI improves its performance based on data and experience.	Supports more accurate analyses, anticipates stakeholder behavior, and helps adapt organizational strategies.
Opacity	The internal processes of AI are difficult to understand or explain.	Allows for complex analyses but requires trust and interpretability mechanisms to fully leverage outcomes.
Materiality	AI is embedded in physical or digital systems, processes, and infrastructures.	Expands the organization's ability to interact with stakeholders through tools, platforms, and applications that support decisions and actions.

To understand what drives companies to adopt AI for stakeholder mapping, very important are perception and knowledge of AI, benefits of AI, and challenges associated with AI. Perception and knowledge of AI, benefits of AI, and challenges associated with AI, differ across contexts in much the same way that stakeholder value perceptions vary within sustainable business model research. Just as value creation cannot be understood without considering the perspectives, needs, and interpretations of diverse stakeholders, attitudes toward AI are shaped by individuals' experiences, expectations, and levels of trust.

The benefits of AI, such as enhanced efficiency, improved decision-making, and the ability to adapt dynamically to user needs, mirror the potential of stakeholder-engaged business models to evolve in response to ongoing feedback. Yet the challenges surrounding AI, including issues of transparency, attribution of responsibility, and the complexity of evaluating its impacts, parallel the difficulties organisations face when attempting to assess value creation across heterogeneous stakeholder groups. Ultimately, understanding AI requires a relational and context-sensitive approach, recognising that its perceived value emerges not from the technology alone but from the interaction between users, systems, and the broader environment in which AI operates.

3.4. Gap Analysis: Western Romania-Eastern Hungary

Gap analysis is the process through which an organization compares its current state with the desired state to identify the critical gaps that need to be addressed. In the context of artificial intelligence adoption, it becomes essential for ensuring an efficient and compliant implementation. Through this analysis,

organizations can understand which skills, processes, data, technologies, or policies they lack to use AI safely, ethically, and in alignment with regulations such as the AI Act[1] și GDPR[2].

Gap analysis helps with:

- prioritizing investments,
- reducing risks,
- establishing a clear action plan,
- ensuring that AI solutions are coherently integrated into business processes, maximizing benefits and minimizing vulnerabilities.

Table 3.5 presents a comparative gap analysis of AI adoption in finance, accounting, and business administration in Western Romania and Eastern Hungary, benchmarked against standard EU criteria.

Table 3.5. Comparative Gap Analysis – AI Adoption in Finance, Accounting & Business Administration in Western Romania and Eastern Hungary vs. Standard EU Criteria

Standard EU Criteria	**Western Romania – Current Level**	**Eastern Hungary – Current**
Basic Digital Skills (DDPP[3])	Moderate level of basic digital skills	Moderate level of basic digital skills
ICT Specialists in Workforce	Moderate availability; manageable shortage	Moderate availability; slight shortage
Connectivity (Gigabit, 5G)	Moderate connectivity, solid 5G coverage, gigabit network still developing; rural gaps persist vs. EU average	Moderate connectivity, solid 5G coverage, gigabit network still developing; rural gaps persist vs. EU average
Cloud / AI / Big Data in SMEs	High adoption in large firms; SMEs adopt slowly	High adoption in industry; SMEs adopt slowly
Digitalization of Public Services	Medium level; higher usage in large urban areas	Medium level; higher usage in urban areas
Digital Identity / eID	Partial implementation; moderate and uneven usage	More advanced implementation; uneven usage, especially among Roma population

[1] The AI Act represents the EU's first comprehensive legal framework for artificial intelligence, implemented gradually between 2024 and 2027. It imposes differentiated obligations on organizations depending on the risk level of their AI systems, including prior risk assessment, user transparency, rigorous data governance to prevent errors and discrimination, technical documentation and traceability for audit purposes, continuous monitoring of performance and safety, the possibility of human intervention in critical processes, and appropriate cybersecurity measures.
[2] Artificial intelligence that processes personal data, complementing the requirements of the AI Act; it imposes principles such as data minimization, purpose limitation, ensuring an adequate level of transparency and consent, conducting impact assessments for high-risk systems, and guaranteeing users' right to receive explanations about how their data is used in automated processes.
[3] Digital Decade Policy Programme

Cybersecurity	Medium cybersecurity level; functional but not yet mature	Medium cybersecurity level; functional but not yet consolidated
Digital Maturity Cluster	Most organizations in lower maturity levels	Organizations more often in intermediate maturity levels
IT Infrastructure	Moderate IT infrastructure; stronger in large firms	Moderate IT infrastructure; stronger in industry
Data Management & Governance	Data management practices developing; partially structured	Better-structured data practices, still evolving
AI Adoption Level	Medium AI adoption; clear trend toward scaling	Medium AI adoption; clear trend toward scaling
Managerial Support for Digitalization	More stable and consistent managerial support	Increasingly stable and coherent managerial support
Digital & AI Skills	Fairly solid skills base, but still insufficient	Relatively solid skills base, still requiring consolidation
Organizational Culture	Open culture with balanced, prudent approach to change	Relatively open culture, marked by prudence in managing change
Structural Gaps	Gaps in cloud, security, and automation	Visible gaps in cloud technologies, protection solutions, and automation tools
High Potential Segments	Young tech start-ups; export-oriented SMEs	Integrated multinational firms; innovative SMEs
Overall Trajectory	Moderate progress, with areas of acceleration	Moderate progress, with a more clearly defined direction in industry

As shown in Table 3.5, the similarities between the current level and the EU standards for Western Romania and Eastern Hungary are more than evident. Consequently, both regions position themselves within an intermediate zone of digital maturity, displaying comparable strengths as well as similar structural challenges. Based on the European criteria analyzed, the following synthetic picture emerges:

- Basic digital skills are at a moderate level in both regions.
- ICT specialists are available to a comparable extent, with a manageable shortage in Western Romania and a slight shortage in Eastern Hungary.
- Connectivity is moderate in both areas, with solid 5G coverage, yet persistent rural gaps compared to the EU average.
- The adoption of Cloud / AI / Big Data technologies is high in large organizations, while SMEs advance slowly in both regions.
- The digitalization of public services remains at a medium level, with more intensive use in urban environments.

- Digital identity (eID) is partially implemented in Western Romania and more advanced in Eastern Hungary, although usage remains uneven.
- Cybersecurity is at a medium level in both regions, with functional measures that are still insufficiently mature.
- Organizational digital maturity is lower in Western Romania, where lower maturity levels predominate, while Eastern Hungary shows a more balanced distribution toward intermediate levels.
- IT infrastructure is moderate in both regions, with a stronger foundation in large firms (Western Romania) and in industry (Eastern Hungary).
- Data management and governance are developing in Western Romania, while Eastern Hungary shows somewhat more structured practices.
- AI adoption is at a medium level in both regions, with a clear trend toward scaling.
- Managerial support for digitalization is strengthening in both areas, with slightly greater coherence in Eastern Hungary.
- Digital and AI skills are relatively solid but require further consolidation in both regions.
- Organizational culture is open and cautious in both contexts, supporting the gradual adoption of change.
- Structural gaps persist in areas such as cloud, security, and automation.
- High-potential segments differ: Western Romania stands out through young tech start-ups and export-oriented SMEs, while Eastern Hungary is characterized by the presence of multinational companies and innovative SMEs.
- The overall trajectory indicates moderate progress in both regions, with areas of acceleration in Western Romania and a more clearly defined direction in industry in Eastern Hungary.

Chapter 4. Goals and Objectives

The adoption of Artificial Intelligence (AI) in finance, accounting, and business administration is rapidly evolving, driven by the need for efficiency, accuracy, and enhanced decision-making capabilities. Based on the strategy for the Bihor–Hajdú-Bihar region (E2U-AI project), a partnership between the University of Oradea and the University of Debrecen, aims to bridge the gap between academic research and the practical needs of the regional business environment. The overarching goal is to strengthen institutional cooperation and create a sustainable ecosystem where AI innovation enhances the productivity, competitiveness, and decision-making capabilities of SMEs and students in the cross-border area.

Based on regional challenges such as gaps in digital skills, SME readiness, differences in infrastructure and institutional capacities between Bihor and Hajdú-Bihar, and the efficiency of public services, the strategy defines clear short- and long-term objectives to support AI adoption and foster sustainable economic, social, and technological development. Short-term and long-term objectives are guided by AI-enabled stakeholder mapping to ensure interventions target the most relevant enterprises, institutions, and public authorities. Examples include AI-supported financial forecasting for SMEs, automated accounting processes, predictive analysis for public service planning, and cross-border knowledge transfer initiatives.

The strategy is built upon short- and long-term objectives designed to transform the regional economic and digital landscape, providing a roadmap for implementation, monitoring, and continuous improvement. Progress will be measured using defined KPIs, such as the number of SMEs adopting AI tools, the percentage of trained personnel, validated prototypes, and improvements in public service efficiency.

4.1. Short-Term Goals and Objectives

These objectives focus on the project implementation period (2025–2026) and aim at the transition phase from awareness to structured use.

- **Strengthening institutional cooperation**: Strengthening the cross-border partnership between the University of Oradea and the University of Debrecen to create a practical framework for AI integration. This will include clearly defined roles, responsibilities, and coordination mechanisms between universities, SMEs, and public authorities.
- **Reduce barriers to adoption**: Identify and mitigate barriers related to lack of specialized skills, cost-benefit uncertainty, and data security concerns through practical guides. KPIs include number of organizations receiving guidance and percentage of staff trained in AI fundamentals.
- **Development of basic digital skills**: Implementation of targeted training programmes to cover the skills gaps identified among employees and managers in the region. Training will focus on ICT skills, AI literacy, and practical applications in finance and accounting.
- **Piloting AI solutions**: Encouraging organizations to move from limited experiments to testing AI tools in specific functions, such as financial analysis and accounting operations. Pilot projects will be tracked and evaluated for scalability and impact.

- **Prototype validation**: Using the national network of test and experimentation spaces (TEF) for rapid validation of AI ideas and prototypes. Validated prototypes will inform long-term deployment strategies.

Short-term initiatives will provide the foundation for long-term regional competitiveness, ensuring that training, pilots, and prototype validations evolve into scalable, sustainable AI adoption across the Bihor–Hajdú-Bihar region.

4.2. Long-Term Goals and Objectives

These objectives aim at the strategic vision for the period after 2026, pursuing sustainability and regional competitiveness.

- **Cross-border model of excellence**: Positioning the Bihor-Hajdú-Bihar region as a European reference model in the use of advanced AI techniques in the economic sector. This includes measurable benchmarks such as adoption rates, regional digital maturity, and recognition by EU innovation programs.
- **Transforming the growth model**: Using AI as a catalyst for innovation and attracting investment, with a quantifiable impact on regional GDP. KPIs could include number of AI-driven investments, new products or services, and growth in SME productivity.
- **Digitalization of public services**: Integrate innovative AI tools into 90% of digital public services by 2027. Examples include automated tax processing, AI-supported scheduling in healthcare, and citizen service portals.
- **Maturing the innovation ecosystem**: Creating sustainable synergies between companies, universities and research centers to generate products and services with high added value and international relevance. This will be monitored through joint projects, patent applications, and cross-border collaborations.
- **Independence and scaling of SMEs**: Ensuring the necessary resources for small and medium-sized enterprises to become fully digitized and able to adopt automation at scale. Support mechanisms will include AI tools, training, and mentoring programs.
- **Strong governance and ethics**: Establishing regional ethical standards and a robust governance framework to ensure the responsible and transparent use of AI, in line with the AI Act and GDPR. This includes clear accountability mechanisms, monitoring, and compliance reporting.

Defining clear short-term and long-term goals for AI adoption in finance, accounting, and business administration allows organizations to strategically integrate technology while ensuring alignment with operational efficiency, user needs, and regional development priorities. By combining KPIs, concrete examples, measurable milestones, and coordinated implementation, progress can be tracked effectively, ensuring continuous improvement. Aligned with EU priorities in digital transformation and sustainable development, this strategy positions the Bihor–Hajdú-Bihar region as a model for cross-border AI-driven innovation, turning technological potential into real economic, social, and educational benefits.

CHAPTER 5. STRATEGIC DIRECTIONS OF ACTION

5.1 Legislative, Strategic, and Institutional Framework of Artificial Intelligence

Artificial intelligence has become a transformative technology with widespread applications in diverse sectors such as finance, education, employment, marketing, and policing. However, the rapid deployment of AI systems has raised significant concerns about their ethical implications and the adequacy of existing legal frameworks to regulate them. These concerns have stimulated a global, multi-stakeholder dialogue on AI ethics and governance (Daly et al., 2020).

The rapid advancement and integration of AI technologies in diverse sectors—such as healthcare, autonomous vehicles, finance, media, and public administration—has raised concerns about potential risks, including bias, discrimination, privacy violations, lack of transparency, and ethical breaches. These risks require robust AI governance frameworks that balance innovation with ethical responsibility. AI governance is conceptualized as a multidimensional construct that encompasses regulations, principles, organizational strategies, and technological mechanisms designed to ensure the alignment of AI systems with human values, societal norms, and legal requirements (Batool et al., 2025).

The European Parliament has taken a historic step by adopting the AI Act, the first set of rules at global level aimed at managing the risks associated with artificial intelligence. This initiative is not only a reaction to current challenges but also reflects a deep recognition of how AI is already transforming society, the economy and the public sector. Against the backdrop of a strong digital infrastructure and a strong commitment to innovation, the European Union is becoming a global pioneer in the governance of emerging technologies. Experts estimate that, by 2035, AI could lead to an increase in labor productivity between 11% and 37%, which translates not only into higher economic performance, but also into more efficient processes in all sectors of activity.

The EU AI Law establishes a legal framework that classifies AI systems according to their level of risk, from minimal to unacceptable risk. It requires transparency, human oversight, risk management, and requires developers to report incidents and failures. The law aims to create a trustworthy AI ecosystem, aligned with EU values and fundamental rights (Camilleri, 2024).

Effective AI governance requires multi-stakeholder engagement and international collaboration, reflecting the global and cross-sectoral nature of AI risks. However, the literature shows limited focus on team-level and industry-level governance, indicating potential gaps in operational governance at the local and sector levels. Geographic variations in governance priorities are notable. Europe prioritizes human rights, data protection, and ethical standards through legislation such as the General Data Protection Regulation (GDPR) and the EU AI Act, focusing on fairness, transparency, and accountability. The United States takes a market-based approach that emphasizes innovation, supported by voluntary guidelines such as the NIST AI Risk Management Framework. Asia-Pacific countries present diverse strategies that balance government control, economic development, and responsible implementation of AI, with Singapore and Japan emphasizing ethical and human-centered frameworks. Australia takes an intermediate approach, integrating ethical standards with incentives for innovation (Batool et al., 2025).

More than two-thirds of Member States have AI initiatives that address climate and environmental challenges, such as energy efficiency, emission reduction, waste management, disaster resilience and sustainable business practices. Fewer countries focus on environmental data collection, monitoring or reducing the ecological footprint of AI. Notable programmes include AI-Lighthouses in Germany, AI-powered energy management in Belgium and AI-powered climate science in Italy. Efforts to reduce the carbon footprint of AI include sustainable computing initiatives in Denmark, France, the Netherlands, Slovenia and Spain (OECD, 2025).

Almost all EU Member States have adopted national AI strategies, many of which have been updated to address rapid technological advances such as generative AI. However, implementation and funding vary widely, with less than half having dedicated AI budgets. Coordination mechanisms and monitoring frameworks are uneven, limiting comprehensive assessment of progress. Countries are increasingly investing in data strategies, cloud computing, high-performance computing (HPC) and semiconductor ecosystems to support AI infrastructure. Research capacities are being strengthened through national AI centers and dedicated programmes, although cross-border collaboration remains limited (OECD, 2025).

The National Strategy for Artificial Intelligence in Romania emphasizes an integrated approach and measurable results. Each objective, whether general or specific, is accompanied by clear outcome and impact indicators, as well as ambitious targets for 2025 and 2027. The strategy aims not only to train specialists in the field of AI, but also to develop a digital culture throughout society, encouraging technological literacy and familiarizing the population with new technologies. The emphasis is on expanding and modernizing the infrastructure, creating and sharing relevant data sets, but also on strengthening the national research, development and innovation system. Cooperation between academia, the private sector and public institutions is seen as an essential driver for technology transfer and stimulating innovation (Authority for the Digitization of Romania, 2024).

