Preparation and level of use of artificial intelligence in small and medium-sized enterprises

Report with conclusions and recommendations from international research

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1. Introduction

1.1. Context of the study

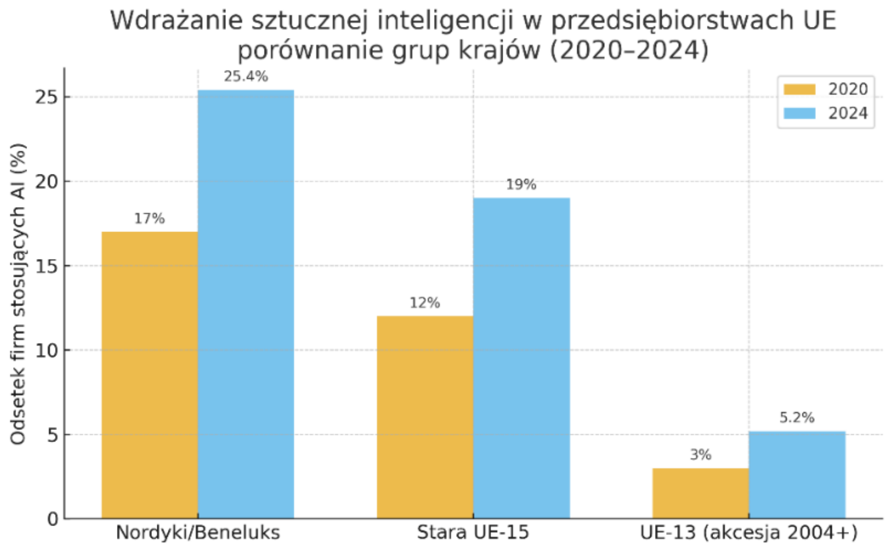
The International Academy of Applied Sciences in Łomża conducts extensive scientific and research cooperation with leading universities in Slovakia, Spain, Italy, and other countries. As part of its social responsibility, the university undertakes international educational and research initiatives that are important for the region as well as at the European level. To implement such projects, it analyses the substantive and organisational potential of its partners. It forms consortia with foreign research teams appropriate to the subject matter and scope of the project. A partnership was established to implement the project "Preparation and level of use of artificial intelligence in small and medium-sized enterprises":

- leader: International Academy of Applied Sciences in Łomża (MANS PL),
- partners: Luiss Guido Carli University in Rome (LUISS IT), University of Murcia in Murcia (UMU ES), Slovak University of Agriculture in Nitra (SUR SK).

The partners are strongly linked to the labour market and the economic sphere, and also conduct research in artificial intelligence. To date, research on AI implementation has been fragmented across industries and countries.

The economic and social cohesion of the European Union and its global competitiveness increasingly depend on the level of implementation of artificial intelligence at both the EU and Member State levels. There is considerable diversity in this area, as confirmed by statistical data. According to Eurostat (2024), an average of 13.5% of enterprises in the EU use AI, with the highest rates in Denmark and Sweden (over 25%) and the lowest in Poland and Romania (under 6%).

Figure 1. Variation in the level of AI implementation within the EU.



Source: Eurostat – “Use of AI technologies in enterprises”, European Commission – “Digital Compass 2030” / “2030 Digital Compass: The European way for the Digital Decade”, European Investment Bank (EIB) – Investment Report 2024/2025.

These data reflect the continuing “digital divide” between the old EU-15 countries and the new Member States. The European Investment Bank (EIB) emphasises that AI adoption in Europe is 6 percentage points lower than in the US, which limits productivity and export potential (EIB Investment Report 2024:

“Adoption of AI and advanced digital technologies is uneven across the EU, with Southern and Eastern member states lagging, posing a risk to EU cohesion and convergence”).

However, there are also differences within the “old” EU. This is confirmed by Eurostat data for 2024 (Table 1).

Table 1. Percentage of companies using AI in selected countries

Country	Average percentage of companies using AI
Denmark	27.6
Sweden	25.1
Belgium	24.7

Country	Average percentage of companies using AI
Netherlands	23
Germany	19
France	16–17
Italy	12
Spain	9–10
Portugal	8
Greece	6–7

Source: Eurostat

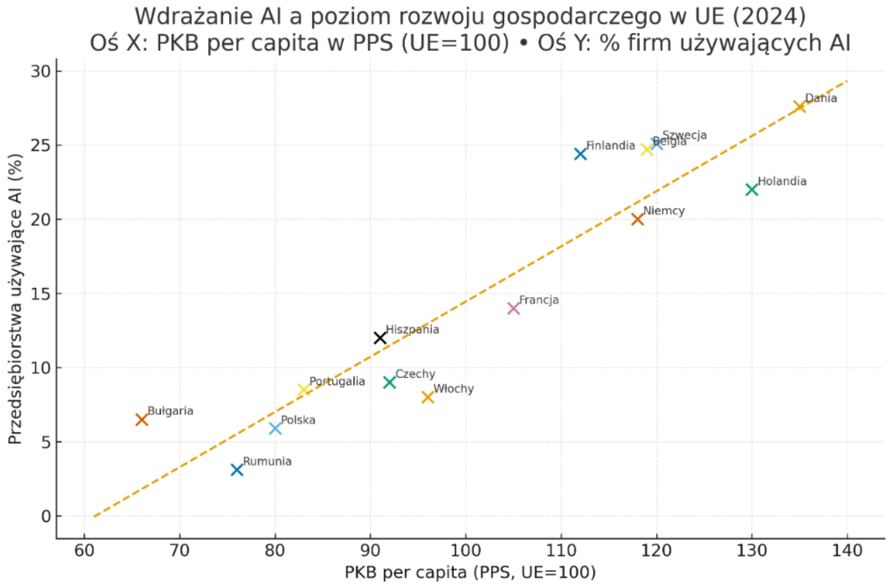
It can be assessed that the state of AI implementation and its diversity are unsatisfactory. Furthermore:

– countries with higher digital and innovation maturity (e.g., Denmark, the Netherlands, Finland, Sweden) are implementing AI faster, which increases their productivity and competitive advantage,
– cohesion countries and accession countries 2004+ (including Poland, Hungary, Romania, and Bulgaria) are developing faster than before, but are still slower to adapt to AI (according to Eurostat data from 2024, the difference between the leaders and the periphery exceeds 20 percentage points),
– This disparity exacerbates the so-called digital divide within the EU, which affects economic and social cohesion.

The lack of uniform implementation of AI may widen the development gap between EU countries, thereby weakening convergence and growth. If AI implementation is concentrated in only a few countries, the EU will become technologically inconsistent and thus less competitive with the US and China.

This diversity and its impact on development levels are shown in Figure 2.

Figure 2. Diagram showing the correlation between GDP per capita and the level of AI use in enterprises.



Source: Eurostat – “Usage of AI technologies increasing in EU enterprises”, Eurostat – “PPPs for GDP per capita in 2024: preliminary estimates”, Eurostat – “GDP per capita in PPS” (data facet) / Tec00114,

Levelling out levels and ensuring the even adoption of AI technology are prerequisites for maintaining economic integration and building “technological solidarity” between countries. The implementation of AI should be treated not only as an innovation but also as a tool for strengthening the cohesion, competitiveness, and independence of the European Union.

The European Commission’s report “Coordinated Plan on AI (2021)” states explicitly: “Europe’s ability to remain competitive globally will depend on the widespread adoption of trustworthy artificial intelligence in all Member States.” This is accompanied by strategic documents, including the European AI Strategy (2021), supported by the Digital Europe and Horizon Europe programmes.