While AI adoption among businesses, especially SMEs, remains uneven, European Digital Innovation Hubs (EDIHs) and testing facilities provide essential support for innovation adoption. Skills development initiatives range from primary education to adult reskilling, but AI-specific training and attracting talent beyond academia need to be scaled up. Sectoral leadership is emerging in health, public services, mobility, agriculture and climate/environment, but challenges remain in data sharing, coordination and sustainability of AI deployment (OECD, 2025).

In Romania, fostering partnerships between business and research institutes is vital for the rapid transfer of scientific results to the market. Joint projects, the development of AI solutions tailored to the specific needs of industry and the establishment of testing and experimentation centers (TEF) will accelerate the adoption of advanced technologies and increase the added value of Romanian products and services. The adoption of AI in the public sector and SMEs is another strategic objective, with a direct impact on the quality of services and the competitiveness of the economy. By 2027, it is aimed that 90% of digital public services integrate innovative AI tools, and that SMEs become increasingly open to digitalization and automation, which will contribute to increasing administrative efficiency and developing new business models.

The EU AI Law marks a watershed moment in the governance of artificial intelligence, establishing a robust, risk-based and ethically sound regulatory framework. It balances the promotion of innovation with the imperative to protect fundamental rights, safety and societal values. The law's comprehensive scope,

extraterritorial coverage and detailed obligations for providers, implementers and other operators underline the EU's commitment to trustworthy AI (Bird & Bird, 2025).

The success of the law depends on effective enforcement, regulatory cooperation and the development of technical standards and codes of conduct. As AI technology evolves rapidly, the "living" nature of the AI Law – supported by delegated acts, guidelines and ongoing oversight – ensures adaptability. Stakeholders from all industries need to actively engage in the evolving regulatory landscape to ensure compliance and contribute to the safe and responsible deployment of AI in Europe and beyond. The law also sets a global example, influencing AI regulation worldwide and promoting international cooperation, thereby shaping the future trajectory of AI governance globally (Bird & Bird, 2025).

The European Commission's 2020 White Paper on AI proposes a risk-based regulatory framework targeting "high-risk" AI applications, with additional requirements such as human oversight, robust training data and transparency on AI interaction. The EU aims to export its values globally and promote international cooperation based on fundamental rights. The EU also faces challenges such as harmonizing AI-related legislation across Member States and addressing intellectual property issues. Legislative debates and reports continue to shape the evolving regulatory landscape (Daly et al., 2020).

Increasing the number of graduates and specialists in AI and ICT in Romania is one of the pillars of the strategy, reflecting an acute need for advanced skills for the country's technological development. University and vocational training programs will be adapted to market requirements, to ensure a constant flow of talents prepared to meet the challenges of the digital future. The number of graduates in the field of information technology, communications and artificial intelligence is growing rapidly, which announces the emergence of a much larger and well-prepared generation of specialists by 2027. They will bring new ideas, innovative methods and contribute to the profound transformation of the Romanian digital ecosystem, including influencing the way in which companies and public institutions adopt and use AI (Authority for the Digitization of Romania, 2024).

The introduction of an effective governance and regulatory framework for AI in Romania is essential to ensure a balance between innovation and societal protection. Romania aims to move up in global rankings on government readiness for AI, create clear, predictable legislation and develop specialized certification and auditing mechanisms, thus creating a safe and attractive environment for the development of emerging technologies. Romania will establish a robust governance system for AI, including the certification of over 200 applications by 2027. This framework will ensure compliance of technologies with ethical and security standards, increase user trust and stimulate responsible innovation (Romanian Authority for Digitalization, 2024).

From an economic perspective, generative AI is estimated to contribute trillions of dollars annually to global GDP growth by increasing productivity in sectors such as customer operations, software engineering, marketing, and research and development. AI also opens up new value streams in education (personalized learning, immersive AR/VR environments), science (accelerated discovery through autonomous experimentation and AI scientists), transportation (autonomous vehicles and logistics), and agriculture (precision agriculture and supply chain optimization) (International Telecommunication Union, 2025).

In Romania, the development of scientific research and innovation centers in AI aims both to increase the number and quality of publications, and to form clusters of excellence that will become regional

and European benchmarks. The emergence of new research centers, as well as the expansion of collaboration platforms, indicates a maturation of the national innovation ecosystem, capable of attracting and retaining talent and funding (Romanian Authority for Digitalization, 2024).

The EU remains a world leader in AI research publications, but faces increasing competition from China and India. 23 Member States have AI R&D funding programmes, including large-scale national initiatives and thematic projects focusing on language technologies, healthcare and manufacturing. Over half have established AI research centers of excellence; some coordinate them within national networks, although cross-border collaboration is limited. University-led and specialist AI research institutes complement national centers focused on niche or interdisciplinary areas (OECD, 2025).

The publication and wider use of open datasets in various economic and social sectors is essential for stimulating innovation. Romania's target of reaching 2% of all datasets published on European platforms by 2027 illustrates the ambition to transform data into a strategic resource, laying the foundations for the development of AI solutions with a direct impact on the well-being of citizens and the efficiency of public administration. Romania aims to become a key player at European level in open data, by publishing 2% of European datasets by 2027. This initiative opens significant opportunities for the development of AI applications relevant to society, stimulating international collaboration and ensuring access to valuable resources for research and innovation. (Romanian Authority for Digitalization, 2024).

The exponential growth and integration of Artificial Intelligence (AI) into organizational activities have highlighted the need for ethical and responsible implementation of AI. Although numerous national and international regulations, policies and frameworks have been developed to guide responsible AI, the operationalization of these principles during the design, implementation, monitoring and evaluation of AI remains underexplored (Papagiannidis et al., 2025).

Monitoring and evaluating the implementation of AI in Romania, as envisaged in the National Strategy, is not just an administrative necessity, but an essential condition for real progress in this area. Only through a flexible, transparent, data-driven and continuous learning mechanism can Romania hope to harness the potential of AI, manage risks and build an inclusive and responsible digital society. The success of this approach will depend on the commitment of institutions, the quality of intersectoral collaboration and the ability to quickly integrate innovations and lessons learned, in an increasingly competitive and demanding international context (Romanian Authority for Digitalization, 2024).

Periodic reporting, carried out at regular intervals — semi-annually and annually — represents the backbone of a robust monitoring system, which ensures not only continuous supervision, but also the generation of a constant flow of constructive feedback. This sustained frequency not only facilitates the early identification of any deviations from the established trajectory, but also provides the opportunity to quickly and efficiently correct any slippages. Thus, the monitoring process becomes a dynamic one, in which the analysis of the results is carried out both in the medium and long term, providing a comprehensive perspective on the evolution and impact of the measures adopted. At the same time, this framework opens the space for dialogue and continuous collaboration between all the actors involved, from those responsible for implementation, to the final beneficiaries and experts in the field (Romanian Authority for Digitalization, 2024).

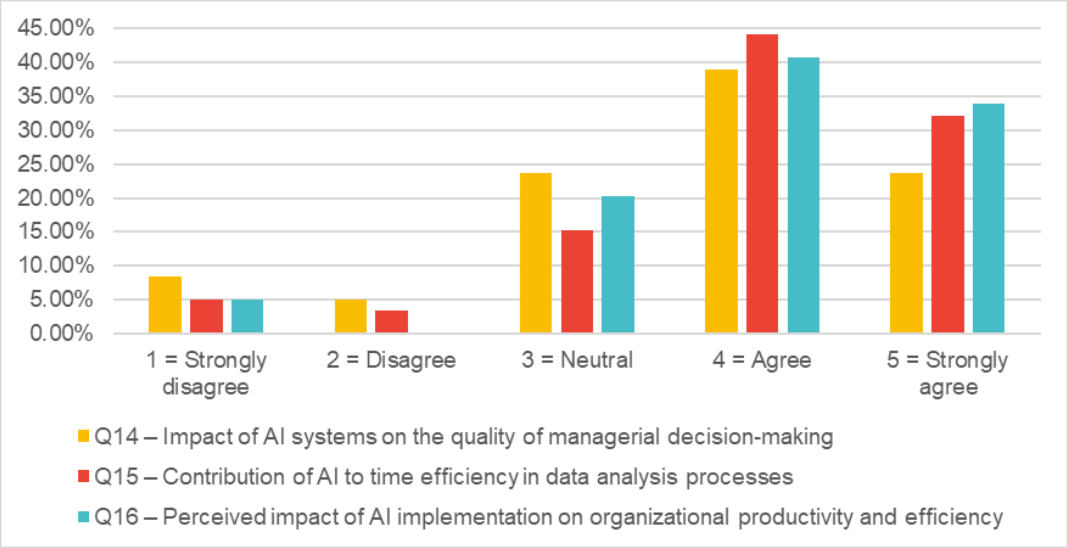
In line with the theoretical framework in this subchapter, we move on to the **empirical analysis** examines organizations' short-term implementation horizons and the factors that may accelerate or delay

this trajectory. The study is based on survey data collected from organizations operating in the Bihor-Hajdú-Bihar cross-border region and focuses on three interconnected dimensions: short-term intentions to adopt AI in the next twelve months, perceived ease of implementation and operational integration, and regulatory constraints and uncertainty affecting the timing of implementation. These dimensions are measured using Likert-scale indicators and summarized by mean values, allowing for the identification of prevailing trends rather than frequency-based adoption rates.

The graphical representations illustrate progression from initial consideration to concrete implementation intentions, while highlighting perceptions of feasibility and external constraints that may shape the timing of implementation. Together, these findings provide empirical support for the theoretical assumption that AI adoption follows a gradual and structured path, conditioned by organizational readiness and the broader regulatory environment.

Figure 5.1 on *operational and decision-making impact* shows by what method people see AI shaking up their work routines. Most respondents think AI helps a lot, especially when it comes to speeding up data analysis and almost 85% agree or strongly agree with that. When it comes to overall productivity and efficiency, about 75% see a clear benefit. Speaking about managerial decision-making, over 62% of respondents feel positive, and nearly a quarter sit on the fence.

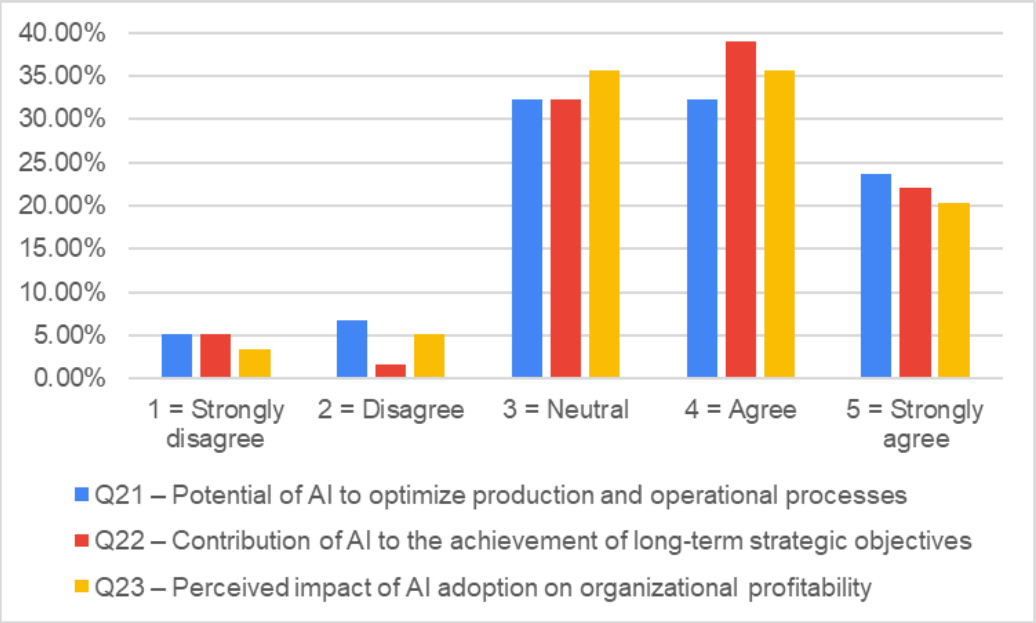
Figure 5.1. – Operational and decision-making impact



Source: Own elaboration based on survey responses

That split suggests people see the real advantage of AI in decision-making only when organizations actually know how to use it well and trust it. All in all, the graph makes one thing clear, AI's operational benefits show up quickly, but the payoff in strategic decision-making takes more time and depends on how mature and confident the organization is with AI.

Figure 5.2. – Strategic Impact and Performance



Source: Own elaboration based on survey responses

Figure 5.2 for the *Strategic Impact and Performance dimension* shows how people see AI's role in their organizations. Most respondents think AI really helps streamline production and operations, about 56% agree or strongly agree with that (Q21). Still, around 32% of respondents are undecided. When it comes to hitting long-term strategic goals (Q22), the numbers look a lot alike: 61% are on board, but that same amount—32%—are neutral. With other words, there's confidence, but also some reluctance.

Looking at profitability (Q23), 57% believe AI boosts the bottom line, but 36% remain undecided. Its clear people see the real financial upsides showing up over the medium to long term, not right out of the gate.

All in all, the graphic paints a picture of AI as a strategic powerhouse, but people still have questions about how much and how soon it'll really pay off. The timing and the maturity of AI adoption still shape how confident folks feel about its impact.

5.2. Budget Plan

Integration of advanced artificial intelligence technologies in areas such as finance, accounting or business administration starts with a rigorous budget, based on a clear strategy and intelligent allocation of resources.

Artificial Intelligence has moved from the experimental stage to an essential pillar of the transformation of global financial markets. Its ability to process huge volumes of data in real time, identify complex patterns and anticipate risks has radically transformed the tools available for trading, risk management, compliance and personalization of customer services (Masood, 2024).

According to the Romanian Digitalization Authority (2024), Romania ranks 18th out of 27 in terms of AI investments relative to GDP. This gap shows that, although interest in AI is growing, the level of investment remains modest compared to other European countries. In order to recover the gap, it is essential

to create an attractive environment for investors, facilitate access to financing, as well as stimulate collaboration between academia, companies and the public sector.

Looking closer, the AI sector is still in its infancy. Most AI startups are in the Seed and Series A stages according to studies conducted by (Gahtow, 2025). Technological complexity and high risks cause investors to be more cautious. Thus, they prefer to invest in smaller, longer-term tranches, and have expectations of profitability over an extended period.

Compared to AI, Fintech is a much more mature sector, with clear business models, attracting consistent funding. Investors tend to prefer sectors where risks are well understood and regulations are clear, which explains why AI has not yet attracted the same volume of investment, despite its disruptive potential (Gahtow, 2025).

From a geographical point of view, the study by Gahtow (2025) shows that disparities are evident. The US benefits from a solid venture capital ecosystem, advanced technological infrastructure and favorable policies. This allows American AI startups to attract funding that is about 40-45% higher than those in Europe or other regions. Europe, on the other hand, suffers from strict regulations, fragmented markets and loss of human resources, which limits access to funding and the possibilities for scaling for AI startups. This imbalance highlights the need for regional policies that stimulate investment and strengthen local ecosystems.

A country's technological level says a lot about how well it can invest intelligently and how much it has evolved through its own national programs. Countries that have reached a technologically advanced level do not only gain access to state-of-the-art equipment and modern infrastructure. They also rely on a highly trained workforce, capable of managing and innovating in complex fields. In such places, the business environment is already mature. Public-private partnerships are not just recent attempts, but solid traditions built over time. These partnerships do not stop at simple investments of money. They also involve the transfer of know-how, the building of innovation networks and the support of large-scale research and development (Romanian Authority for Digitalization, 2024).

The situation is different in countries that joined the European Union later. Romania, for example, is just starting to build such collaborations, but the potential is great. For Romania, European funds play a crucial role. They open up access to financial resources far beyond what the local budget, whether public or private, can offer. In other words, the funds absorbed are vital for large infrastructure, digitalization, education or health projects, projects that can be difficult to implement using only internal resources (Romanian Authority for Digitalization, 2024).