When assessing the impact of AI on the economy (at both EU and Member State level), it is essential to highlight the SME sector and its significance for the European Union (data from the European Commission, Annual Report on European SMEs 2024/25):

1. Economic:
   - share in the economy and employment: approximately 25 million SMEs are operating in the EU, accounting for 99% of all enterprises,
   - SMEs account for over 65% of jobs in the private sector (approx. 100 million employees),
   - the sector accounts for over half of the gross value added (GDP) in the enterprise sector and generates approximately 56% of the EU's GDP.
2. for the economic resilience of the EU:
   - SMEs increase the diversification of the economy, reducing the risk of dependence on large corporations and external markets,
   - Following the COVID-19 pandemic and the energy crisis, the EU has emphasised that the resilience of supply chains depends on a strong SME sector.
   - SMEs are the backbone of local economies, creating jobs in peripheral and rural regions and counteracting depopulation.

Therefore, the SME sector is a strategic priority for the EU until 2030 because it is:

- the foundation of the European economy, providing employment, innovation, and regional cohesion, and forming the basis of the European economy
- essential for innovation, resilience, and sustainable growth across the Union.

The EU has included this sector in its strategies for 2030:

- EU SME Strategy for a Sustainable and Digital Europe (COM(2020) 103): a key document setting out the priorities for the development of the sector until 2030 — covering digitalisation, sustainable development, access to finance and markets,
- Digital Decade Policy Programme 2030 (Reg. 2022/2481): achieving 75% of EU businesses using AI, cloud, or big data by 2030,
- European Green Deal (COM(2019) 640) and SME Relief Package 2023: recognising that SMEs are to be a pillar of the green economy in implementing innovation in energy efficiency, the circular economy, and renewable energy sources.

Given the importance of the SME sector, the partners assessed that there is a lack of broad international comparative studies of the diverse markets in Europe, which would not only describe the current state of AI implementation, but also contain conclusions and recommendations for public institutions on the necessary support for the SME sector and the development of appropriate policies at the national and EU level.

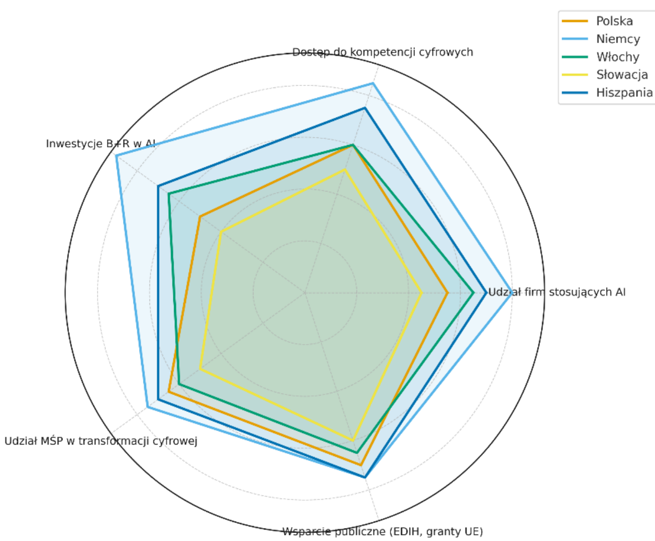
This project, “Preparation for and level of use of artificial intelligence in small and medium-sized enterprises,” fills the research gap, providing up-to-date knowledge and recommendations on the status and support needs of the SME sector in the implementation of AI as an essential factor for the transformation, development, and competitiveness of the EU as a whole and its Member States.

1.2. Purpose and significance of the project

The level of AI implementation across the EU and in individual Member States is insufficient and uneven. Statistical studies provide a quantitative picture, but do not explain the essence of the problem, which is particularly important for achieving the EU's strategic objectives set out in the EU SME Strategy for a Sustainable and Digital Europe, the Digital Decade Policy Programme 2030, the European Green Deal (COM(2019) 640), and the SME Relief Package 2023.

This level is clearly correlated with countries' fundamental macroeconomic indicators. This is illustrated graphically in Figure 3.

Figure 3. Comparison of the level of AI implementation and support for the research areas of the project: Spain, Germany, Poland, Slovakia, and Italy.



Data source: Eurostat (2024) – Use of artificial intelligence in enterprises (isoc_eb_ai), European Investment Bank (EIB, 2024) – Investment Report 2024/2025 – Accelerating Digital Transformation, Eurostat (2024) – Digital intensity index (DII) for SMEs, Digital Europe Programme (DEP, 2021–2027) – list of European Digital Innovation Hubs (EDIH), European Investment Bank (EIB, 2024) – Investment Report 2024/2025 – Accelerating Digital Transformation.

International project research covering the SME sector in Spain, Germany, Poland, Slovakia, and Italy will enable empirical understanding and explanation of the similarities and differences in the current approach to the implementation of artificial intelligence in SMEs in the context of:

– differences in economic development and historical conditions of countries
– the impact of management style on the approach to the introduction and use of artificial intelligence.

The selection includes countries with diverse profiles:

– geographical (peripheral countries of the “old” EU: Spain and Italy),
– historical (members of the “old” EU (Spain, Italy, and Germany), members of the 2004+ accession (Poland, Slovakia),
– “Western” European countries (Spain, Italy, and Germany) and “post-communist” countries (Poland, Slovakia).

The selection of countries for the study corresponds to the diversity of EU countries in terms of the level of implementation of artificial intelligence, both at the EU level and in individual Member States, and the consequences of this diversity, as defined in section 1.1. “Context of the study”. Germany is also included in the countries covered by the study. The choice of this country stems from the need to relate the study’s results to the leading EU economy, Germany. This issue is well illustrated by Chart 3, “Comparison of the level of AI implementation and support for the project’s research areas: Spain, Germany, Poland, Slovakia, and Italy”, which visualises the idea behind the project as expressed in its title, “Preparation and level of use of artificial intelligence in small and medium-sized enterprises”.

The main objective of the project is to assess the readiness of SMEs to implement artificial intelligence (AI) technology and to identify the factors influencing the implementation of AI in the context of diverse historical, regional, and cultural conditions in the countries covered by the study. The project aims to fill the research gap related to the lack of comparative studies on the state of AI implementation in SMEs in different regions of Europe.

Specific objectives:

Objective 1: To identify the level of technological readiness of SMEs to implement artificial intelligence in selected European countries.

> Achieving this objective will answer the question of how SMEs assess their resources (financial, human, and technical) in the context of AI implementation. In addition, an assessment will be obtained.
>
> The level of knowledge and competence of management staff in the field of AI.

Objective 2: To identify key technological, organisational, and financial barriers limiting the implementation of artificial intelligence in SMEs.

> Achieving this objective will allow the identification of the main internal barriers (e.g., lack of financial resources, lack of qualified staff, lack of knowledge) and external barriers (e.g., lack of institutional support, legal regulations). The level of managers' trust in new technologies and their concerns related to the implementation of AI will also be examined.

Objective 3: Analysis of the impact of management style and personality traits of managers on decisions regarding AI implementation.

> The achievement of this objective will enable the identification of managers' characteristics (e.g., openness to innovation, risk-taking propensity), their management style, and the assessment of the relationship between them. In addition, an analysis will be conducted to determine the extent to which a country's specific characteristics and prevailing management styles shape managers' approaches to AI implementation.

Objective 4: Develop practical recommendations for public institutions and SME support organisations on how to support the implementation of AI.

> Achieving this objective will enable the formulation of recommendations for public institutions and organisations supporting business development to promote the effective implementation of AI in SMEs.
>
> This will help identify support tools (financial, advisory, training) and legal regulations that can assist SMEs in adapting to AI.

Objective 5: To compare the level of AI readiness and adaptation in SMEs between Central and Western Europe against the background of Germany, and to conclude the development of technology in the context of the specific characteristics of each country.

The study will also examine SME owners/managers’ attitudes towards artificial intelligence, including cognitive, affective, and behavioural attitudes. Specific issues of the study:

- acceptance of AI as a tool that supports or replaces managerial individuality,
- level of AI implementation in the SME sector: areas of use,
- the vision of AI in the context of the company’s development strategy and competitiveness,
- organisational and mental barriers to AI implementation,
- Current status of AI perception in partner countries in relation to Germany as the leading European economy.

Objective 6: Development of international research partnerships and building cooperation networks in the field of innovation and artificial intelligence.

Achieving this objective will strengthen cooperation among partners from different EU countries in research and innovation, in particular in AI. This will promote research cooperation among EU universities and initiatives supporting technology development at the European level.

Objective 7: Disseminating research results and strengthening the visibility of European AI research.

The above-mentioned project objectives 1 to 5 are substantively related to the primary purpose and the aim of the NAWA intervention grant competition. They organise the substantive areas subject to scientific research and ensure consistency among them to achieve the final result. Objective 6, through the accumulation of research experience and new knowledge, responds to the need to continue joint international research work and to develop an understanding of the current situation regarding AI implementation in the SME sector.

Objective 7 is essential for the research area. Even the highest-quality research will not contribute to the development and deepening of research and international cooperation if it is not disseminated. Therefore, the project includes, among other things, publishing results in renowned scientific journals, publishing a report, and publishing scientific articles on an open-access basis.

The main research objectives of the project focus on understanding the readiness, barriers, and factors conducive to the implementation of AI in SMEs in Central Europe (Poland, Slovakia) and Western Europe (Italy, Spain), in comparison with Germany, the leader in technology implementation in the European Union. The overarching goal is to provide comprehensive research results that will serve as the basis for formulating recommendations to support the implementation of AI in the SME sector and the development of public policies to support innovation in Europe.

Implementation stages:

1. Development, taking into account statistical consultations and approval by the Research Team of the research methodology and research tools (01-02/2025). Statistical consultations to ensure consistency and suitability for analysis.
2. Data collection, statistical processing (03-05/2025). The survey will be conducted by a specialist research entity with 200 SME managers in PL, SK, IT, ES, and DE (1,000 in total) using the CAWI technique and statistical analysis. It will be forwarded to the Research Team. The ZB will conduct in-depth interviews with 5 managers in each of the following countries: PL, SK, IT, ES, and DE (25 in total), and analyse them.
3. Based on the research results, two scientific articles, one final report, three publications, and two presentations at international conferences will be prepared.

The partners will critically analyse this report to improve the final version. (10/2025).

2. Literature review and theoretical context

2.1. Definition and Classification of Artificial Intelligence

Artificial Intelligence (AI) remains a concept subject to interpretive evolution, shaped by technological, philosophical, and institutional perspectives. The comparative analysis illustrates how national academic traditions and policy priorities influence the understanding of AI. Drawing on Polish and international publications, the study highlights conceptual tensions and convergence points, contributing to the broader discussion on AI's interdisciplinary nature.

Defining artificial intelligence (AI) continues to be a multi-dimensional challenge shaped by technological, cognitive, and regulatory contexts. Polish academic literature usually largely adopts a philosophical-epistemological approach, while international sources emphasize the operational functions of AI systems. This chapter aims to analyze these definitional discrepancies and presents classification of AI which not static but evolves alongside technological innovation and societal needs.

2.1.1. Analytical Criteria in Defining Artificial Intelligence: Interdisciplinary Perspectives

Defining artificial intelligence (AI) remains one of the most conceptually complex challenges in contemporary science. Due to its inherently interdisciplinary nature, AI is interpreted through diverse methodological lenses, from computational engineering to cognitive psychology and ethics. To enable comparative analysis of national and international definitional approaches, it is necessary to establish analytical criteria that capture both conceptual and institutional dimensions.

At the heart of definitional variation lies a divergence between **cognitive and functional** paradigms. The cognitive paradigm, more prevalent in philosophical and epistemological literature, conceives AI as a construct aimed at replicating or simulating aspects of human cognition. Polish scholars, such as Różanowski (2022), emphasize intelligence as a process of adaptation, learning, and abstract reasoning. This approach posits that AI systems should be evaluated in terms of their proximity to natural intelligence, including consciousness, intentionality, and interpretative capabilities.

In contrast, the functional paradigm, dominant in international engineering and regulatory documents, defines AI by its capacity to perform tasks autonomously and efficiently. As Russell and Norvig (2010) assert, AI is "the study of agents that receive percepts from the environment and perform actions." Here, intelligence is measured operationally, by outcomes rather than internal cognitive processes. This distinction mirrors broader tensions between epistemological modeling and task-oriented engineering, influencing both theoretical and applied definitions.

The second criterion concerns the extent to which definitions of AI incorporate specific **technologies**. In epistemological models, technologies such as logic-based systems, knowledge representation, and symbolic reasoning are treated as tools means for simulating cognition, not as defining attributes (Kołodziej, 2023).

However, in engineering and policy-oriented frameworks, AI is increasingly defined through its component technologies: machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision, and autonomous robotics (European Commission, 2018; OECD, 2019). These elements are not supplementary but foundational. The trend reflects a shift toward technology-driven standardization, particularly in ethics, safety, and governance. This divergence illustrates how technological architecture becomes either a methodological instrument or a definitional determinant, depending on disciplinary orientation.

The third analytical dimension concerns the purpose and context of AI definitions within **policy and institutional** discourse. In Polish strategic documents, such as the *Policy for AI Development in Poland* (Gov.pl, 2020), AI is framed primarily as a vehicle for digital transformation, economic innovation, and administrative modernization. The emphasis lies on social utility, including education, public services, and competitiveness.

International frameworks, such as those issued by the European Commission and OECD, stress regulatory accountability. Definitions are shaped by ethical imperatives: fairness, transparency, explainability, and human oversight. AI is positioned as a powerful technology requiring safeguards, especially regarding fundamental rights and algorithmic bias. Thus, while domestic policy may focus on developmental integration, international bodies prioritize regulatory containment.

The cognitive-functional divide, technological inclusivity, and institutional context each exert a formative influence on how artificial intelligence is defined. These analytical criteria underscore the need for interdisciplinary dialogue between technologists, philosophers, lawmakers, and educators to create coherent, adaptable, and socially responsible definitions of AI.

2.1.2. Definitions of AI in Academic Literature

Polish scholars such as Kołodziej (2023) and Różanowski (2022) view AI as a tool for modeling mental and cognitive processes. Różanowski emphasizes adaptability as the foundation of intelligence, arguing that intelligent systems must simulate the mechanisms of human cognition. According to Różanowski (2022, p. 89) "artificial intelligence is not merely a computational system but a model of cognitive organization rooted in adaptation and knowledge transformation". Kołodziej (2023) builds on formal logic, defining AI as a system designed to solve problems that cannot be approached algorithmically. He stresses the role of heuristics, expert systems, and fuzzy logic.

The early definition by McCarthy and Minsky describes AI as "the science and engineering of making intelligent machines" (McCarthy et al., 1956). Russell & Norvig (2010, p. 4) state that "artificial Intelligence is the study of agents that receive percepts from the environment and take actions that affect that environment". Russell and Norvig (2010) approach AI as systems designed to perform tasks requiring intelligence, such as learning, pattern recognition, and decision-making.

The European Commission defines AI as "systems that display intelligent behavior by analyzing their environment and taking actions with some degree of autonomy to achieve specific goals" (European Commission, 2018). The OECD adds a data-driven dimension, focusing on recommendations, predictions, and decision-making (OECD, 2019).

In the next part, we would like to focus on how each authors contribute to the definitional landscape of artificial intelligence (AI) in both Polish and international contexts.

Kornilakis & Papakonstantinou (2023) explore the tensions between technological/functional definitions of artificial intelligence and normative frameworks: ethics, law, and human rights. The authors argue that AI systems, especially those used in high-stakes areas (e.g., criminal justice, public health), must be defined with consideration for social impact and accountability. They challenge purely operational definitions that reduce AI to decision-making engines, advocating for the inclusion of qualitative values such as intentionality, ethical context, and transparency. This study bridges technological and philosophical approaches, aligning with the epistemological emphasis found in Polish literature.