In recent years, public institutions around the world have begun to use AI to modernize their services. One step is to automate administrative processes. This has reduced bureaucracy and found new ways to communicate with citizens. In other words, services are faster and more efficient. AI opens up unprecedented opportunities, such as using data from social networks to inform smarter public policies. Faced with these challenges, many countries have created national strategic plans to manage the risks and maximize the benefits of AI, considering technical, social and public policy aspects (Fatima et al., 2020).

The lack of long-term budgetary and strategic planning affects the public sector in the sense that it cannot support social and economic development. According to studies by Fatima et al. (2020), the solution is measured by a vision for at least five years, built after consulting a wide range of actors and after a serious analysis of options. Unlike the private sector, public institutions must take into account diverse political

and social interests, which makes the process much more complicated. Public policy instruments such as economic incentives, regulations, taxes, transform strategies into real actions. A strategic AI plan cannot ignore either national strengths or vulnerabilities. Thus, they must clearly describe capacity development initiatives and establish solid governance rules to control AI-related risks (Fatima et al., 2020).

The main differences between countries with a tradition in AI and emerging countries, such as Romania, arise from the experience gained in public-private partnerships, the level of infrastructure development and the culture of collaboration between research and industry. In Romania, the lack of a consolidated tradition is partially compensated by the mobilization of European funds, which provide significant resources to accelerate progress. This development model, based on external financing and rapid adaptation, can turn the initial disadvantage into a competitive advantage, allowing Romania to adopt the latest technologies without being constrained by old infrastructures or outdated practices (Romanian Authority for Digitalization, 2024).

The rapid and diverse expansion of AI in the financial sector is bringing about a profound transformation that affects all components of the financial ecosystem, from banks and insurance to capital markets and fintechs. The United States, China and the European Union are at the forefront of research and implementation of these technologies, driving the pace of innovation globally. Advanced machine learning models and neural networks are becoming the backbone of modern financial analysis, enabling the identification and interpretation of complex, non-linear and dynamic market relationships that traditional methods cannot capture (Bahoo et al., 2024).

Effective public-private collaboration models, supported by stimulating fiscal policies and dedicated research funds, accelerate the adoption of AI and multiply the positive economic impact. Such partnerships allow the capitalization of complementary expertise and the mobilization of resources on a large scale (Tonieva et al., 2025).

When it comes to European funds dedicated to research and innovation, Romania has a poor performance. Between 2009 and 2018, the country managed to attract less than 2% of the funds made available through the FP7 and Horizon 2020 programs. Of this, in the period 2014-2020, approximately 301 million euros reached Romanian research, but the success rate of the submitted projects was disappointingly low, at only 12.1%. This rate reflects both the difficulty of preparing competitive projects at European level, as well as a possible lack of administrative expertise and strategy in selecting research topics with high funding potential. In the absence of concrete measures to improve the capacity to attract and manage European funds, Romania risks losing essential opportunities for modernizing its research infrastructure and increasing its long-term competitiveness (Romanian Authority for Digitalization, 2024).

The literature identifies several major research directions, from credit risk modeling to fraud detection, portfolio optimization, and investment decision automation. Increasingly stringent transparency and regulatory requirements require the development of explainable models, and AI is becoming an indispensable tool in detecting, preventing, and managing financial risks and crises. In the future, an ambitious, interdisciplinary, and application-oriented research agenda will be essential to expand and strengthen the role of AI in finance (Bahoo et al., 2024).

An analysis of the structure of beneficiaries of European funds shows that private companies in Romania attracted the largest share of funding (approximately 37% in 2020), followed by research institutes and universities. This shows that the private sector has the potential and agility to initiate innovative

projects, but also highlights the need for closer collaboration with academia. A robust innovation ecosystem is built through synergies between companies, universities and research centers, which can lead to higher-impact projects and the development of products and services with high added value. The lack of such collaborations limits knowledge transfer and reduces the chances of generating disruptive innovations with international relevance (Romanian Authority for Digitalization, 2024).

The efficiency and innovation brought by AI must be permanently balanced with a robust governance framework, based on transparent rules, to maximize the potential of emerging technologies and prevent adverse effects on society and the economy according to studies conducted by Tonieva et al. (2025). The discrepancies between developed and developing countries are manifested not only in digital infrastructure, but also in the level of qualified human resources and digital literacy policies. Cooperation between authorities and the private sector accelerates the process of innovation and expansion of AI technologies, ensuring robust and scalable implementation (Tonieva et al., 2025).

Looking at the distribution of investments by Romania's region, discrepancies are evident. The Competitiveness Operational Programme shows that in less developed regions private investments and public support for research and innovation remained below the targets set for 2023, while in the Bucharest-Ilfov area these investments are completely absent. This imbalance accentuates regional disparities and perpetuates an uneven development model, in which certain areas lag behind. The lack of investment in intellectual capital and research infrastructure in these regions not only limits local potential, but also affects national competitiveness in the long term. An effective strategy would involve measures to stimulate investments and the creation of regional centers of excellence that would reduce gaps and encourage the uniform development of the country (Romanian Authority for Digitalization, 2024).

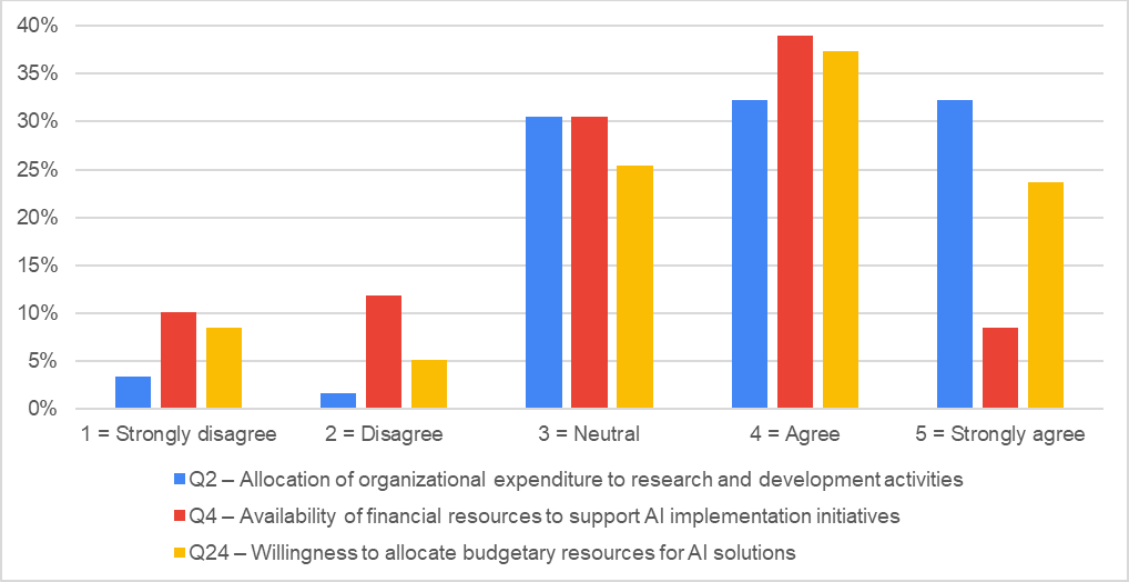
The macroeconomic efficiency of AI is not limited to automating processes or optimizing costs, but fundamentally transforms economic growth models. AI acts as a catalyst for innovation, creating new sectors and attracting investments, with a direct and quantifiable impact on GDP. For these effects to be sustainable, the integration of AI must be anchored in national development strategies, with clear objectives and well-defined performance indicators. The role of digital readiness and infrastructure cannot be underestimated: countries that invest heavily in human capital formation and digital infrastructure development become leaders in harnessing AI, managing to attract talent, investment and innovative projects. The absence of these factors drastically limits growth opportunities, especially in developing economies, where gaps risk becoming irreversible if rapid intervention is not taken (Tonieva et al., 2025).

Romania urgently needs an integrated strategy that combines public and private investments, stimulates collaboration between the business environment, universities and research centers, and makes efficient use of the funds available at European level. Without such an approach, progress will remain slow, and the economy risks losing its competitive advantage compared to other states that invest heavily in innovation and technology. Strengthening administrative capacity, simplifying procedures for accessing funds, and developing public policies that emphasize digitalization, research and innovation are essential (Romanian Authority for Digitalization, 2024).

For the literature review and budget analysis, it was put together a questionnaire and sent it out to professionals in finance, accounting, and business administration. Their answers gave a window into how companies see investments, what their cost structures look like, and where they turn for financing—especially when it comes to bringing artificial intelligence into the picture. The questionnaire didn't just skim the surface. It addressed the core issue directly: *Is it cost-effective and financially feasible to adopt AI*

in these fields, specifically in the Bihor–Hajdú-Bihar Euroregion? We structured it to capture the current state of digital maturity and to gauge how much companies are already using AI-based solutions. In short, based on input from 59 companies (BH)+261 companies (BH+Hajdu Bihar), we now have a solid reference point for making budgeting decisions in this context.

Figure 5.3. Financial Capacity and Budget Allocation



Source: Own elaboration based on survey responses

Figure 5.3 illustrates the survey results, which lean to positive when it comes to funding research and development or rolling out AI projects. For spending on R&D (that's Q2), about 64% agree or strongly agree with it, while 30% stay neutral. This shows there's still a gap between having resources and using them well. When it comes to having enough money for AI (Q4), companies get a bit more cautious. As a result, 47% agree or strongly agree, and 22% disagree, which just shows how different organizations are when it comes to their current budgets.

The answers to the question regarding investing in AI solutions (Q24), support jumps back up. Around 61% say yes, they're on board, while 25% stay on the fence. All in all, organizations that are open to investing in AI see its value and potential, but they're also suspicious.

5.3. Capacity Building and Research & Development

Modern research in the field of artificial intelligence covers a wide range of tasks: from the creation of autonomous systems and intelligent assistants to the development of models capable of analyzing emotions, predicting events and even generating new ideas. Technology transfer and partnerships between the private and academic sectors are gaining strategic importance. Research results do not remain at the theoretical stage, but are quickly transformed into concrete products, services and solutions that meet market demands. The increase in the number of companies specializing in AI and the intensification of collaborations with research institutes demonstrate the ecosystem's maturation, its orientation towards applicability and its capacity to generate economic and social value (Romanian Authority for Digitalization, 2024).

Romania - Hungary

The transition to an economy based on advanced technology in Romania is based primarily on the development of digital skills. The formation of professional qualities in the Romanian educational system is below the minimum level of funding. A general indicator of the quality of pre-university education is also represented by the harmonized scores of the Programme for International Student Assessment (PISA) tests conducted by the OECD and the Trends in International Maths and Science Study (TIMSS) and Progress in International Reading Literacy Study (PIRLS) tests conducted by the International Association for the Evaluation of Educational Performance. In Romania, compared to OECD countries, a relatively higher performance is observed in the field of mathematics and sciences, but below the average of developed countries. This highlights the considerable gap with European standards, but also a pressing need for reforms (Romanian Authority for Digitalization, 2024).

Artificial intelligence has recently emerged as a promising tool for simplifying and improving scientific writing. Using machine learning and natural language processing algorithms, AI assistance can improve the quality and effectiveness of scientific writing. However, as with any new technology, the use of AI assistance in scientific writing has both advantages and disadvantages. AI is now an essential factor. Tools such as big data analysis, machine learning and generative AI are not only changing the technical skills of economics graduates in areas such as marketing or finance but also promote the improvement of non-technical skills: critical thinking, leadership, lifelong learning. This combination shows how complex the requirements for tomorrow's talents are and why education must keep pace with industry expectations. Wu et al. (2026).

The authors (Faqihi and Miah, 2023) analyze how artificial intelligence can help manage risks by collecting digital data and learning from it. However, adopting artificial intelligence for risk management is not simple - lack of know-how, limited budgets, hesitant leaders and the degree of preparation of a company are all obstacles.

Recent years have brought a visible increase in venture capital investments in the field of AI, but Romania still lags behind other European countries in terms of accessing funds for research, innovation and technological development. This gap significantly restricts the growth and scaling potential of innovative companies. The lack of a coherent strategic framework for attracting and managing European funds, as well as excessive bureaucracy, discourages innovative initiatives. In order to fully capitalize on existing opportunities, better coordination between authorities, academia and the private sector is necessary, as well as the implementation of clear strategies for accessing funding available at European level, including through the Horizon Europe or Digital Europe programs. Also, stimulating private investments and creating dedicated AI funds can accelerate the development of the sector, generating a multiplier effect in the economy (Romanian Authority for Digitalization, 2024).

AI research in Romania suffers from modest funding, well below the European average, which limits both the possibility of initiating ambitious projects and the attraction or retention of top researchers. The private sector, especially small and medium-sized companies, rarely invest resources in partnerships with universities, and technology transfer remains at an incipient level. This lack of collaboration reduces the impact of innovation and prevents the transformation of scientific results into products or services with added value for the economy (Romanian Authority for Digitalization, 2024).

SMEs have difficulty adopting artificial intelligence because they do not have the same resources or infrastructure as large corporations. However, these small and medium-sized enterprises keep economies moving and provide jobs for millions of people around the world. Authors Faqihi & Miah (2023) argue that

SMEs need artificial intelligence frameworks designed specifically for them. Specifically, companies need flexible elements that are easy to integrate into their real goals and that work with the way they already manage their employees.

Access to state-of-the-art technological infrastructure, such as supercomputers and hybrid cloud solutions, plays a fundamental role in boosting research in Romania, especially in the field of artificial intelligence. The lack of essential resources shows us that Romanian researchers risk losing touch with the rapid pace of international progress. Integrating these advanced technologies into work processes and ensuring equitable access for all research institutions can guarantee Romania's active and competitive participation in the global AI innovation landscape (Romanian Authority for Digitalization, 2024).

Most studies are empirical, but there is a real lack of research from developing countries. The way the labor market is restructuring, personalized learning supported by AI, and new ways in which different groups can work together are major issues facing developing countries (Lai et al., 2025).

In the European Union, as well as in Romania, expanding the base of specialists in the field of AI and acquiring digital skills as quickly and efficiently as possible is based on investing in teacher training, developing interactive educational platforms, and stimulating collaboration between academia and industry (Romanian Authority for Digitalization, 2024).

The first major objective (GO1) emphasizes the importance of education and continuous training as the foundations of a society prepared to capitalize on and manage the AI revolution. In other words, an integrated educational path is proposed, with initiatives targeting not only universities and research centers, but also high schools, vocational schools and even adult education. The emphasis is on updating study programs, adapting curricula to labor market requirements and close collaboration with industry to ensure the practical relevance of the knowledge acquired. By introducing interdisciplinary modules and partnerships with the private sector, Romania aims to create a new generation of AI specialists, but also to increase the general level of digital literacy. Public information programs and awareness campaigns will contribute to increasing the population's trust in AI, explaining both the benefits and risks associated with this technology (Romanian Authority for Digitalization, 2024).

The use of generative artificial intelligence technologies in education has the potential to revolutionize learning and educational assessment by personalizing the learning experience, providing immediate feedback, and improving the overall learning experience. The relevance of the research is due to the spread of artificial intelligence technologies and the lack of practices for formative assessment of educational achievements in higher education.

As for Romania, OG3 focuses on strengthening the national research, development and innovation (RDI) system in the field of AI. This approach involves supporting fundamental research to advance theoretical knowledge, but also applied research oriented towards concrete solutions for industry and society. In other words, the aim is to reduce the fragmentation of resources by creating centers of excellence and interconnected national networks at European level. Dedicated funding, mentoring programs and stimulating participation in international scientific events will encourage Romanian researchers to become globally competitive. Thus, the emphasis is on interdisciplinarity, on collaboration between fields such as IT, mathematics, social sciences, medicine and economics, generating innovative solutions to complex problems (Romanian Authority for Digitalization, 2024).

The latest research shows that AI excels at identifying each individual's skills, how they prefer to learn, and where they want their career to go. It then creates micro-learning modules and training programs that motivate people and help them acquire new skills. In large, international companies, AI-powered knowledge-sharing platforms have increased satisfaction and retention - especially in areas where innovation matters most (Yanamala, 2024).

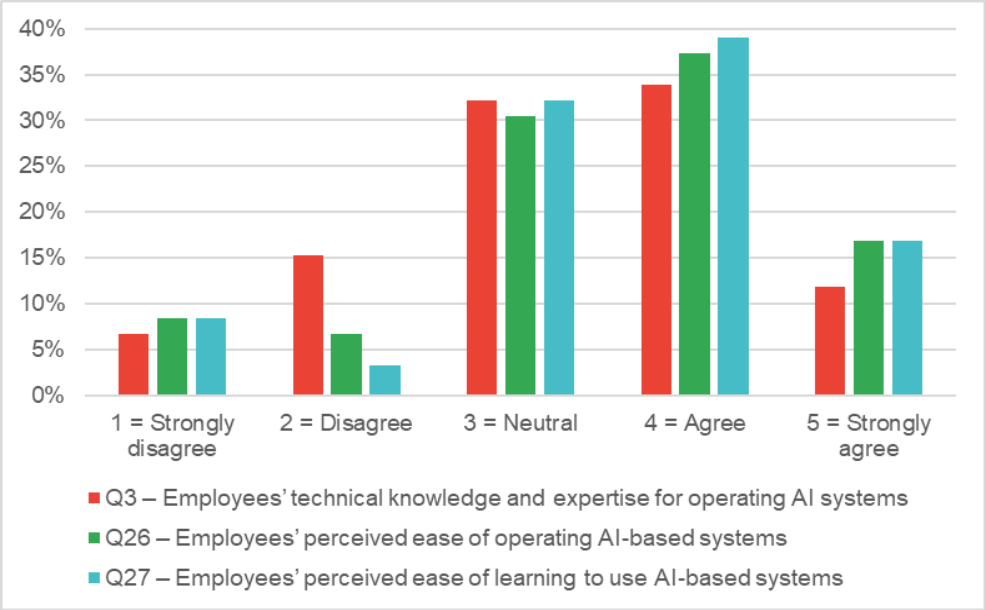
Joshi (2024) takes a detailed look at how generative artificial intelligence (GenAI) and agent-based artificial intelligence are revolutionizing the world of financial services, particularly when it comes to workforce training and bridging the AI skills gap. Joshi examines how these new AI technologies are currently being used, what works, what doesn't, and how they are boosting productivity, improving customer experiences, and changing the way people work in banks and financial institutions.

This study draws on firsthand data collected through detailed questionnaires sent to organizations across a range of economic sectors in the Bihor-Hajdú-Bihar border region. The goal? To really get at how these organizations weave artificial intelligence into their daily work. We zeroed in on capacity building and research and development, since both sit at the heart of successful AI adoption and ongoing innovation. During our evaluation of workforce capabilities, the study didn't just stop at what employees already know about AI concepts. The research went further asking about hands-on skills and, just as importantly, their ability to keep learning. In the fast-moving world of AI, that willingness to adapt and pick up new tools matters just as much as any technical know-how. Workers need to master what's current, but they also have to stay nimble for whatever comes next. From the organizational side, the study wanted to show the culture around innovation. Are teams open to experimenting? Do they try out pilot projects to test AI solutions? Are they building partnerships with universities or research centers? These collaborations can make a real difference, helping to move ideas from theory into practice and sparking new solutions that tackle real business problems. The respondents were asked to pinpoint the toughest barriers they face, anything from not having enough skilled people or money, to doubts about whether investing in AI will pay off, or trouble finding external funding. Using a five-point Likert scale, it was measured just how much these issues weigh on organizations.

These numbers offer concrete evidence that links big-picture theories of AI-driven capacity building and innovation to what organizations are actually experiencing. By shedding light on both the opportunities and the headaches that come with putting these models into practice, the study gives real, actionable insights. The findings capture where AI adoption stands right now in the Bihor-Hajdú-Bihar border region and offer a solid foundation for crafting strategies and policies that drive smarter, more inclusive AI-based growth in the years ahead.

Figure 5.4. shows the findings on "*skills and learning capacity*" capture a picture of employees who are well-prepared and adaptable when it comes to using AI systems.

Figure 5.4. – Skills and learning capacity

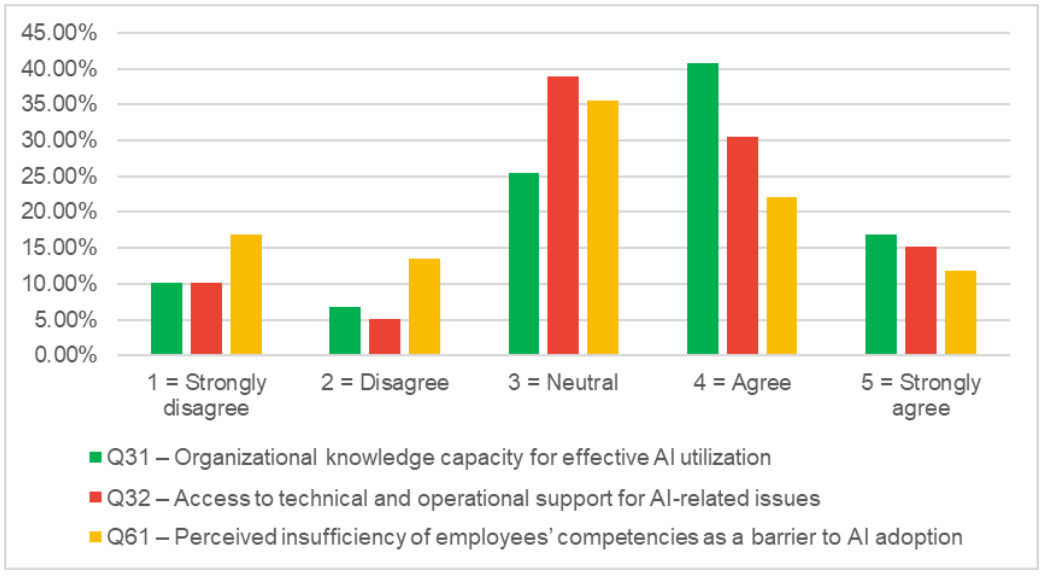


Source: Own elaboration based on survey responses

When asked about their technical knowledge for operating AI (Q3), nearly 46% agreed or strongly agreed that they had enough know-how. About a third felt neutral, which shows technical skills vary quite a bit across the group. Now, when it comes to using AI systems (Q26), the numbers get a little better. Over half—54%—said they found operating AI accessible. Even more encouraging, 56% agreed or strongly agreed that learning to use these systems comes easily (Q27). Still, it's not unanimous. Around 30 to 32% consistently chose a neutral response.

This large piece of neutrality hints at a transitional phase. These organizations aren't quite digital-first yet, they're somewhere between just starting out and building stronger digital skills and organizational learning abilities.

Figure 5.5. – Organizational knowledge and support



Source: Own elaboration based on survey responses

A third of respondents see a lack of employee skills as a barrier to adopting AI. But a large share, over 35%, are undecided, so there's some uncertainty about how much this skills gap really matters for adoption. Overall, people feel their organizations have a decent knowledge base for AI. Still, it's clear they need stronger support systems and more focused skills development if they want to adopt artificial intelligence smoothly and for the long tow.

5.4 Infrastructure and Technology

Deep learning has revolutionized the world of finance. These systems have changed the way we approach credit scoring, identify fraud, automate transactions, manage risk, and optimize portfolios. (Mienye et al., 2024) takes a close look at the main deep learning architectures used in finance: Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), Long-Term Memory Networks (LSTM), Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), Transformers, Generative Adversarial Networks (GAN), Deep Reinforcement Learning (Deep RL), and Deep Belief Networks (DBN). Each of these models brings something different to the table and discusses both their strengths and weaknesses (Mienye et al., 2024).

Industry 4.0 combines digital, physical and biological systems using technologies such as AI, IoT, cloud computing and cyber-physical systems. These new connections are pushing industries to make fast and intelligent decisions that keep complex operations running smoothly. This is where AI-based Decision Support Systems come in as a game-changer. They help organizations analyze massive and messy data sets and provide real-time insights that people can actually use. Unlike old Decision Support Systems, which depend on fixed models and rigid rules, AI-based systems learn on the fly. In other words, they adapt as things change and automate difficult decisions with a level of speed and accuracy we've never seen before. This shift increases efficiency, strengthens predictive maintenance, improves quality management, and makes supply chains more resilient while keeping companies agile and sustainable. In this essay, I bring together what we know so far about AI-powered DSSs in Industry 4.0, analyzing the technology behind them, how they are used, their architecture, the challenges they face, and where research is headed next (Soori et al., 2026).

The world of financial services is changing rapidly. According to research by Ghazi et al. (2025), traditional IT systems cannot keep up with the volume and complexity of information, making it difficult to obtain meaningful information in real time. Thus, cloud computing is not just a technical update but a backbone of how financial institutions operate now. The cloud gives them the flexibility to instantly scale up or down and pay only for what they use. Banks and other financial firms are moving to hybrid and public cloud configurations not just to save money or reduce cumbersome infrastructure, but to move faster and innovate more easily (Ghazi et al., 2025).

In the context of global competitiveness, Romania aims to massively modernize its hardware and software infrastructure, facilitate access to advanced resources such as supercomputers, and develop high-performance cloud platforms. These efforts are complemented by initiatives to collect, standardize, and open data sets from all key areas, generating an enabling environment for research, innovation, and the development of AI-based products and services. The rules for data access will be transparent and fair, stimulating collaboration between the public, private, and academic sectors. At the same time, investments are planned to bring the infrastructure up to European standards and for active participation in international networks and projects (Romanian Authority for Digitalization, 2024).

In addition to these infrastructure upgrades, machine learning has truly earned its status as an essential tool in finance. Traditional statistical methods have their limits – machine learning models go further. They detect nonlinear patterns, keep up with changing data, and simply provide better predictions. What started with credit scoring and fraud detection is now expanding to algorithmic trading, robo-advisory, and even personalization of the customer experience (Ghazi et al., 2025).

Hoang and Wiegratz (2023) examine in detail what differentiates machine learning from traditional econometrics. They review the growing literature on machine learning (ML) in finance and outline a new way to classify how these methods are emerging in the field. Their taxonomy divides ML applications into three main types: building better or entirely new measures, reducing prediction errors in economic forecasting, and extending existing econometric tools.

Banks face strict regulations designed to maintain the stability of the financial system, protect customers and ensure that everything works properly. To ensure they meet these standards, they undergo compliance audits that involve rigorous checks on safety, anti-money laundering controls, consumer protection, IT security and how their internal systems work. Recently, banks have started using artificial intelligence to speed up and refine these checks. They use machine learning and advanced analytics to track transactions, identify risks, and flag anything that seems amiss. But there's a problem. When banks rely on complicated artificial intelligence models, such as deep neural networks, things get blurry. These models are so complex that it's difficult to explain their decisions in simple terms. Regulators expect clear, understandable reasons behind every call, and the "black box" nature of artificial intelligence doesn't make this easy (Desai, 2025).

Even with all these advances, there are still major obstacles to the way financial data is processed. Encryption, data storage in specific locations, and the use of privacy-preserving machine learning methods such as federated learning are essential. Regulators demand transparency, explainability, and auditability, making the use of "black box" machine learning models much more challenging (Ghazi et al., 2025).

In the context of global competitiveness, Romania aims to massively modernize its hardware and software infrastructure, facilitate access to advanced resources such as supercomputers, and develop high-performance cloud platforms. These efforts are complemented by initiatives to collect, standardize, and open data sets from all key areas, generating an enabling environment for research, innovation, and the development of AI-based products and services. The rules for data access will be transparent and fair, stimulating collaboration between the public, private, and academic sectors. At the same time, investments are planned to bring the infrastructure up to European standards and for active participation in international networks and projects (Romanian Authority for Digitalization, 2024).

Romania enjoys a solid digital infrastructure, with high-speed internet and high accessibility at low costs, which gives us a significant competitive advantage in the region. However, major disparities between urban and rural areas affect the equity of access to technology, leaving a significant part of the population behind digitally. If these differences are not addressed, the risk of social and economic polarization increases. In addition to infrastructure, an essential aspect for the development of artificial intelligence is access to quality data, in large volumes and in an open format. Digitizing the public sector, standardizing and opening up government data could stimulate innovation, facilitating the development of relevant AI solutions for citizens and businesses. The implementation of efficient platforms that allow for data sharing and reuse, as well as clear policies on personal data protection, is needed to encourage public trust and participation in this process. Also, inter-institutional collaboration and the involvement of the private sector

in the development of digital infrastructure can accelerate the reduction of regional gaps and the increase of the degree of digitalization at the national level (Romanian Authority for Digitalization, 2024).

As technology continues to advance, regulations such as the EU Artificial Intelligence Act, GDPR, and the Digital Operational Resilience Act (DORA) set real limits on how AI is used – especially when it comes to sensitive activities such as credit scoring or handling personal data. These laws promote transparency, fairness, and strong data security. They don't just suggest best practices; they truly shape how AI is used responsibly in high-risk financial contexts (Alonso-Robisco, 2025).

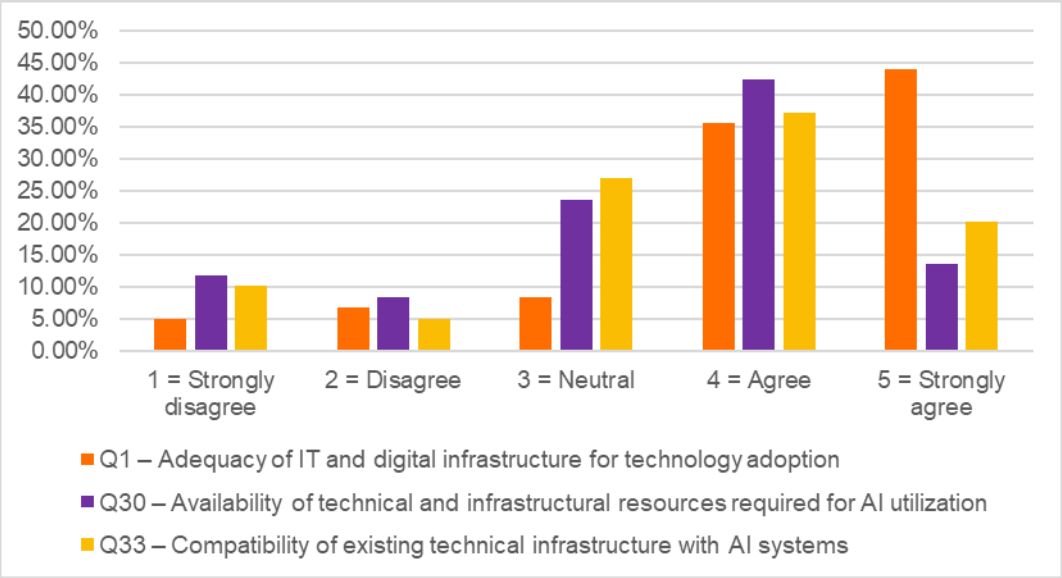
Building on the previous theoretical exploration of how infrastructure and technology drive AI adoption, in the following we provide a nuanced perspective through which to examine the multifaceted process of AI integration. The analysis is structured around three key areas, in line with the general framework introduced in this subchapter, the sophistication and interoperability of digital infrastructure, the extent and manner in which organizations use AI technologies and decision support systems, and the perceived reliability and security of AI-based applications.

To capture the depth of organizational readiness and sentiment, the study uses a series of Likert-scale questions that probe multiple dimensions. These include the accessibility and robustness of cloud-based and technical infrastructure, the penetration and diversity of AI solutions, both generative and personalized, and managerial perspectives on how AI impacts decision quality, operational efficiency, and strategic outcomes. The data is interpreted primarily through descriptive statistics, providing a clear picture of prevailing attitudes and levels of adoption. Visual representations, such as graphs and charts, are used to further illustrate and corroborate emerging trends, making complex models easier for stakeholders to digest and act upon.

The findings provide compelling empirical support for the theoretical premise that a robust digital infrastructure, coupled with deliberate and well-planned technology integration, forms the foundation for successful and sustainable adoption of AI. This is particularly evident in sectors such as finance, accounting, and business administration, where the stakes for accuracy, speed, and security are particularly high. Organizations that invest in modernizing their IT environments and ensuring compatibility between systems are better positioned to unlock the full potential of AI-powered tools, achieving not only immediate productivity gains but also long-term resilience in an increasingly digital landscape. Furthermore, the research highlights that managerial attitudes and strategic vision play a crucial role; leaders who recognize the transformative impact of AI and prioritize its safe and ethical implementation are more likely to foster innovation and maintain a competitive advantage. Finally, the study reinforces the interconnection between infrastructure, technology, and organizational culture in driving meaningful advances through artificial intelligence.