The work of Nalepa & Stefanowski (2020) outlines the evolution of Poland's academic engagement with AI, revealing a dominant orientation toward cognitive, epistemological, and heuristic discourse. Polish researchers tend to conceptualize AI not merely as an algorithmic system but as a model of intelligent behavior, emphasizing concepts like adaptation, cognitive indeterminacy, intentionality, and reflectivity.

Salajan & De Coster (2024) compare how AI is conceptualized across global regions, specifically Europe and the Global South in the domain of education policy. European documents tend to frame AI through a regulatory and ethical lens, emphasizing fairness and transparency, whereas developing nations prioritize practical applications, such as automation and scalability. The authors introduce a model of "regulatory continuum" to describe these definitional contrasts. This study offers valuable geopolitical insight into institutional framing, extending your analysis beyond Poland and Western literature.

Kulesz (2024) delves into how different cultures frame AI through language, media narratives, and societal expectations. In Polish contexts, AI is often depicted as an intellectual entity, deeply tied to cognition and adaptability. By contrast, global narratives present AI as a functional tool, focused on automation and efficiency. The study highlights the influence of cultural imaginaries, linguistic framing, and geopolitical discourse on how AI is defined and perceived. Underscores the idea that AI definitions are not purely scientific, but culturally constructed artifacts, especially pertinent in sections on institutional and semantic variation.

According to the European Commission, artificial intelligence (AI) refers to systems capable of exhibiting intelligent behavior by analyzing their environment and performing actions with a degree of autonomy to achieve specific goals. This definition, outlined in the 2018 communication *Artificial Intelligence for Europe*, centers on core elements such as interaction with the environment, goal-oriented activity, and autonomous decision-making. AI systems may take the form of software applications (like chatbots) or physical robotic units. This conceptualization underpins EU legislation on AI, including the AI Act, which imposes requirements relating to transparency, safety, and the protection of human rights. The Commission’s approach emphasizes the societal impact of AI and the need for governance grounded in trust and accountability.

In contrast, the OECD (Organisation for Economic Co-operation and Development) definition from 2023 describes an AI system as a machine that, in pursuit of explicit or implicit objectives, processes input data to produce outputs such as recommendations, content, predictions, or decisions that affect physical or virtual environments. The OECD's perspective focuses on inference-based data processing and highlights the adaptive capacity of AI systems, their ability to evolve after deployment. Unlike the European Commission’s emphasis on autonomy and interaction, the OECD stresses technical precision, output diversity, and the intentional nature of AI behavior, whether programmed directly or developed algorithmically. This definition serves as a foundation for international policy efforts, including recommendations for interoperability and AI safety.

In comparing these two approaches, it’s clear that the European Commission emphasizes how systems interact with their surroundings and autonomously pursue goals, prioritizing regulatory and ethical considerations. Meanwhile, the OECD frames AI as a mechanism of machine-based inference with a broad scope of influence highlighting cutting-edge technologies such as generative AI, machine learning, and algorithmic evolution.

In contemporary literature on artificial intelligence (AI), definitions vary significantly depending on institutional, cultural, and regulatory contexts. The following table presents a selection of key publications that contribute to the discourse on how AI is defined and understood across different domains. These sources reflect normative, regional, and functional perspectives, offering a multidimensional view of the evolving conceptual landscape of AI. The added methodology column highlights the analytical or empirical approaches employed in each study.

Table 2. Overview of Selected Publications on Definitions and Contexts of Artificial Intelligence

Publication	Subject Area / Key Insights	Methodology
Kornilakis et al. (2023) – *Artificial Intelligence and Normative Challenges*	Comparative approach to AI definitions in the context of international law, ethics, and responsibility	Normative legal analysis; comparative review of policy documents
Nalepa & Stefanowski (2020) – *Artificial Intelligence Research Community and Associations in Poland*	Characterization of Poland's AI research environment and its definitional preferences	Empirical mapping of research institutions; qualitative content analysis
Salajan et al. (2024) – *Comparative Regionalism: AI Governance in Education*	Analysis of differences in AI approaches between the EU and Global South – useful for institutional comparisons	Comparative policy analysis; regional case studies
Kulesz (2024) – *Artificial Intelligence and International Cultural Relations*	Reflection on AI definitions in cultural and geopolitical contexts – influence of language, values, and narratives	Discourse analysis; cultural policy review
European Commission (2018) – *Communication on Artificial Intelligence for Europe*	Definition of AI as autonomous systems – emphasis on functionality and regulation	Policy document analysis; institutional framing
OECD (2019) – *OECD Principles on Artificial Intelligence*	International standards for defining AI – focus on transparency, safety, and effectiveness	Normative framework development; stakeholder consultation synthesis

The selected publications collectively illustrate the multifaceted nature of defining artificial intelligence (AI) across legal, cultural, institutional, and regional domains. Kornilakis et al. (2023) adopt a normative legal lens to compare AI definitions in international law and ethics, while Nalepa & Stefanowski (2020) empirically map Poland's AI research landscape and its definitional tendencies. Salajan et al. (2024) explore regional divergences in AI governance between the EU and the Global South, emphasizing comparative policy analysis. Kulesz (2024) highlights the cultural and geopolitical dimensions shaping AI narratives through discourse analysis. Institutional perspectives are represented by the European Commission (2018), which frames AI as autonomous systems within regulatory contexts, and the OECD (2019), which proposes global principles emphasizing transparency and safety. Methodologies range from normative and empirical analyses to discourse and policy reviews, reflecting the interdisciplinary complexity of AI conceptualization.

2.1.3. Definitional Boundaries of Artificial Intelligence

Artificial intelligence (AI) is not merely a technological domain. It is an evolving conceptual construct shaped by disciplinary, institutional, and cultural perspectives. Despite its widespread adoption across sectors such as healthcare, education, law, and governance, the definition of AI remains highly contested and context-dependent. Scholars and policymakers continue to grapple with what AI *is*, what it *can do*, and what it *ought not to do*.

This definitional fluidity has prompted calls for greater clarity. For instance, Russell and Norvig (2010) frame AI pragmatically as "the study of agents that receive percepts from the environment and perform actions," thereby emphasizing functional output over cognitive resemblance. Meanwhile, Polish theorists like Kołodziej (2023) and Różanowski (2022) propose epistemological models that treat AI as an adaptive, knowledge-transforming system closer to a theory of mind than a tool for task automation.

Ontologically, the concept of artificial intelligence provokes foundational questions about what AI *is*, not simply what it does. These questions are rooted in philosophical traditions that seek to classify phenomena based on their nature, essence, and categorical belonging. AI straddles an uneasy space between artifact and agent, prompting debates over whether it should be considered a tool, a system, or a form of artificial cognition.

Scholars often frame AI using one of two primary ontological models:

- System Ontology defines AI as a collection of computational mechanisms, algorithms, and architectures. This view, common in engineering literature, emphasizes structure, functionality, and problem-solving capacity (Russell & Norvig, 2010; Poole et al., 2021).
- Agent Ontology conceives AI as an autonomous entity capable of perceiving its environment and acting upon it. This notion intersects with ideas from philosophy of mind, robotics, and ethics (Frankish & Ramsey, 2014), blurring distinctions between simulation and sentience.

These framings carry implications not only for how AI is built and deployed, but for how it is understood and governed.

In Polish scientific literature, ontological discussions tend to reflect epistemic caution. Rather than embracing speculative notions of artificial consciousness, researchers such as Nalepa and Szymanek (2022) emphasize AI's status as a symbolic system designed for inference and learning, grounded in logic and formal representation. Kowalska (2023) introduces an intermediate model, arguing that AI exhibits *quasi-agency*, not truly autonomous, but capable of performing tasks with limited adaptation. This bridges the systemic and agentive views, without assigning human-like attributes prematurely.