Figure 5.6. on *technical infrastructure and compatibility* show a strong digital foundation for adopting artificial intelligence. Most respondents, almost 80%, feel confident about their organization's IT infrastructure. That's a solid base when it comes to technical resources for using AI (Q30). Results show that about 56% agree they're in good shape, but nearly a quarter feel neutral. This points to some variation between organizations. Looking at compatibility with AI systems (Q33), about 58% see their infrastructure as compatible, while over 27% stay neutral. Clearly, some organizations still need more integration and investment to get their systems fully ready for AI.

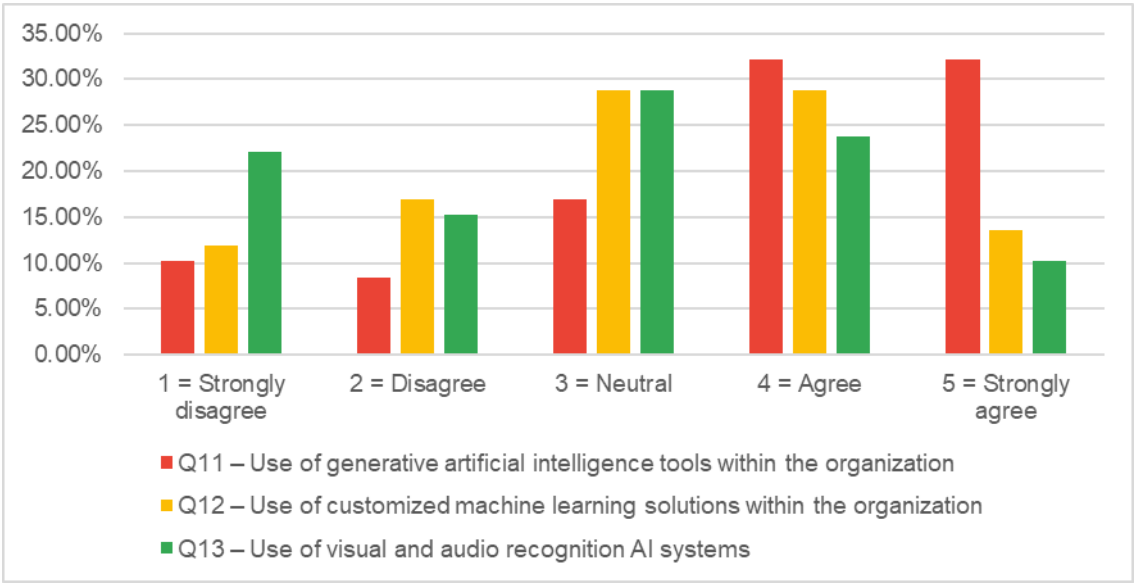
Figure 5.6. – Technical infrastructure and compatibility



Source: Own elaboration based on survey responses

All things considered, technical infrastructure isn't the main hurdle for AI adoption. The bigger challenges lie in building skills, putting the right support in place, and making sure everything lines up strategically.

Figure 5.7. – AI technology use



Source: Own elaboration based on survey responses

Figure 5.7. AI technology use shows some clear trends across organizations right now. Generative AI tools stand out with 64.40% of respondents which say they agree or strongly agree their organizations use them. That's the highest level of acceptance among the technologies surveyed. Personalized machine learning solutions tell a different story. Here, responses cluster in the neutral zone (28.81%), and only 42.37% express agreement. So, adoption is more selective. With other words, organizations seem to weigh

resources and specific needs before jumping in. Visual and audio recognition AI systems look even earlier in their adoption curve.

The responses spread more evenly, with lots of neutral answers (28.81%) and just 10.17% showing strong agreement. From the data, it's clear that generative AI leads the way, while more specialized applications lag behind, probably because they demand more maturity and investment.

5.5. Collaboration and Partnerships

The digital transformation of the economy depends largely on the degree of adoption of emerging technologies by the business environment. When universities and industries collaborate, they drive the digital transformation of businesses. This partnership is not just about exchanging ideas, it stimulates innovation, connects research with real-world needs and helps both parties implement new technologies faster. In other words, universities see their theories in action, while industry partners access cutting-edge knowledge. Ultimately, both parties increase their digital skills (Evans et al., 2023).

In Romania, only 30.2% of innovative enterprises have innovation collaborations, of which very few are with universities or public institutions (5.1%). In fact, Romania has 11 Digital Innovation Hubs (DIH) and 6 European DIHs (EDIH), with a role in supporting the adoption of AI. The lack of testing and experimentation centers for AI solutions is a major problem, influenced by the uncertainty of the European legislative framework (Romanian Authority for Digitalization, 2024).

Collaborative teaching and learning create a real bridge between universities and industry. They push both parties to share knowledge and rethink what students learn. This is seen in joint courses, collaborative teaching, and when companies organize seminars or workshops (Evans et al., 2023).

Looking at it from another perspective, industry professionals have access to scientific research from universities and research institutes, which implies a two-way exchange, where education meets industry, creating a culture that values learning and new ideas. It also ensures that what individuals learn in the classroom aligns with what companies really need, especially when it comes to digital know-how (Evans et al., 2023).

Artificial intelligence is shaking up global commerce, especially cross-border e-commerce companies. It is not only changing the way companies create knowledge, but also pushing them to rethink the way they innovate and remain sustainable. Given all the environmental, social and economic challenges that exist, transforming artificial intelligence into real and sustainable know-how is crucial. In this regard, companies need more than just smart technology. They need the right organizational habits and systems that allow them to continue learning and adapting, even when situations become unforeseen (Wang et al., 2025).

In Romania, large companies and multinationals are the ones that prioritize investing in AI solutions, while most local firms, especially SMEs, face reluctance, lack of expertise and limited financial resources. This situation leads to a slow adoption of AI and the loss of opportunities for efficiency and innovation. In addition, the exodus of IT specialists to Western markets, combined with the lack of infrastructure for testing and experimentation, affects the competitiveness of Romanian companies. However, the ecosystem of AI start-ups is growing, with promising initiatives in areas such as fintech, health, smart agriculture or cybersecurity. Support provided through PNRR, acceleration funds and innovation support policies can stimulate wider adoption of AI, but an entrepreneurial culture that

encourages risk-taking and cross-sector collaboration is also needed. Also, creating regional innovation poles and facilitating access to international research networks can contribute to the development of a business environment open to digitalization and advanced technologies (Romanian Authority for Digitalization, 2024).

Implementing and using AI tools works as a meta-capability built on three connected pillars: planning, integration, and reconfiguration. Planning prepares the organization of resources and ensures that AI projects align with strategy. Integrating AI into current systems allows organizations to access operational know-how in smarter ways. Reconfiguration keeps things flexible, so that AI resources change and adjust as technology evolves or external factors change. They open new avenues for innovation that lead to better outcomes across all domains – environmental, social, and economic. A prime example is AI-based predictive analytics. It improves supply chain efficiency, shapes personalized experiences for stakeholders, and uncovers new revenue opportunities that align perfectly with sustainability goals (Wang et al., 2025).

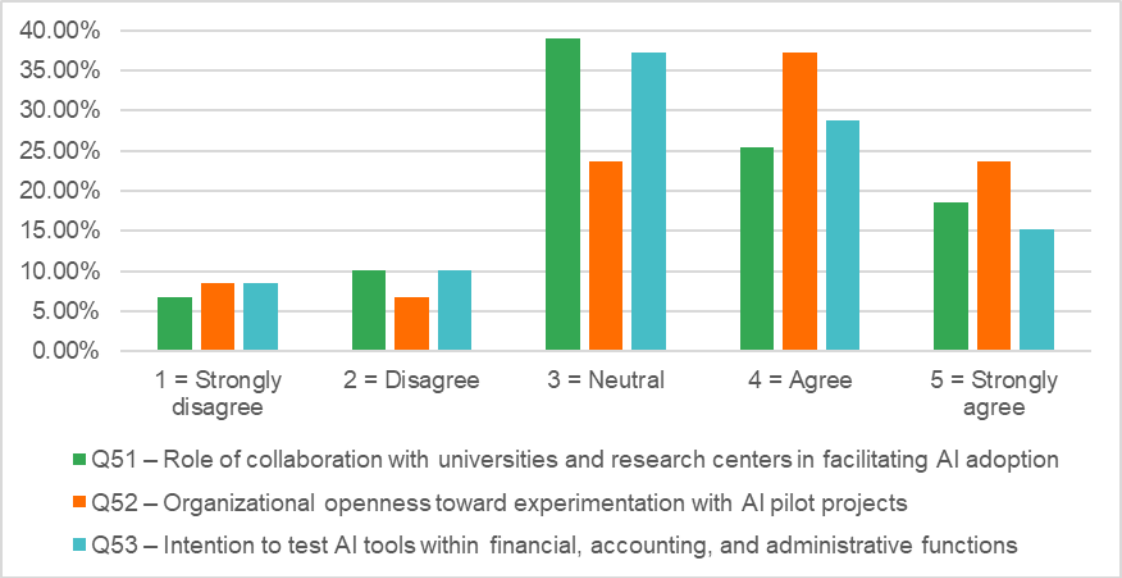
Partner ecosystems play a huge role in accelerating the adoption of artificial intelligence (AI) in banking. They allow banks to share resources, spread risks, and grow faster than they ever could on their own. KPMG's 2025 Banking Technology Study supports this – 74% of banks say they plan to expand their partner networks in the next three years to drive innovation, reach new markets, and connect with more customers (KPMG, 2025). The banking system is moving directly through dynamic ecosystems that allow it to partner with technology companies, FinTech's, and other specialized partners, overcoming old limitations. By focusing on both innovation and robust risk management, banks are accelerating their journeys to AI without losing sight of compliance or security. This approach not only makes back-office operations smoother, but also changes the way banks connect with customers up front. In an industry shaped by AI, building the right partnerships helps banks do more than just keep up with technological changes. In other words, it prepares them to be leaders (KPMG, 2025).

In line with the theoretical framework in this subchapter, we move on to the empirical analysis focuses on the intensity of organizational openness and perceived support for collaborative innovation, rather than the proportion of firms involved in such activities.

Figure 5.8. synthesize these findings by illustrating the average levels of agreement across the analyzed dimensions, thus supporting a nuanced interpretation of collaboration readiness as a matter of organizational orientation and strategic intent, rather than a binary or frequency-based phenomenon.

Figure 5.8. *on Cooperation and external openness* really shows how important outside partnerships and an open attitude are for getting artificial intelligence off the ground. When it comes to working with universities and research centers (Q51), most people land right in the middle. Almost 39% say they're neutral about these collaborations, which points to partnerships that happen now and then, not something done regularly.

Figure 5.8. – Cooperation and external openness



Source: Own elaboration based on survey responses

Looking from the perspective of how organizations handle AI pilot projects (Q52), the difference is clear. Over 62% respondents say they're on board, either agreeing or strongly agreeing that their organizations are open to trying out AI in a hands-on way. It's a practical approach to testing things out, seeing what works and learn along the way. The same pattern can be seen with testing AI in finance, accounting, and admin roles (Q53). About 44% are ready to try, but there's still a big chunk that shows over 37% who sit on the fence. With other words, decision-making is still finding its footing here.

All in all, the graph makes one thing obvious: companies are more willing to experiment with AI inside their walls than commit to steady, formal partnerships outside. Still, that external collaboration side has a lot of room to grow and could really pay off down the line.

5.6 Governance, Sustainability and Competitiveness in the AI Era

Looking at the global picture, economic data points to a future where AI will redefine economic competitiveness. According to analyses by Accenture and PwC, the widespread implementation of AI can even double the rate of economic growth in some countries, with the potential to increase global GDP by up to 14% by 2030. These impressive figures are based on three main drivers: increasing productivity, automating repetitive tasks and stimulating innovation. The service industry, the HORECA sector, but also areas such as health, education or transport will feel a major boost, with benefits not only for companies, but also for consumers and society, through faster, better and more personalized services.

The impact of AI on labor markets is complex. While routine and low-skilled jobs face risks of replacement by automation, AI is also amplifying middle-skilled roles, increasing productivity and reshaping workflows. Freelance platforms show declining demand for some creative and routine tasks, but hybrid human-AI workflows are emerging. Public attitudes favor automation of repetitive tasks but oppose AI in sensitive relational domains (International Telecommunication Union, 2025).

AI adoption among EU businesses is growing but uneven; around 13.5% of businesses use AI, with significant variations by country and firm size. Venture capital investment in EU AI startups remains low

compared to the US. Most EU AI startups focus on downstream applications of fundamental models. Almost half of Member States have testing and experimentation facilities (TEFs), mainly in agriculture, healthcare, manufacturing and smart communities (OECD, 2025).

To capitalize on these benefits, however, substantial and sustained investment is needed. In 2019 alone, the European Union invested between €7.9 and €9 billion in AI, an increase of almost 40% compared to the previous year. The €20 billion target by 2030 is ambitious but achievable, given the growing interest from both the private and public sectors. France, Germany and Spain stand out as investment leaders, setting a fast pace of technological development. On the other hand, countries such as Bulgaria, Slovenia and Croatia, although starting from lower levels, are recording rapid growth, a sign that there is huge potential to catch up if supporting policies are coherent and well-targeted (OECD, 2025)

European Digital Innovation Hubs (EDIHs) provide SMEs with support, training, testing platforms and facilitation of innovation in the field of artificial intelligence; they are active in all Member States. Two-thirds of Member States support the adoption of artificial intelligence in SMEs through financial and advisory programmes, largely integrated into digitalization efforts. Support for access to finance for AI start-ups/scale-ups is increasing, but mainly through general innovation programmes; specific AI/deep tech initiatives are expanding. Some countries have AI-specific start-up accelerator programmes and public-private platforms to encourage knowledge transfer (OECD, 2025).

As for Romania, the impact of AI can be anticipated based on European trends, but it is essential to take into account local particularities. For Romania to fully benefit from the advantages offered by AI, it is necessary to allocate a budget dedicated not only to the development of the technology, but also to the implementation and monitoring of compliance with the European legal framework. The government has to make a strategic choice between creating a new supervisory structure or delegating this responsibility to an existing institution, each option having important financial and administrative implications. Strengthening partnerships between sectors, creating integrated policies and supporting a continuous dialogue with civil society are essential to ensure a framework for sustainable development. In addition, it is important that the strategy is flexible and allows for rapid adaptation to rapid developments in the field, in order not to lose touch with the global pace of innovation (Romanian Authority for Digitalization, 2024).

Hosawi & Stone (2025) define AI broadly as systems capable of human-like cognitive tasks – learning, decision-making, problem-solving – highlighting the immense potential benefits that AI offers in enhancing human capabilities and operational efficiency. However, the implementation of AI in collaborative contexts fundamentally depends on the establishment and calibration of trust. Trust is described as a dynamic psychological state characterized by the willingness to accept vulnerability under conditions of uncertainty, based on positive expectations about the future behavior of the AI, including competence, predictability, reliability, and alignment of goals with the operator. The authors identify three facets that interact and influence trust: the performance of the AI system (reliability, accuracy), the transparency of the process (understandability, explainability), and the alignment of the AI with the goals and goodwill of the operator.

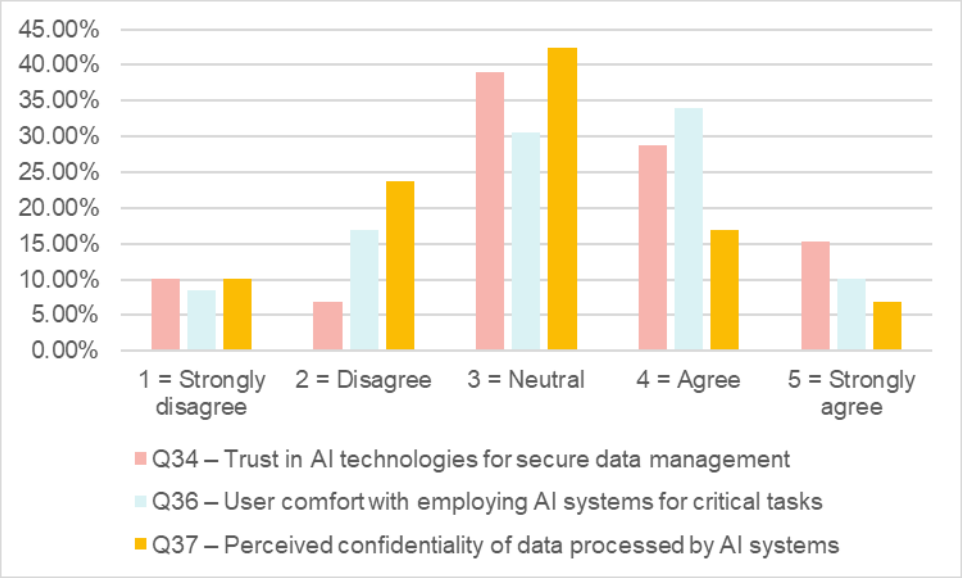
A literature review by Afroogh et al. (2024) presents a nuanced and multi-layered understanding of trust in AI, highlighting that trust is not just a technical attribute, but a complex social construct, influenced by human psychology, societal values, ethical considerations, and organizational contexts. Successful adoption and integration of AI across domains depends on a careful balance between transparency, explainability, fairness, confidentiality, empathy, and accountability, while recognizing the diversity of user

needs and cultural contexts. In conclusion, promoting trustworthy AI requires a holistic approach that integrates technical rigor with ethical and social awareness, thereby enabling AI systems to become reliable collaborators and augmenters of human endeavors.

In line with the theoretical framework in this chapter, we move on to the empirical analysis examines organizational perceptions related to trust, explainability and ethical alignment of AI systems. The study is based on survey data collected from organizations operating in the Bihor-Hajdú-Bihar cross-border region and focuses on key dimensions relevant to communication and awareness, including comfort with the use of AI in critical tasks, the perceived role of AI as a support for human decision-making and concerns related to human supervision and control.

In addition, the analysis investigates the level of ethical awareness within organizations, as well as the perceived alignment of AI systems with organizational values and employee interests. These aspects are measured using Likert-scale indicators allowing the identification of predominant orientations, rather than binary outcomes of adoption. Graphical representations synthesize these findings by illustrating the average levels of agreement across the analyzed dimensions, thus providing empirical support for the theoretical argument that effective communication and awareness-raising mechanisms are essential for promoting trust and acceptance of AI technologies.

Figure 5.9. – Trust and Data Security



Source: Own elaboration based on survey responses

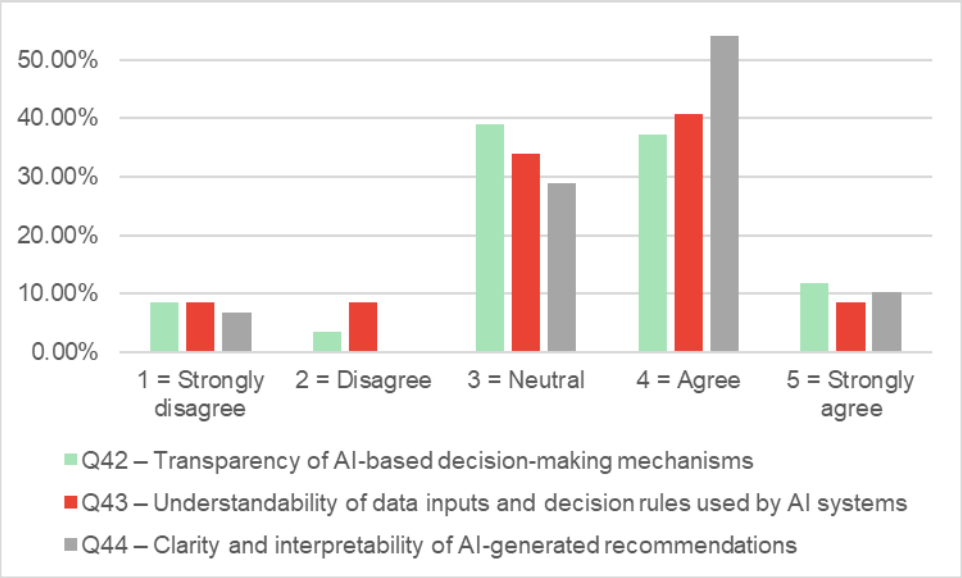
Figure 5.9 *Trust and Data Security* show how people really feel about using AI when it comes to keeping data safe and confidential. Most responses land right in the middle as people seem cautious, not fully convinced but not entirely distrustful either. For instance, when asked about trusting AI to manage data security (Q34), nearly 39% are hesitant, while about 44% felt confident or very confident. That means some trust is there, but it's still shaky, not quite solid yet.

Looking at how comfortable users feel letting AI handle critical tasks (Q36), the answers split up more evenly. Around 46% feel good or very good about it, but about 31% don't lean either way. So, people are starting to warm up to the idea, but there's still plenty of hesitation.

The biggest red flag pops up with data confidentiality (Q37). Here, over 42% of respondents stay neutral, and only about 24% really trust AI to keep their data private. That gap shows people still worry about how AI handles sensitive information.

All in all, trust and data security clearly matter a lot. They shape how fast and how widely people are willing to accept AI, and they tie directly to how organizations handle governance, transparency, and compliance. If those pieces aren't strong, AI adoption slows down.

Figure 5.10. – Transparency and Explainability



Source: Own elaboration based on survey responses

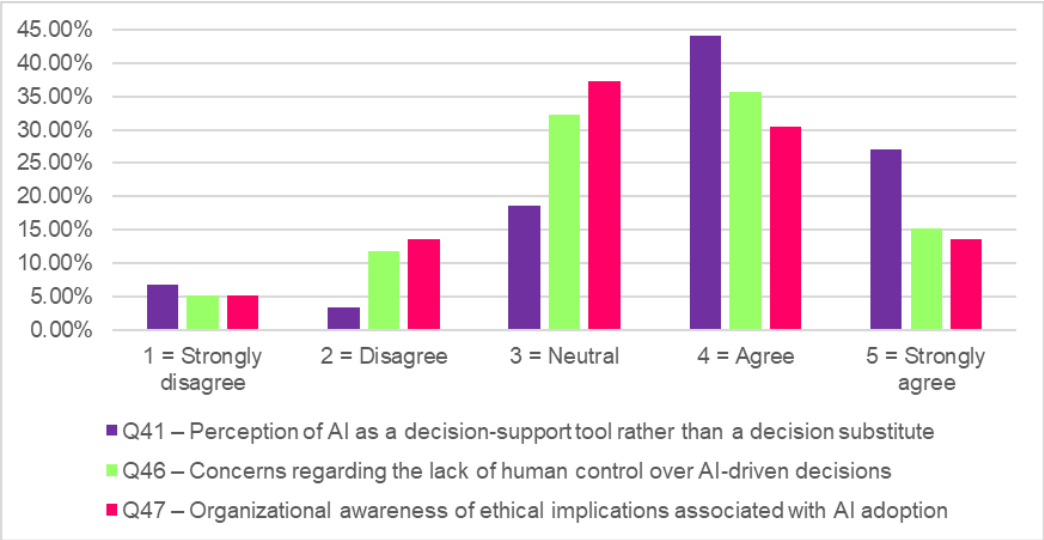
Figure 5.10 on *Transparency and Explainability* shows how people view the clarity and openness of AI systems in their organizations. Most respondents seem favorable with how clear the AI's recommendations are—64.41% agree or strongly agree that they understand what the AI suggests (Q44). That's a solid endorsement of the results these systems provide. However, regarding the transparency behind AI decision-making (Q42), people hesitate. About 39% sit on the fence, answering neutrally. This indicates they are still having difficulty understanding the manner in which these decisions actually happen. The case is much the same for understanding data inputs and decision-making rules (Q43): 46.75% say they agree or strongly agree that these rules are clear, but a notable 33.9% remain neutral.

Respondents find the outputs of AI and the recommendations it provides reasonably easy to understand. However, examined closely, the mechanism of these systems gets overcast. That lack of clarity inside the "black box" impacts how much people trust AI, and it shapes how organizations govern these technologies.

Figure 5.11 on Ethics, Control, and Accountability demonstrates how individuals perceive AI's part in decision-making, the extent of control humans maintains, and how aware they are of the ethical issues AI brings. Most respondents, 71.19%, accept AI as a tool to support decisions, not to replace humans entirely (Q41). That communicates an unmistakable message: individuals still desire humans to lead concerning crucial decisions. Yet worries about losing human control over AI decisions remain strong. Half the group—50.84%—agree or strongly agree they're concerned about this (Q46), and another 32.20% sit on the fence, unsure. That split reveals some real uncertainty about how much freedom AI systems should

have. Regarding ethics, 43.56% agree or strongly agree they understand the ethical stakes of bringing AI into organizations (Q47).

Figure 5.11 – Ethics, Control, and Accountability



Source: Own elaboration based on survey responses

However, a significant part, 37.29%, feel neutral, which shows there's room to grow when it comes to building stronger ethics and governance around AI. In the end, the graph does not indicate an easy solution. It outlines the push and pulls between wanting to use AI and needing control, transparency, and accountability qualities that matter if we want AI to fit into society in a fair and sustainable way.

Considering all perspectives, it is evident that businesses are implementing artificial intelligence in a landscape that's mostly positive, but far from uniform. People are open, sometimes even eager, to learn and use AI, but advanced technical skills aren't evenly spread out. This unevenness points to a real need for ongoing training and serious investment in professional growth. Generative AI tools are seeing the most use right now. In terms of impact, AI's biggest wins are operational. Teams notice it boosts efficiency and productivity right away. The strategic gains, profits, long-term performance, aren't as obvious yet. Individuals remain optimistic, but they're still watching and waiting for those results to develop over time. Inside organizations, there's a strong drive to experiment with AI, but this enthusiasm doesn't always extend outward to partnerships or formal collaborations. Trust, data security, ethics, and keeping humans in control, these are still big concerns. They shape how fast and how far AI adoption goes.

In the end, the real barriers aren't about technology itself. The tools exist. What matters now is strategic direction, skill-building, strong governance, and clear ethical guidelines. These things will decide whether AI becomes a sustainable, responsible part of the organization's future.

Chapter 6. Monitoring and Evaluation

The digital transformation brought about by Artificial Intelligence (AI) represents one of the most significant structural changes in the contemporary economic environment. Companies aim to implement strategies based on artificial intelligence to increase the efficiency of operational activities and investments, reduce costs, improve decision-making processes, and, last but not least, consolidate competitive advantage. (Brynjolfsson & McAfee, 2014; Davenport & Ronanki, 2018).

The implementation of an Artificial Intelligence (AI) strategy means a complex process that involves significant investments, organizational transformations, organizational adaptations, cultural transformations, and the redefinition of financial and administrative processes. Artificial Intelligence is a major vector of the company's digital transformation, with a direct impact on economic performance, operational efficiency, and competitive advantage. However, implementing AI tools does not automatically mean achieving success. The lack of clear mechanisms for measuring efficiency and financial performance can lead to underperforming investments and difficulties in justifying allocated budgets.

The success of an AI strategy cannot be measured solely by technological adoption but requires a coherent system of Key Performance Indicators (KPIs). Key performance indicators (KPIs) for artificial intelligence tools and solutions enable monitoring their implementation, measuring company progress, and evaluating the financial, accounting, and organizational impact of these solutions.

Developing a system of indicators aligned with the company's strategic objectives is a way to ensure the efficiency and sustainability of digital transformations. This chapter proposes an integrated framework for monitoring AI strategy, structured in three areas: finance, accounting, and business administration. Conceptual models, quantifiable indicators, and their correlation with the implementation stages are presented.

In this context, KPIs become essential tools for monitoring implementation, measuring progress, assessing economic and organizational impact, and substantiating strategic decisions. KPIs for AI must pursue three major dimensions:

- Financial efficiency and return on investment
- Impact on accounting processes and internal control
- Administrative performance and organizational transformation

An integrated model for evaluating the AI strategy is presented in **Figure 6.1**, highlighting the interdependence among the three dimensions of organizational performance.

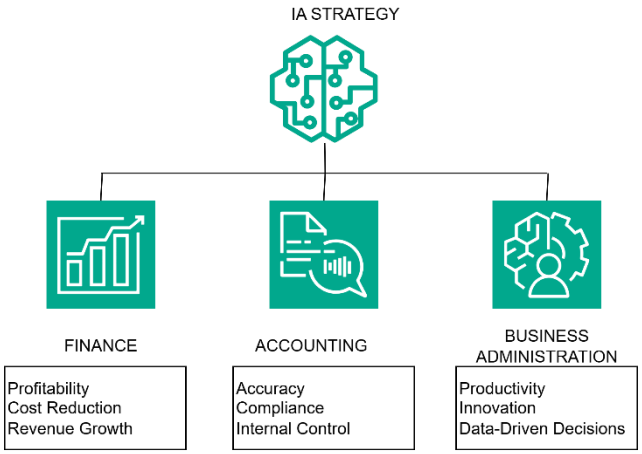


Figure 6.1. Interdependence of the dimensions of organizational performance

The model proposes a three-dimensional approach, in which overall performance results from the interaction among the three domains.

6.1. Key Performance Indicators for Finance

The financial strategic objective is to maximize the value generated by investments in AI and ensure economic sustainability. Implementing AI involves significant investments in technology, infrastructure, training, and organizational change. Financial KPIs are essential to assess the profitability and sustainability of the strategy. Some proposals for key financial KPIs for finance are presented in Table 1.

Table 6.1. Key performance indicators for Finance

Indicator	Formula / Measurement	Purpose
ROI IA	(Net Benefits / Total IA Cost) × 100	Measure profitability
TCO	Total Lifecycle Cost	Sustainability Assessment
Payback Period	Initial Investment / Annual Net Flow	Return on investment
Operational savings	Cost reduction (%)	Efficiency
Revenue growth	Δ revenue attributed to IA	Strategic impact
Financial productivity	Profit/employee	Resource optimization
Degree of financial automation	Percentage of AI-automated financial processes	Optimization of the activity

Return on Investment (ROI), calculated according to the formula:

$$ROI = \frac{Net\ benefits\ generated\ by\ AI}{Total\ costs\ of\ AI} \times 100$$

measures the profitability of AI projects and shows whether investments produce real economic value. The monitoring of this indicator is carried out by project, AI solution portfolio, and period (quarterly/annually). Initially, the costs are high, but the benefits appear progressively as the implementation matures. This indicator reflects the ability of AI projects to generate real financial value and is the primary tool for economic justification of technology investments (Porter, 1985).

The **Total Cost of Ownership (TCO)** includes development/acquisition costs, Infrastructure costs (cloud, servers, licenses), Maintenance costs, Training costs, and integration costs. The purpose of this indicator is to assess long-term financial sustainability. TCO provides a complete picture of the financial effort required to maintain AI solutions, avoiding underestimating indirect or recurring costs.

The **Payback Period** is the time required to recover the initial investment. A mature AI project should have a payback period of 2–3 years or less (depending on the industry). This indicator enables assessing how quickly AI investment becomes profitable and contributes to financial risk analysis.

AI-generated operational savings measure reductions in administrative costs, personnel costs (through automation), and financial errors. Examples: decreasing the cost of processing an invoice, reducing the cost per transaction, etc. Operational savings highlight the efficiency of AI deployment by decreasing repetitive costs and optimizing resource utilization.

The revenue growth attributable to AI can be measured by indicators such as sales growth driven by predictive analytics, higher customer retention rates, or price optimization enabled by AI models. This indicator demonstrates the strategic impact of AI on business development and the organization's ability to generate new revenue streams.

Financial productivity measures revenue per employee, operating profit per employee, or the volume of transactions processed automatically. Financial productivity reflects the efficiency with which capital and labor are used in the context of digitized financial processes.

The degree of financial automation can be used in the entity's activities, such as invoice processing, bank reconciliation, or risk analysis. This indicator highlights the level of digitalization of the finance function and the organization's ability to reduce manual intervention.

Advanced Financial Efficiency Indicators **can also be used**, such as: cost per transaction processed automatically, Percentage reduction in financial errors, Volume of transactions processed by AI, and Percentage of digital budget of total budget.