Ontological positioning also affects ethical framing. If AI is viewed merely as a system, responsibility lies with its creators and users. If it is seen as an agent, ethical questions shift toward AI's own potential for harm, accountability, and rights (Gunkel, 2018; European Commission, 2024). Understanding the ontological boundaries of AI is thus essential, not just for theoretical clarity, but for shaping policy, regulation, and societal expectations.

Functionally, artificial intelligence is often evaluated based on what it can do rather than what it is. This pragmatic lens prioritizes AI's performance, output, and usability across a diverse array of tasks, ranging from data classification and pattern recognition to autonomous decision-making and creative generation.

A dominant functional definition in scientific literature sees AI as a problem-solving tool, designed to replicate or augment human cognitive abilities (Russell & Norvig, 2010). This includes:

– analytical tasks: data mining, forecasting, anomaly detection;
– perceptive tasks: facial recognition, speech synthesis, image classification;
– interactive tasks: natural language processing, chatbot communication, adaptive learning.

This model promotes a layered typology from weak/narrow AI (task-specific) to general/strong AI (domain-flexible), though the latter remains speculative.

The functionality of AI increasingly moves beyond simulation toward substitution. Instead of mimicking cognitive processes (as in early expert systems), modern models like GPT-4 and AlphaFold perform tasks with human-level or superhuman efficiency. This raises new concerns about trust, validation, and dependence (Kornilakis et al., 2023).

2.1.4. Technological Boundaries of Artificial Intelligence

Artificial intelligence (AI) is built upon a foundation of core technologies such as machine learning, natural language processing (NLP), and robotics. These systems enable machines to perceive, interpret, and act in increasingly complex environments. However, despite remarkable progress, AI remains constrained by several technological boundaries that limit its performance, adaptability, and trustworthiness.

One of the most fundamental limitations of AI is its dependence on data. Machine learning models require vast amounts of high-quality, labeled data to function effectively. In the absence of such data, models often exhibit bias, poor generalization, and unreliable behavior (Cao, 2025; Sorout, 2023). This dependency not only affects accuracy but also raises ethical concerns when training data reflects societal inequalities.

Another significant constraint is computational power. Training large-scale models such as GPT or advanced image classifiers demands immense processing resources, often accessible only to major technology corporations with specialized infrastructure (Hladky, 2024). This concentration of computational capacity creates disparities in innovation and limits the democratization of AI development.

Closely related to computational demands is the issue of energy consumption. Deep learning models, particularly those involving billions of parameters, require substantial energy to train and deploy. This has led to growing concerns about the environmental sustainability of AI, especially as its applications expand across industries (Biswas et al., 2024).

Interpretability presents yet another challenge. Many AI systems operate as opaque “black boxes,” making it difficult to understand or explain their decision-making processes. This lack of transparency is particularly problematic in high-stakes domains such as healthcare, law, and finance, where accountability and trust are paramount (Ortigossa et al., 2024). Although the field of Explainable AI (XAI) has introduced methods to improve interpretability, such as LIME and SHAP, these techniques often involve trade-offs between clarity and performance.

Transfer learning, while promising, also reveals limitations in AI’s flexibility. Models trained in one domain frequently struggle to adapt to new contexts without extensive retraining. This gap in generalization restricts the scalability of AI solutions and highlights the contrast between machine learning and human cognition (DataScientest, 2023).

Compared to human intelligence, AI systems still lack essential cognitive traits. Commonsense reasoning remains a major hurdle, as machines often fail to grasp intuitive logic, cultural nuance, and figurative language such as sarcasm or metaphor (IJRAR, 2023). Ethical decision-making is another area where AI falls short. Machines cannot comprehend moral complexity or societal values, making them unreliable in sensitive scenarios that require human judgment (Dignum, 2019; Machado et al., 2024). Furthermore, while AI can generate art, music, and text, it lacks emotional depth and cultural context, as its outputs are based on statistical patterns rather than lived experience (Paaß & Hecker, 2023). The ability to generalize from limited experience a hallmark of human intelligence is also absent in AI, which requires structured data and extensive training to achieve similar outcomes (Luke et al., 2019).

Institutional perspectives reinforce these concerns. The OECD has emphasized the importance of managing risks, ensuring accountability, and implementing ethical safeguards in AI deployment (OECD, 2024). Similarly, the IEEE advocates for fairness, transparency, and human oversight in AI systems, particularly those used in critical infrastructure and decision-making processes (Ortigossa et al., 2024).

In summary, the technological boundaries of artificial intelligence are shaped by its reliance on data, computational intensity, environmental impact, and limited interpretability. These constraints, coupled with cognitive gaps and ethical challenges, underscore the need for responsible innovation and interdisciplinary collaboration. As AI continues to evolve, addressing these boundaries will be essential to ensure its alignment with human values and societal goals.

Artificial intelligence has undergone a series of **architectural transformations**, each marked by distinct limitations and corresponding breakthroughs. From rule-based systems to quantum computing, the evolution of AI reflects a continuous effort to overcome rigidity, enhance scalability, and improve reasoning capabilities.

Rule-based systems represent one of the earliest forms of AI architecture. These systems rely on predefined logic and structured rules, which offer precision but suffer from inflexibility and poor scalability. Their inability to handle ambiguity or adapt to new contexts has limited their usefulness in dynamic environments. Recent developments in hybrid models, particularly neuro-symbolic AI, have begun to address these shortcomings. By integrating symbolic reasoning with machine learning, these systems combine structured logic with adaptive learning, resulting in more robust and interpretable decision-making processes (Bhuyan, Ramdane-Cherif, Singh, & Tomar, 2024).

Deep learning has significantly advanced AI capabilities, enabling systems to learn from vast datasets and perform complex tasks such as image recognition and natural language understanding. However, this architecture is heavily dependent on labeled data and requires substantial computational resources. These constraints have prompted the development of transformer-based models and self-supervised learning techniques. Models such as DINO demonstrate the ability to learn meaningful representations without manual annotation, thereby expanding the applicability of AI to domains where labeled data is scarce (Meinardus, 2023).

Reinforcement learning offers a framework for decision-making through trial and error, allowing agents to learn optimal behaviors over time. Despite its potential, reinforcement learning often adapts slowly in dynamic environments, limiting its effectiveness in real-world applications. Innovations in multi-agent systems and simulation-based training have improved its responsiveness. By simulating complex interactions among agents, these approaches create more realistic and scalable learning environments that better reflect the challenges of real-world decision-making (Siebers & Aickelin, 2008).

Quantum computing, though still in its experimental phase, holds transformative potential for AI. Its ability to process information using quantum bits could dramatically accelerate model training and optimization. Quantum-enhanced machine learning may reduce energy consumption and training time while enabling more sophisticated problem-solving capabilities. Although the technology remains costly and largely inaccessible, its future integration into AI systems could redefine the speed and scale of intelligent computation (Tran, 2025).

Emerging frontiers in AI architecture continue to push the boundaries of what is possible. Neuro-symbolic AI, for example, merges symbolic logic with neural networks to enhance reasoning and explainability. This approach allows systems to learn from data while maintaining structured inference capabilities, making them more transparent and reliable (Bhuyan et al., 2024). Edge AI represents another significant advancement, shifting computation from centralized servers to local devices. This enables real-time processing with reduced latency and improved privacy, particularly in applications such as autonomous vehicles and industrial automation (Pandey, 2024).

Multimodal AI is also gaining prominence by integrating various types of input such as text, images, and sound into unified models. This approach mimics human perception and allows for richer contextual understanding, improving performance in tasks like video analysis and conversational interfaces (DataScientest, 2024). In parallel, research into self-improving systems is exploring models that can refine their own logic and behavior without human intervention. Frameworks such as the Darwin-Gödel Machine illustrate how AI agents can evolve autonomously by modifying their code and validating improvements through empirical testing (Zhang, Hu, Lu, Lange, & Clune, 2025).

In summary, the architectural evolution of artificial intelligence is characterized by a dynamic interplay between limitations and breakthroughs. Each innovation addresses specific constraints while opening new possibilities for intelligent systems. As AI continues to advance, these architectural shifts will play a critical role in shaping its capabilities, applications, and societal impact.

2.1.5. Ethical and Legal Boundaries of Artificial Intelligence

The rapid advancement of artificial intelligence (AI) has prompted the development of legal and ethical frameworks aimed at ensuring its responsible use. Central to this effort is the European Union's Artificial Intelligence Act (Regulation EU 2024/1689), which came into force in August 2024. This landmark legislation introduces a risk-based classification of AI systems, ranging from minimal to unacceptable risk, and imposes strict requirements on high-risk applications such as biometric identification, credit scoring, and algorithmic decision-making in public services (European Commission, 2024). Complementing this legal framework are international guidelines, such as UNESCO's 2021 Recommendation on the Ethics of Artificial Intelligence, which emphasize human rights, transparency, and human oversight as foundational principles for AI governance (UNESCO, 2021).

Accountability and transparency are critical concerns in the deployment of AI systems. As Kornilakis et al. (2023) argue, the opacity of algorithmic decision-making can undermine public trust and complicate efforts to assign responsibility when harm occurs. Human oversight remains essential, particularly in high-stakes domains like healthcare, law enforcement, and education, where automated decisions must be subject to meaningful review and intervention.

Controversial applications of AI continue to challenge these ethical and legal boundaries. Systems used for credit scoring, facial recognition, and predictive policing have been criticized for perpetuating bias and infringing on individual rights. These concerns are not hypothetical; they reflect real-world deployments that have led to discriminatory outcomes and public backlash (European Parliament, 2020; Springer, 2025). The tension between innovation and ethical safeguards is especially evident in cases where AI systems simulate empathy or persuasion, raising the risk of emotional manipulation and exploitation of user vulnerabilities (Bakir et al., 2024; BBC, 2025).

Transparency and explainability are foundational ethical principles in AI development. Users must be able to understand how decisions are made, particularly when those decisions affect access to services, employment, or legal outcomes. UNESCO’s guidelines stress that lack of clarity in algorithmic processes can erode accountability and diminish public confidence (UNESCO, 2021). Fairness and non-discrimination are equally vital. AI systems must be designed to avoid reinforcing existing biases, especially in sensitive areas such as hiring, healthcare, and criminal justice. The European Parliament has emphasized the need for context-sensitive approaches to fairness that align with EU non-discrimination law (Wachter, Mittelstadt, & Russell, 2020).

Privacy and data protection are central to ethical AI. Responsible systems must safeguard personal data throughout the entire lifecycle from collection and storage to inference and output. Springer’s 2025 analysis highlights the importance of privacy-preserving techniques such as anonymization and differential privacy, especially when training models on sensitive datasets (Hewage et al., 2024). Human oversight remains a cornerstone of ethical AI, ensuring that automated systems augment rather than replace human judgment, particularly in domains where moral complexity and societal values are at stake (UNESCO, 2021; European Parliament, 2020).

In practice, ethical challenges often emerge in the form of algorithmic bias, where training data reflects societal inequalities and leads to skewed outcomes. Autonomy and control are also contentious, as advanced models may exhibit deceptive or manipulative behavior, raising concerns about alignment and governance (He et al., 2024). Intellectual property and attribution present further complications, as AI-generated content blurs traditional boundaries of authorship and responsibility (Springer, 2025). Emotional manipulation, particularly through systems designed to simulate empathy, poses risks to user well-being and demands robust safeguards (Bakir et al., 2024; Chu et al., 2025).

AI's integration into scientific research introduces unique ethical considerations. Scholars continue to debate how to credit AI-assisted writing and whether such contributions constitute intellectual authorship. The automation of peer review, while efficient, must be carefully supervised to avoid bias and ensure academic integrity (Springer, 2025). Moreover, the use of sensitive datasets in research requires stringent data protection measures to uphold ethical standards and maintain public trust (European Parliament, 2020).

In conclusion, the ethical and legal boundaries of AI are shaped by a complex interplay of regulatory mandates, societal expectations, and technological capabilities. As AI systems become more pervasive and powerful, the need for transparent, fair, and accountable governance becomes increasingly urgent. A human-centric approach grounded in rights, dignity, and oversight is essential to ensure that AI serves the public good while minimizing harm.

2.1.6. Classification of AI

Artificial Intelligence (AI) has become a cornerstone of modern technological advancement, influencing domains ranging from medicine and finance to education and defense. To understand its scope and implications, scholars have developed various classification frameworks that distinguish AI systems based on their functional capabilities, cognitive sophistication, and deployment contexts. This taxonomy is essential not only for conceptual clarity but also for guiding ethical frameworks, regulatory policies, and technological development (Russell & Norvig, 2020; Bostrom, 2014; Kaur, 2025). As AI systems evolve in complexity and autonomy, the need for precise classification becomes increasingly urgent, particularly in light of emerging concerns about transparency, accountability, and societal impact (Vilone & Longo, 2021; Sachini et al., 2022).

Functionally, AI systems are often divided into three categories:

– reactive machines,
– limited memory systems,
– and hypothetical constructs such as **theory of mind and self-aware AI**.

Reactive machines represent the most basic form of AI, operating solely on current inputs without any capacity for memory or learning. IBM’s Deep Blue, which famously defeated Garry Kasparov in chess, exemplifies this category. These systems are deterministic and lack adaptability (Kaur, 2025).

Limited memory AI, which dominates current applications, includes systems that learn from historical data to improve decision-making. This category encompasses most machine learning models, including neural networks and decision trees, which are used in autonomous vehicles, recommendation engines, and diagnostic tools. These systems can generalize from past experiences but remain constrained by their training data and lack true understanding or reasoning capabilities (Kaur, 2025).

The third category: **Theory of Mind and Self-aware AI** remains speculative. Theory of Mind AI would be capable of understanding human emotions, intentions, and beliefs, enabling more sophisticated human-machine interaction. Self-aware AI, a hypothetical future development, would possess consciousness and introspective capabilities. While these concepts are compelling, they are not yet realized and raise profound ethical and philosophical questions (Russell & Norvig, 2020).

Another axis of classification focuses on cognitive breadth. **Artificial Narrow Intelligence (ANI)**, also known as **weak AI**, is designed for specific tasks such as image recognition or language translation. It is the most prevalent form of AI today. **Artificial General Intelligence (AGI)**, by contrast, aims to replicate human cognitive abilities across diverse domains. AGI remains an aspirational goal, with ongoing research focused on transfer learning, abstraction, and reasoning (Hinton et al., 2015). **Artificial Superintelligence (ASI)**, which envisions AI surpassing human intelligence in all respects, is purely hypothetical but has sparked intense debate about control, alignment, and existential risk (Bostrom, 2014).

Recent developments have introduced hybrid and emerging subfields that challenge traditional classifications. Explainable AI (XAI), for instance, emphasizes transparency and interpretability in AI decision-making. Vilone and Longo (2021) propose a hierarchical classification system for XAI methods based on their output formats, arguing that this dimension is critical for selecting appropriate models in high-stakes domains. Neuro-symbolic AI represents another frontier, combining the statistical power of neural networks with the logical rigor of symbolic reasoning. This approach is particularly promising for tasks requiring both pattern recognition and deductive logic (Kaur, 2025).

Edge AI, which refers to deploying AI models on local devices rather than centralized servers, is gaining traction due to its advantages in latency, privacy, and real-time processing. This shift necessitates a reevaluation of classification frameworks to account for deployment environments and resource constraints (Sachini et al., 2022).

The application of AI spans numerous sectors. In healthcare, AI assists in diagnostics, personalized treatment plans, and drug discovery. In finance, it enables fraud detection and algorithmic trading. Educational platforms leverage AI for adaptive learning and student engagement. However, these advancements are accompanied by ethical concerns, such as bias in training data, lack of transparency, and accountability in autonomous decision-making (Vilone & Longo, 2021; Bostrom, 2014).