6.2. Key Performance Indicators for Accounting

The strategic objective of accounting is to process and provide relevant information to those interested in the economic entity. In this regard, it is very important to increase the accuracy, transparency, and speed of accounting processes through automation and predictive analytics. AI profoundly influences accounting processes through automation, anomaly detection, and improved internal control. Some proposals for key financial KPIs for accounting are presented in Table 2.

Table 6.2. Key Performance Indicators for Accounting

Indicator	Formula / Measurement	Purpose
Accounting Process Automation Rate	Automated processes / total processes	Efficiency
Accounting error rate	No. of errors / total transactions	Accuracy
Financial Close Time	No. of days	Speed
Number of anomalies detected	AI Monitoring	Internal control
Cost audit	Total audit cost / no. Processes	Optimization
Document Digitization Degree	% electronic documents	Modernization

Automation rate of accounting processes, calculated according to the formula:

$$Accounting\ process\ automation\ rate = \frac{Number\ of\ processes\ automated}{Total\ number\ of\ processes} \text{ x } 100$$

It measures the shares of automatically processed invoices, automatically reconciled transactions, and automatically generated reports, thereby reducing manual work and human error. The indicator shows the level of technological efficiency of the accounting department and the degree of reduction of repetitive activities.

The accounting error rate, calculated according to the formula:

$$The\ accounting\ error\ rate = \frac{Number\ of\ errors}{Total\ number\ of\ transactions} \text{ x } 100$$

expresses credibility in the accounting information provided. In this sense, AI should reduce errors and increase the accuracy of financial data. The decrease in the error rate confirms improvements in the accuracy of financial information and in internal control. As automation increases, the error rate decreases significantly.

The Financial Close Cycle is the number of days required for monthly, quarterly, or annual closing. The implementation of AI should significantly reduce this range. The reduction in this indicator reflects increased processing speed and improved, timely reporting.

The quality of accounting data is the foundation of managerial decisions and compliant financial reporting. It can be measured by indicators such as: Degree of completeness, Data consistency, and Elimination of duplicates. In this sense, AI enables automatic data cleansing and real-time record validation.

The degree of accounting digitization is measured by the share of electronic documents in the total documents entered and exited from accounting, the extent of ERP integration with AI systems, and system interoperability. This indicator reflects the level of modernization of the accounting system and the ability to integrate with digital platforms.

The degree of compliance and internal control can be measured by indicators such as: the number of deviations automatically detected, the number of frauds identified by algorithms, and the level of compliance with the legal regulations in force.

The efficiency of internal audit can be measured by average audit time, audit cost per process, and the number of proactively detected anomalies. AI is useful for automating checks and identifying risks in real time. The use of AI also allows for real-time fraud detection, analysis of abnormal transactions, continuous compliance monitoring, and automated reporting to authorities.

6.3. Key Performance Indicators for Business Administration

The strategic administrative objective is to transform the organization into a data-driven organization. AI transforms business administration through data-driven decisions, process optimization, and improved customer experience. Some proposals for key financial KPIs for accounting are presented in Table 3.

Table 6.3. Key Performance Indicators for Business Administration

Indicator	Formula / Measurement	Purpose
AI Adoption Degree	No. of user departments	Integration
Digital Maturity	Rating level (1–4)	Evolution
Administrative process time	Minutes/Hours	Productivity
Employee satisfaction	Internal Score	Cultural impact
NPS customers	Net Promoter Score	Customer Orientation
No. of AI initiatives	Annual	Innovation

The level of AI adoption in the organization is measured by indicators such as the number of departments using AI, the number of active users, and the share of decisions made with AI analytics.

The AI maturity model, shown in Figure 2, indicates the degree to which the organization has integrated AI into decision-making and operational processes and reflects the four-level assessment of the development of the organization's digital and analytical capabilities (OECD, 2021).

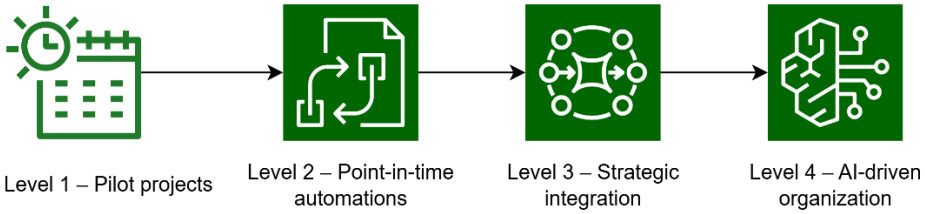


Figure 6.2. Organizational maturity levels

The strategic objective is to reach level 4, where AI supports real-time decision-making.

Net Promoter Score (NPS) is the net score of promoters and is calculated according to the formula:

$$NPS = \frac{Number\ of\ Promoters - Number\ of\ Detractors}{Total\ Number\ of\ Respondents} \text{ x } 100$$

Where:

- Promoters = respondents who give a score of 9–10
- Neutral (Passive) = respondents who score 7–8 (not included in the NPS calculation)
- Detractors = respondents who give a score of 0–6

NPS ranges from −100 to +100. Positive values greater than +50 indicate strong promoter customers and loyalty; values close to 0 indicate a balance between promoters and detractors; and negative values indicate more detractors than promoters, which is an alarm signal for the company.

The measurement of qualitative characteristics can be achieved through indicators regarding:

- **Operational productivity**, which represents the ratio between the operational output and the resources used: average administrative process time, response time to customers, and administrative cost per unit. Increased operational productivity demonstrates the efficiency of process reorganization through automation and predictive analytics

- **Quality of managerial decisions**: accuracy of forecasts, Reduction of budget deviations, Speed of reaction to changes
- **Employee satisfaction**: degree of satisfaction, level of digital skills, retention rate of qualified personnel, time to adapt to change, and share of employees trained in AI. A high level of satisfaction indicates acceptance of technology and positive adaptation to digital transformation.
- **Customer satisfaction** measures the organization's loyalty and likelihood to recommend: Net Promoter Score (NPS), response time, and complaint rate. Improved customer satisfaction reflects the impact of AI on service quality and user experience.
- **Innovation capacity**: number of AI initiatives, time to launch new products, revenue from AI-based products. This indicator highlights the organization's innovation capacity and strategic orientation towards digitalization.

For an effective assessment, KPIs should be structured in stages (Table 4).

Table 6.4. Linking KPIs to AI implementation steps

Step	Key KPIs	Observations
Planning	Allocated budget, cost-benefit analysis	Goal Definition
Implementation	Meeting deadlines, cost vs budget	Degree of adoption
Operation	Automation rate, ROI, productivity	Algorithm performance
Optimization	Scalability, innovation, cumulative ROI	Continuous improvement

Therefore, the evaluation of AI performance must combine financial indicators, operational indicators, cultural and organizational indicators, and innovation and competitiveness indicators. An unbalanced (exclusively financial) system can underestimate the impact of organizational transformation.

Monitoring the implementation of the Artificial Intelligence strategy requires a coherent system of KPIs covering:

- **Financial dimension** – to ensure financial performance, profitability, and sustainability of investments.
- **Accounting dimension** – to increase the accuracy, compliance, and efficiency of financial processes.
- **Administrative dimension** – to transform the organization into a data- and innovation-oriented one.

The success of AI implementation is not only measured by reducing costs, but also by:

- Strategic value creation
- Improving the quality of decisions
- Increasing competitiveness
- Strengthening long-term sustainability

A well-structured system of KPIs enables continuous strategy adjustment and transforms AI from a technological project into a sustainable competitive advantage.

Chapter 7. Risk Management

In this chapter, risk is treated as the combined effect of uncertainty on the strategy's objectives, including schedule, budget, quality, legal compliance, stakeholder trust, and long-term sustainability. The risk management approach follows a lifecycle perspective: identifying risks early, reducing the probability of occurrence where feasible, limiting impact through controls and contingency plans, and continuously monitoring emerging risks as technology, regulation, and stakeholder expectations evolve.

7.1. Introduction and context of risk management

The implementation of advanced Artificial Intelligence (AI) techniques in the fields of finance, accounting and business administration is a complex undertaking, marked by significant opportunities, but also by inherent uncertainties. Within the ROHU00120 project, risk management is conceived as a strategic tool to ensure the resilience and success of technological integration in the Bihor–Hajdú-Bihar cross-border region. This approach aims to proactively identify obstacles and develop mitigation strategies adapted to the socio-economic context and digital maturity specific to the two counties.

The implementation of advanced Artificial Intelligence (AI) techniques in the Bihor–Hajdú-Bihar region, coordinated by the University of Oradea and the University of Debrecen, requires a structured approach to risk management to overcome the barriers identified within the ROHU00120 project. Universities play a key role in mitigating human risks, identified in sources as factors such as lack of internal skills and employee alienation from technology. Intervention strategies include:

- *Developing the material base*. Universities can organize specific training programs to correct the insufficiency of technical knowledge of employees, a major barrier reported by organizations.
- *Facilitating adoption through collaboration*. Surveys indicate that collaboration with research centers and universities would facilitate the adoption of AI. Through joint projects, universities can provide expertise to make AI systems easier to understand and operate.
- *Promoting experimentation*. Universities can support organizations in implementing pilot projects, providing a safe environment for testing, which reduces resistance to change and increases favorable attitudes towards the technology.

The risk management process supports four practical objectives. First, it protects the strategy's deliverables: digital maturity assessment, pilot AI use cases, training activities, and cross-border knowledge transfer. Second, it protects stakeholders, including students, researchers, public institutions, SMEs, and citizens affected by the deployment of AI in financial and administrative processes. Third, it ensures compliance with evolving EU and national requirements for data protection, cybersecurity, and AI governance.

Fourth, it builds credibility and adoption by ensuring that AI systems are reliable, explainable, and aligned with business value.

The following principles guide implementation:

- *proportionality*: controls are matched to risk severity and the maturity of the implementing organization
- transparency: assumptions, limitations, and decision rationales are documented and communicated.
- *accountability:* ownership of each material risk is assigned, with clear escalation paths

- *security and privacy by design*: safeguards are integrated into data and model pipelines from the start
- *human oversight:* AI supports decisions but does not remove responsibility from humans.

7.2. Risk identification and classification

Effective AI risk management requires clear governance. The recommended structure includes: a Steering Committee responsible for strategic direction, approvals of major changes, and acceptance of residual high risks; a Risk Owner for each major workstream (data, models, IT infrastructure, legal/compliance, training, and stakeholder engagement); a Project Management Office function that maintains the risk register, ensures periodic reviews, and verifies that mitigation actions are executed; a Data Protection Officer or privacy lead that validates GDPR compliance for data processing, sharing, and retention and an Information Security lead that ensures secure infrastructure, access controls, and incident response. Reporting should be routine and measurable. A monthly risk review meeting is recommended during implementation and pilot phases, with a quarterly summary for senior leadership. Risk indicators and key control metrics (for example model performance drift, number of security alerts, time to resolve incidents, training completion rates) should be used to detect early warnings.

The risk identification process was based on a needs assessment and analysis of barriers identified among organizations in the region, from micro-enterprises to large companies. Risks should be identified through a combination of workshops with academic and industry stakeholders, process mapping of AI-enabled workflows in finance and administration, review of previous project lessons learned, regulatory scanning for AI, data protection, and cybersecurity obligations and technical assessment of data quality, systems integration, and operational constraints.

A structured *Risk Register* should record for each risk: description, category, root causes, probability, impact, overall rating, owner, mitigation plan, contingency plan, early warning indicators, and review date. The register should be a living document updated throughout the project.

The risks are classified into five fundamental categories:

A. Technological and infrastructure risks. A major barrier to AI adoption is the incompatibility of existing technical infrastructure.

- *Digital maturity deficit*. Many organizations lack the appropriate infrastructure (cloud services, high-speed internet) needed to support advanced AI systems.
- *System errors and lack of reliability*. There are concerns about the reliability of AI operations, especially in critical processes such as financial reporting or management decisions.
- *Integration issues.* The difficulty of integrating personalized machine learning tools or generative AI into daily processes without excessive technical effort.

AI pipelines increase the attack surface through additional software dependencies, APIs, and data flows. Risks include unauthorized access, data breaches, ransomware, and model manipulation (such as data poisoning). Mitigation includes least-privilege access controls, encryption in transit and at rest, vulnerability management, secure MLOps practices, and incident response planning.

Business continuity risk is also relevant. If AI services are embedded in operational processes, outages may disrupt finance and administrative activities. Mitigation includes redundancy, clear fallback procedures to manual processing, and tested disaster recovery plans.

B. Human and organizational risks. The human factor is a central pillar in the success of the strategy, but also a main source of risk.

- *Lack of internal skills*. The survey indicates that the lack of knowledge and expertise of employees to operate AI systems is a critical barrier.
- *Resistance to change and employee alienation*. There is a risk that employees will feel alienated by new technologies or perceive AI as a threat to their professional roles.
- *Lack of managerial support*. Success is conditional on management commitment; the absence of a clear vision of the benefits of AI can block investments.

Misalignment between AI initiatives and organizational priorities can lead to low adoption and poor return on investment. This risk is amplified when stakeholders view AI as a technology push rather than a solution to specific business problems. Mitigation includes a clear use-case selection framework, measurable success criteria, and joint ownership between technical and business representatives. Talent and change management risk is also material. Limited AI skills, resistance to process changes, and lack of user trust can delay implementation. Mitigation includes phased training, user-centered design, and involvement of end-users in pilot evaluation.

C. Economic and financial risks. Implementing AI requires considerable financial resources, and economic uncertainty can discourage adoption.

- *Difficulty estimating return on investment (ROI).* Organizations face difficulties in quantifying the short- and medium-term financial benefits of AI technologies.
- *Limited access to external financing*. Lack of clear information about available funds or their insufficiency are major obstacles for SMEs in the region.
- *High implementation and maintenance costs*. Budget allocation for AI solutions is often constrained by other operational priorities.

Budget overrun risk may result from underestimated integration complexity, licensing costs, or required data cleaning. Mitigation includes realistic budgeting with contingencies, phased delivery, and procurement due diligence. Vendor lock-in risk can reduce flexibility and increase long-term costs. Mitigation includes preference for open standards, portable data formats, and contractual safeguards.

D. Security, ethics and privacy risks. In areas such as finance and accounting, data integrity is vital.

- *Data security and management*. There are major concerns about how AI systems handle sensitive data and whether it is processed confidentially.
- *Lack of transparency and the "black box".* Difficulty in understanding the rules and data that AI uses to make decisions can lead to a loss of human control over critical tasks.
- *Ethical implications*. Lack of awareness of the ethical consequences of using AI in business management can generate reputational risks.

Ethical risks include discrimination, exclusion, and unfair treatment, especially when AI influences credit, pricing, fraud detection, recruitment, or resource allocation. Mitigation includes bias assessments, fairness metrics, diverse evaluation datasets, and stakeholder consultation. Reputational risk can arise if AI systems are perceived as opaque or untrustworthy, or if incidents are handled poorly. Mitigation includes transparent communication, clear accountability, and timely disclosure and remediation in case of issues.

E. Legal and regulatory risks. The legislative framework for AI is constantly evolving, generating legal uncertainties.

- Compliance with legal requirements. Organizations report difficulties in complying with country-specific regulatory requirements (Romania and Hungary).
- Legal liability for damages. The absence of clear information on the legal consequences of errors caused by AI represents a significant risk for financial decision makers.

The regulatory framework for AI emphasizes the need to manage legal risks by adapting to the legal requirements specific to the cross-border region. The influence of this legal framework is manifested through:

- *Clarifying legal liability*. A major risk identified is the lack of clear information on the legal consequences of damage caused by AI. Risk management involves creating transparency mechanisms to understand the rules that AI uses in decision-making.
- *Ensuring compliance.* Organizations report difficulties in complying with legal requirements. The mitigation strategy involves constant monitoring of European and national legislation to ensure that the implemented systems are reliable and compliant.
- *Ethics and data confidentiality.* The regulations impose high standards for secure and confidential data management, a major concern for managers in Bihor and Hajdú-Bihar.