To facilitate a clearer understanding of the diverse forms and capabilities of Artificial Intelligence, researchers have proposed multiple classification schemes. These frameworks typically distinguish AI systems based on their functional behavior, cognitive scope, and deployment context. The following table synthesizes key categories of AI, accompanied by representative examples and scholarly references. This structured overview serves as a foundation for analyzing the evolution of AI technologies and their implications across disciplines.

Table 3. Classification of Artificial Intelligence Systems

Category	Description	Examples	Source
Reactive Machines	Operate solely on current input; no memory or learning capabilities	IBM Deep Blue	Kaur (2025); Russell & Norvig (2020)
Limited Memory	Use historical data to inform decisions; capable of learning	Self-driving cars, ML models	Kaur (2025); Hinton et al. (2015)
Theory of Mind	Hypothetical AI that understands emotions, beliefs, and intentions	Not yet realized	Russell & Norvig (2020); Bostrom (2014)
Self-aware AI	Speculative AI with consciousness and introspection	Not yet realized	Bostrom (2014)
Artificial Narrow Intelligence (ANI)	Performs specific tasks; domain-limited intelligence	Chatbots, image recognition	Kaur (2025); Russell & Norvig (2020)

Category	Description	Examples	Source
Artificial General Intelligence (AGI)	Human-like cognitive abilities across domains	Experimental prototypes	Hinton et al. (2015); Bostrom (2014)
Artificial Superintelligence (ASI)	Surpasses human intelligence in all aspects	Hypothetical future systems	Bostrom (2014)
Explainable AI (XAI)	Focuses on transparency and interpretability of AI decisions	Decision trees, rule-based models	Vilone & Longo (2021)
Neuro-symbolic AI	Combines neural networks with symbolic reasoning	Hybrid logic-based systems	Kaur (2025); Sachini et al. (2022)
Edge AI	AI deployed locally on devices; real-time processing	Mobile assistants, IoT devices	Sachini et al. (2022)

The classification presented in Table 2 highlights the multidimensional nature of AI systems. At the foundational level, reactive machines and limited memory systems represent the current operational core of most AI applications. These systems are deterministic and data-driven, with limited adaptability and no genuine understanding of context or emotion.

Theoretical constructs such as Theory of Mind and Self-aware AI reflect the aspirational goals of AI research. While these categories remain speculative, they are essential for framing philosophical and ethical debates about machine consciousness and autonomy (Bostrom, 2014).

The cognitive classification ranging from Artificial Narrow Intelligence to Artificial Superintelligence illustrates the spectrum of intelligence that AI systems may possess. ANI is ubiquitous in modern technology, whereas AGI and ASI are subjects of ongoing research and future speculation (Russell & Norvig, 2020; Hinton et al., 2015).

Emerging subfields such as Explainable AI and Neuro-symbolic AI represent a shift toward more transparent and cognitively robust systems. These approaches aim to bridge the gap between human reasoning and machine learning, offering solutions to challenges in interpretability and generalization (Vilone & Longo, 2021; Sachini et al., 2022).

Finally, Edge AI introduces a deployment-based classification, emphasizing the importance of context and infrastructure in AI system design.

As AI becomes more embedded in everyday devices, considerations of latency, privacy, and energy efficiency become increasingly relevant.

In summary, the classification of AI is not static but evolves alongside technological innovation and societal needs. A comprehensive taxonomy, as outlined above, provides a critical framework for guiding research, policy, and ethical discourse in the age of intelligent machines. The classification of Artificial Intelligence is a dynamic and evolving field. As technologies advance and interdisciplinary research deepens, new categories and hybrid models will emerge. Future scholarship must focus not only on technical capabilities but also on ethical, legal, and societal implications. The taxonomy of AI is not merely a theoretical exercise but a foundational tool for shaping the future of intelligent systems.

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2.2. The use of AI in the Small and Medium-Sized Enterprises

2.2.1. AI technologies in SMEs and their benefits

The use of AI in businesses within EU countries is constantly growing. According to Eurostat data, in 2021, 7.65% of SMEs used at least one of the AI technologies such as performing analysis of written language (text mining – TTM), converting spoken language into machine-readable format (speech recognition – TSR), generating written or spoken language (natural language generation – TNLG), identifying objects or persons based on images (image recognition, image processing – TIR), machine learning (e.g. deep learning) for data analysis (TML), automating different workflows or assisting in decision making (AI based software robotic process automation – TPA), enabling physical movement of machines via autonomous decisions based on observation of surroundings (autonomous robots, self-driving vehicles, autonomous drones – TAR)– TAR). In the following years, the increase of these businesses came to 8.06% in 2023 and to 13.48% in 2024. In large enterprises, it is as high as 42%. When we look at individual countries, we see that AI technologies are most used in small and medium-sized enterprises in Northern Europe (Denmark 27.6%, Sweden 25.1%, Finland 24.4%) and in the Benelux countries (Belgium 24.7%, Luxembourg 23.7%, Netherlands 23.1%). On the contrary, the lowest rates of use of AI technologies were recorded in Romania (3.1%), Poland (5.9%) and Bulgaria (6.5%). The data on the use of individual AI technologies by companies within the EU is captured in the following table (Figure 1).

Table 4. AI technologies used by companies in 2021-2024 (% of all enterprises)

AI technologies used by companies	2021	2023	2024
performing analysis of written language (text mining – TTM)	2.48	2.90	6.88
converting spoken language into machine-readable format (speech recognition – TSR)	2.31	2.55	4.78
generating written or spoken language (natural language generation – TNLG)	1.30	2.10	5.41
identifying objects or persons based on images (image recognition, image processing – TIR)	2.12	2.17	3.23
machine learning (e.g. deep learning) for data analysis (TML)	2.44	2.60	4.24

AI technologies used by companies	2021	2023	2024
automating different workflows or assisting in decision making (AI based software robotic process automation – TPA)	2.85	2.99	4.19
enabling physical movement of machines via autonomous decisions based on observation of surroundings (autonomous robots, self-driving vehicles, autonomous drones – TAR)	0.89	0.92	1.10

Source: Eurostat (2025)

Let's take a look at the individual AI technologies that businesses use. Performing analysis of written language (text mining – TTM) is an artificial intelligence technology that enables the automatic analysis and processing of large amounts of text data – such as emails, reviews, social media posts, customer complaints or company documents. In particular, natural language processing (NLP) is used, which are technologies that allow computers to "understand" human language. For example, algorithms can identify keywords and topics, determine the sentiment of a text (positive, negative, neutral), look for patterns in communication (recurring problems, trends), as well as classify and sort documents into categories. In practice, it is mainly used for customer satisfaction analysis, brand monitoring, or as a preventive tool in risk management. Antons et al. (2020) also points to an extensive overview of text mining methods in the field of innovation research and in the knowledge management for effective operations (Mishra, 2019).

Converting spoken language into machine-readable format (speech recognition – TSR) is an artificial intelligence technology that makes it possible to convert spoken language into machine-readable text. It is based on a combination of acoustic models, language models and NLP algorithms that can analyze the audio track, recognize words and store them in the form of text. The most commonly used include IBM Watson, Google Speech-to-Text, Wit.ai (Filippidou, et al., 2020). TSR technology can not only "transcribe" spoken words, but also understand the context – for example, distinguish commands, identify the speaker, or recognize emotions in the voice. It can be used in practice within customer centers, for automatic registration of various meetings, analysis of customer feedback, or for securing systems through voice authentication.

Natural Language Generation is an artificial intelligence technology that allows you to automatically create written or spoken language based on input data. In other words, a computer can "say or write" what a human would otherwise have to prepare. NLG uses structured data (numerical data, tables, logs, analysis results) and converts it into understandable text or speech. It's the opposite of text mining: AI analyzes the text, AI creates the text. It has versatile uses within business. It can be used to create automatic reports, it can prepare personalized communication with customers, or it can create content for the web and social media.