Compliance risks include GDPR violations, insufficient legal basis for processing data, inadequate transparency to data subjects, and failure to meet sector-specific requirements. Mitigation includes clear documentation of processing purposes, lawful bases, retention schedules, and mechanisms for rights requests. The EU AI Act introduces additional obligations depending on the system's risk classification. Even if a system is not classified as high-risk, organizations may be expected to implement governance, transparency, and oversight measures. Mitigation includes early legal review, mapping of obligations to controls, and maintaining technical documentation.

7.3. Risk mitigation strategies

For practical project control, risks can be assessed using a probability–impact matrix (for example a 1–5 scale for each dimension) and ranked by a combined score. High-rated risks should have immediate mitigation actions and an assigned contingency plan. Medium-rated risks should be monitored with targeted controls. Low-rated risks should be tracked but not over-controlled. Risk prioritization should consider criticality of the affected process (e.g., financial reporting versus exploratory analytics), sensitivity of the data involved, regulatory exposure, potential impact on stakeholders and dependencies between risks (e.g., data quality issues increasing model risk).

As mitigation strategies and control a layered control approach is recommended. Organizational controls include governance structures, role definitions, training, and documented procedures. Technical controls include secure infrastructure, version control, monitoring, audit logs, and model validation. Process controls include change management, approvals for model releases, and periodic review of assumptions. Concrete examples include data quality gates before model training and before production scoring, model documentation and approval prior to deployment, human-in-the-loop review for high-impact outputs, continuous monitoring for performance drift and fairness drift and security testing and access reviews.

To ensure the successful implementation of the strategy in the Bihor–Hajdú-Bihar region, the following courses of action are proposed to mitigate the identified risks:

1. Capacity building and skills development (human risk mitigation): organizing continuous training programs for employees and managers in collaboration with research centers and partner universities (University of Oradea and University of Debrecen) and promoting an organizational culture favorable to experimentation through pilot projects.

2. Infrastructure development and technological collaboration (technological risk mitigation): facilitating access to cloud services and modern digital infrastructure through public-private partnerships and encouraging cross-border collaboration for the exchange of best practices in the integration of AI systems.

3. Data governance and security frameworks (security and ethical risk mitigation): implementing rigorous data security protocols and ensuring algorithmic transparency (explainable AI - XAI) to increase user trust and define regional ethical standards for the use of AI in finance and accounting.

4. Financial support and consultancy for ROI (economic risk mitigation): creating best practice guides for estimating the return on investment in AI and providing centralized information on external funding sources and strategic resource allocation through the budget plan established in Strategy ROHU00120.

5. Legal monitoring and adaptation (legal risk mitigation): constant monitoring of European and national legislation (AI Act and local regulations) and providing legal assistance to organizations through regional innovation clusters.

7.4. The role of stakeholders in risk management

The success of risk mitigation depends on the active involvement of all actors identified in the stakeholder map:

- *Academic institutions*. They will play the role of facilitators of knowledge transfer, reducing the skills gap.
- *Public authorities.* They will support the creation of a favorable regulatory framework and access to infrastructure.
- *Private companies.* They must assume a proactive role in testing technologies and reporting on barriers encountered.

7.5. Monitoring, early warning indicators, and incident management

Risk management is effective only if monitored. Early warning indicators should be defined for each high and medium risk. Examples include a drop in model accuracy beyond a pre-defined threshold, unexpected changes in input data distributions, increased number of user complaints or overrides of AI recommendations, security alerts or anomalous access patterns or delays in data ingestion or pipeline failures. Incident management should define detection, escalation, containment, investigation, communication, and post-incident learning. If personal data is involved, the process should integrate GDPR breach notification obligations.

Some residual risk will remain even after mitigation. Acceptance criteria should be established, defining what level of residual risk is tolerable for pilots and what requires redesign or additional controls before scaling. The strategy should institutionalize continuous improvement through post-implementation reviews, regular audits of data governance and model governance, updating risk controls based on regulatory changes, and new best practices, expanding collaboration between academia and industry to share lessons learned.

Risk management within the strategy for the Bihor–Hajdú-Bihar region should not be seen as a static process, but as a dynamic one, integrated into the monitoring and evaluation mechanism. By early identification of technological, human and legal barriers, and by applying the proposed mitigation strategies, the region can transform the challenges of digitalization into a sustainable competitive advantage, ensuring a safe and efficient transition to an AI-based economy.

Risk management and the success of AI adoption depend largely on how ethical challenges are managed. Addressing them involves:

- *Alignment with organizational values*. AI systems must be designed and implemented to operate in strict accordance with the company's values and objectives.
- *Maintaining human control*. A major concern identified is the lack of human control over automated decisions; therefore, the strategy recommends that AI should support, not replace, human decision-making.
- *Transparency and accountability*. It is essential that decision-making mechanisms are transparent, allowing managers to understand the data and rules used by the algorithm, thus facilitating the explanation of possible errors.
- *Ethical awareness.* There is already an awareness of ethical implications among regional actors, which constitutes a starting point for responsible use policies.

AI adoption in finance, accounting, and business administration can substantially improve efficiency and decision quality in the Bihor–Hajdú-Bihar region, but it also introduces strategic, technical, legal, and ethical risks. A structured risk management framework supported by governance, documented controls, and continuous monitoring helps ensure that innovation leads to sustainable and trusted outcomes.

Chapter 8. Conclusions

The **"Strategy for Inclusion of AI Advanced Techniques in Finance, Accounting, and Business Administration in the Bihor–Hajdú-Bihar Region"** represents more than a deliverable of the **ROHU00120 (E2U-AI)** project; it constitutes a fundamental roadmap for the digital maturity of the cross-border academic and economic ecosystem. Developed through the collaborative efforts of the **Faculty of Economic Sciences, University of Oradea** and the **Faculty of Economics and Business, University of Debrecen**, this document bridges the gap between the theoretical potential of Artificial Intelligence and its practical applicability in the specific regional context.

Synthesizing the analyses, objectives, and strategic directions outlined in the previous chapters, the following key conclusions emerge:

1. A Necessary Paradigm Shift in Economic Education to ensure the transfer of know-how to the business environment. The context analysis (Chapter 3) and the assessment of digital readiness highlighted a critical reality: traditional methods in finance, accounting, and business administration are no longer sufficient to meet the demands of Industry 4.0. The strategy confirms that integrating AI—ranging from automated auditing and predictive financial modeling to data-driven business decision-making—is not optional but imperative.

2. The Power of Cross-Border Synergy. One of the strategy's core strengths lies in its transnational approach. The challenges identified—such as the need for infrastructure, the fragmentation of digital adoption among SMEs, and the retention of talent—are common to both Bihor and Hajdú-Bihar counties. The strategy demonstrates that **institutional cooperation** is the most effective lever for development, by sharing resources (software, laboratories), knowledge (joint research), and best practices.

3. Strategic Alignment with European Governance As detailed in Chapter 5, the strategy is deeply anchored in the European legislative and ethical framework (EU AI Act, GDPR). It moves beyond mere technological adoption to advocate for **"Trustworthy AI"**. The strategic directions emphasize that innovation must be accompanied by robust governance, ethical responsibility, and data security. This alignment ensures that the region's development is sustainable, legally compliant, and socially responsible, mitigating the risks identified in Chapter 7.

4. From Vision to Measurable Action Unlike theoretical studies, this strategy proposes a concrete implementation framework supported by a clear budget plan, specific capacity-building activities, and rigorous monitoring mechanisms (Chapter 6). The definition of specific Key Performance Indicators (KPIs) for Finance, Accounting, and Business Administration ensures that progress can be quantified. Whether it is the number of SMEs adopting AI tools or the increase in research output, the strategy provides the metrics necessary to evaluate success and adapt to future changes.

5. Long-Term Impact on Regional Competitiveness Ultimately, the successful operationalization of this strategy will generate a multiplier effect across the Bihor–Hajdú-Bihar economy. By fostering a closer link between academia and the business sector (through the goals set in Chapter 4 and partnerships in Chapter 5), the strategy facilitates the transfer of technology from research labs to the real economy. This will lead to optimized public services, more efficient businesses, and a higher value-added economy.

In conclusion, the **E2U-AI Strategy** serves as a catalyst for transformation. It signifies the commitment of the Faculty of Economic Sciences, University of Oradea and the Faculty of Economics and Business, University of Debrecen to lead the digital transition, turning the challenges of the AI era into tangible opportunities for students, researchers, and the entire business community of the Bihor–Hajdú-Bihar region. The path forward is clear: investment in **human capital**, adherence to **ethical standards**, and unwavering **cross-border collaboration** are the pillars upon which a prosperous digital future will be built.

Annex 1

SURVEY

ON THE INTEGRATION OF ARTIFICIAL INTELLIGENCE

IN FINANCE, ACCOUNTING, AND BUSINESS ADMINISTRATION

IN THE BIHOR–HAJDÚ-BIHAR REGION

Dear Participant,
This survey is part of a project ROHU00120, a cross-border initiative between the Bihor (Romania) and Hajdú-Bihar (Hungary) regions aiming to assess the current level of knowledge, adoption, and needs related to artificial intelligence (AI) in finance, accounting, and business administration. The responses will contribute to the development of a regional strategy to support the integration of advanced AI techniques and digital transformation in these sectors.
Your responses will remain confidential and will be used strictly for research and strategic planning purposes.
We thank you for your valuable input and for contributing to the future of digital innovation in our region.

General Information about the Company

1. Type of organization (EU Recommendation 2003/361/EC): ☐ Micro-enterprise (1–9 employees) ☐ Small enterprise (10–49 employees) ☐ Medium-sized enterprise (50–249 employees) ☐ Large enterprise (250+ employees)

2. Sector of principal activity (NACE Rev. 2):

☐ A — Agriculture, forestry and fishing
☐ B — Mining and quarrying
☐ C — Manufacturing
☐ D — Electricity, gas, steam and air conditioning supply
☐ E — Water supply; sewerage, waste management and remediation activities
☐ F — Construction
☐ G — Wholesale and retail trade; repair of motor vehicles and motorcycles
☐ H — Transportation and storage
☐ I — Accommodation and food service activities
☐ J — Information and communication
☐ K — Financial and insurance activities
☐ L — Real estate activities
☐ M — Professional, scientific and technical activities
☐ N — Administrative and support service activities
☐ O — Public administration and defence; compulsory social security
☐ P — Education
☐ Q — Human health and social work activities
☐ R — Arts, entertainment and recreation
☐ S — Other service activities
☐ T — Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
☐ U — Activities of extraterritorial organizations and bodies
☐ Other (please specify): _____

3. Number of employees: ☐ 1–9 10–49 ☐ 50–249 ☐ 250+

4. County where the organization is headquartered: ☐ Bihor ☐ Hajdú-Bihar ☐ Other: _____

5. Respondent's position: ☐ General Manager ☐ Innovation/R&D Manager ☐ Digitalization/IT Manager ☐ Chief Financial Officer/Chief Accountant ☐ Other: _____

6. Net revenue in EURO, in the last completed financial year for your company was:

☐ <60.000 euro ☐ ≤2.000.000 euro ☐ ≤10.000.000 euro☐ ≤50.000.000 euro☐ >50.000.000 euro

7. What percentage of the company is owned by someone from abroad?

☐ 0% ☐ ≤5% ☐ ≤25%☐ ≤50%☐ >50% ☐ not applicable

8. 10. Does the company have an IT department?

☐ Yes; ☐ No.

9. What percentage of your company's total expenses was allocated to research and development in the last year?

☐ We do not spend on research and development; ☐ Between 1 and 5%; ☐More than 5 but less than 10%

☐ More than 10%.

10. Does your company actively or passively use advanced artificial intelligence or related technologies in any stage of the production process?

☐ No, we do not use advanced artificial intelligence or related technologies at all; ☐Yes, we use them passively;

☐Yes, we use them actively.

11. If yes, at which stage:

☐During the procurement of raw materials

☐Product design

☐During the preparation and execution of production processes

☐ During logistics processes

☐ During sales processes

☐ During waste management and processing

☐ During data collection and processing

☐ During decision support or forecasting

☐ During human resource management

☐ During financial decision-making

☐ During accounting/control processes

☐Other:...

B. Enterprise Technology Maturity and Factors Influencing AI Adoption

Please rate the following statements on a 5-point scale where:

- 1 = Strongly Disagree
- 5 = Strongly Agree

	Strongly Disagree 1	Disagree 2	Neutral 3	Agree 4	Strongly Agree 5
Technological maturity of the company					
1. Our company has the appropriate infrastructure, e.g. internet, cloud services, to introduce new technologies.					
2. The management is supporting the use of AI committed to continuously introducing and developing new technologies.					
3. The company's employees have the necessary knowledge and expertise to operate the AI system.					
4. Financial resources are available to support AI initiatives.					
5. There is clear information about AI technologies and their applicability to our business.					
6. We understand the potential benefits of AI for our processes (automation, analytics, etc.).					

7. The possibility of reducing labor costs is an important factor to consider when making decisions about technological developments.					
8.It is easy to access information about funding and support for AI/digitalization.					
9. Our organization can articulate concrete AI use cases in processes like accounting, finance, HR or other.					
10. We have a clear understanding of the potential impact of AI on staff roles.					
11. Our organization uses generative AI tools (e.g. ChatGPT, Copilot).					
12. Our organization uses custom machine learning tools.					
13. Our organization uses visual/audio recognition systems.					
Performance Expectancy					
14. Using an AI-based system improves the quality of managerial decisions.					
15. AI helps me save time in data analysis.					
16. Implementing AI can increase company productivity and efficiency.					
17. Accounting processes can be made more efficient through AI.					
18. Financial reporting can be made more efficient through AI.					
19. Inventory management can be made more efficient through AI.					
20. Strategic planning can be made more effective through AI.					
21. The use of AI would be useful in optimizing the company's production processes.					
22. Using AI would help achieve the company's long-term strategic goals.					
23. Using AI would increase the company's profits.					
Effort Expectancy					
24. I am willing to allocate a budget for AI solutions in my company.					
25. The use of AI technology would be clear and easy to understand for your company's employees.					
26. The company's employees would easily operate the AI systems					
27. The company's employees would easily learn to use the AI systems.					
28. The implementation of AI tools would be easy for the company.					
29. Integrating AI into daily activities does not require excessive technical effort.					
Existing conditions in the company and Trust in AI					
30. The company has the infrastructure resources, e.g. financial, technical, necessary to use AI.					
31. The company has the necessary knowledge to use AI.					
32. The company has access to the necessary support to solve problems related to the AI system.					
33. The company's technical infrastructure is compatible with artificial intelligence systems.					
34. There is trust in AI technologies to handle data securely.					

35.AI would be able to competently carry out the tasks entrusted to it.					
36. I feel comfortable using AI for critical tasks.					
37. I believe that data processed by AI is handled confidentially.					
38. The AI system would operate in accordance with the company's values and objectives.					
39. The operation of the AI would be reliable and transparent.					
40. The operation of the AI system would serve the interests of employees.					
41. The use of AI systems would support, rather than replace, human decision-making.					
AI Explainability and Company Behavioral Intent					
42. The AI-based decision-making mechanism would be transparent to you.					
43. You can understand what data and rules the AI uses to make decisions.					
44. The recommendations provided by the AI system would be easy for the company to understand.					
45. In case of a problem, it would be easy to explain why the AI system made a mistake.					
46. I am concerned about the lack of human control over decisions made by AI.					
47. There is awareness of the ethical implications of AI in our industry.					
48. The company is just thinking about using AI technology into management/business processes in the next 12 months.					
49. The company will probably use AI technology in the next 12 months.					
50. The company is already planning to use AI technology in the next 12 months.					
51. Collaboration with universities/research centers would facilitate AI adoption.					
52.Our organization has a favorable attitude toward experimenting with AI pilots.					
53. We plan to pilot AI tools in our finance/accounting/business administration functions.					
Barriers to AI adoption					
54. The main barriers to AI adoption include lack of internal skills or high costs.					
55. The main barriers to AI adoption include lack of clear information or resistance to change.					
56.It is difficult to estimate the return on investment in AI technologies.					
57. Data management and security are concerns.					
58. It is difficult to comply with legal/regulatory requirements.					
59. There is no clear information on the legal consequences of damages caused by the use of AI.					
60. Employees are alienated from the technology.					
61. Employee competence is insufficient.					
62. There are barriers related to economies of scale.					
63. There is a lack of external funding or it is insufficient.					

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