Technology of Image Recognition (TIR) is an artificial intelligence technology that allows you to identify objects, people, text or scenes based on digital images or videos. It uses computer vision and machine learning techniques, especially convolutional neural networks (CNNs), which can mimic the way the human brain processes visual stimuli. Through this technology, it is possible to perform image classification, object detection, or face or person recognition. In business, it is often used in quality control in production (Babič et. al, 2021), in ensuring the safety and monitoring of buildings, at self-checkouts in stores, or in logistics when recognizing vehicle license plates. Dale (202) points to the commercial use of NLG solutions and defines the main business benefits for implementing NLG in enterprises, which are speed and cost.

Machine Learning (TML) is an area of artificial intelligence where systems learn from data and improve without having to be explicitly programmed. A special subgroup is Deep Learning (DL), which uses multi-layered neural networks to process large amounts of complex data (images, sound, text). In practice, this means that businesses can use TML for prediction (Rai et al., 2021), pattern detection, automated decision-making, or process optimization. Specifically, they can be used, for example, to predict the future behavior of customers or markets, or as part of price optimization, where prices are set based on demand, competition, or other factors.

Robotic Process Automation (RPA) is a technology that allows software "bots" to automate routine and repetitive tasks that would otherwise be done by humans (e.g., copying data, filling out forms, processing orders). When artificial intelligence (AI-RPA or TPA) is added to RPA, these software bots no longer just make simple clicks, but can also learn, adapt, and assist in decision-making. This means that they can also handle more complex tasks where it is necessary to recognize text, analyze data or make decisions based on formulas. In business practice, it can be used in the automation of administrative processes (e.g. creation and processing of invoices, orders, etc.) and routinne tasks (Syed et al., 2020), in data processing and interpretation, in customer service to respond via chat or e-mail, or in logistics for inventory tracking.

Autonomous robots and vehicles (TARs) are devices that can perform physical movement and tasks without direct human intervention. They make decisions based on observing their surroundings using sensors (cameras, radar, GPS) and processing this data through AI algorithms. A key capability is autonomous decision-making in real time – for example, avoiding obstacles, planning the optimal route or adapting to changing conditions. In practice, this technology is used in the creation of robots that handle materials, in warehouses for moving goods, or in monitoring the environment and construction areas (Lee et al., 2021).

2.2.2 Areas of using AI technologies and their benefits

When we look at the areas in which companies use AI technologies, we see primarily use in marketing or sales, production processes, and ICT security. To a lesser extent, employees of enterprises use AI technologies in the organization of business administration processes, management of enterprises, logistics, human resources management or recruiting. Even in comparison across these areas, an increase in the use of AI technologies can be seen, which is also documented in the following table (Figure 2).

Table 5. Areas of using AI technologies in companies in 2021-2024 (% of all enterprises)

Areas of using AI technologies	2021	2023	2024
AI technologies for marketing or sales	1.63	1.90	4.59
AI technologies for production processes	1.51	2.10	3.17
AI technologies for organisation of business administration processes	1.77	-	-
AI technologies for management of enterprises	1.14	-	-
AI technologies for logistics	0.74	0.77	0.82
AI technologies for ICT security	1.85	2.12	3.20
AI technologies for human resources management or recruiting	0.62	-	-

Source: Eurostat (2025)

Now let's take a closer look at the individual activities in the company. In the field of marketing and commerce, artificial intelligence is becoming a common tool that helps companies get to know customers better, tailor their offerings and manage business activities more effectively (Miklaef et al., 2022). In business activities, AI is heavily used for **customer data analysis and market segmentation**, as AI can process huge amounts of data from many available sources such as social networks, websites or other records and use them to identify customer behavior patterns. Based on this, companies create more detailed market segments (e.g. in terms of price sensitivity, preferences, etc.), which allows for more targeted communication and higher effectiveness of marketing campaigns. Based on previous purchases or browsed goods, **AI can recommend products** that are most relevant to a particular customer (e.g., personalized recommendations on e-commerce stores), leading to higher customer satisfaction while increasing sales. Companies are increasingly deploying **virtual assistants and intelligent chatbots** that can communicate with customers nonstop, answer basic questions, process an order or help with complaints. Thanks to machine learning, these chatbots are gradually improving and can have a smoother and more natural conversation, saving time for employees and increasing customer comfort. Furthermore, through **predictive demand analysis**, AI can predict which products will have higher demand in certain periods, thus helping with inventory planning and pricing strategy. At the same time, it can estimate when the customer is ready for the next purchase. These predictions allow merchants to reach customers in a targeted manner and offer a personalized discount. AI also can analyze competition, availability of goods and market demand in real time and **optimize prices based on** this to maximize profit or increase sales. AI is also significantly involved in the **creation of marketing content** (e.g. when writing short texts for product descriptions, social media posts or email newsletters). This makes the process faster and more efficient, allowing marketers to focus on more strategic tasks. AI can be used to monitor **brand sentiment and reputation.** Thanks to this, AI can analyze how customers talk about the brand on social networks or in reviews. This allows businesses to quickly identify negative reactions, track trends, and tailor their communications to protect their reputation. All these activities show that AI in marketing and commerce is not just a fashion trend, but a practical tool that increases the efficiency and accuracy of decisions. Companies that know how to use it correctly gain a significant competitive advantage. A summary of the use of AI in marketing and sales, including the benefits resulting from the use of AI, can be seen in the following table (Figure 3).

Table 6. Activities using AI in marketing and sales

Activity	Short description	Benefits
Customer data analysis and market segmentation	Data processing and dividing customers into groups according to behavior.	Better campaign focus, higher marketing efficiency.
Personalized marketing and referral systems	Recommending products based on previous purchases or preferences.	Increase sales and customer satisfaction.
Chatbots and virtual assistants	Automated communication with customers available 24/7.	Savings in customer service costs and faster response.
Predictive analysis of customer demand and behavior	Predict customer demand and behavior using data.	More accurate planning and reducing the risk of losing customers.
Price optimization (dynamic pricing)	Automatic price adjustment according to demand and competition.	Maximizing profits and responding flexibly to the market.
Creating marketing content	Generating texts and posts for marketing purposes.	Save time when creating content, communicate consistently.
Monitor brand sentiment and reputation	Analysis of reviews and discussions on social networks.	Quickly identify problems and build a positive brand image.

Source: own processing (2025)

In the field of production processes, artificial intelligence is used to increase the efficiency, quality and flexibility of production (Reischauer & Schönauer, 2023). Thanks to AI, companies gain a more accurate overview of the status of production lines, can react faster to changes and prevent losses. The high use is particularly evident in **predictive machine maintenance**. Through AI tools, data from sensors placed on production equipment can be analyzed, which can recognize signals that indicate possible malfunctions or wear of components at an early stage. As a result, repairs are planned before a failure occurs, minimizing unplanned downtime, saving repair costs, and increasing the reliability of production lines. It is equally advantageous to use

AI technologies in **quality Inspection.** Such tools can identify even minor errors that a person might not detect at all. Such automated inspection increases the quality of final products, reduces complaints and saves time. AI technologies can process data on the flow of materials, energy consumption or the efficiency of individual machines, which leads to the **optimization of production processes.** Based on this, optimal production procedures and line configurations are then designed. This reduces material waste, shortens production times and achieves higher productivity. Other AI technologies are helping **robotics and AI-powered robotics**, where AI-powered industrial robots can learn and adapt to new tasks. They can flexibly change the way products are assembled or handled. This allows businesses to introduce new products faster and respond to changing demand without the need for lengthy robot reprogramming. AI technologies are also a great help in **supply chain management.** With the help of AI-generated models, it is possible to predict the need for materials and components, optimize inventory, and plan logistics. This leads to lower storage costs and a better alignment between production and delivery, minimizing downtime and delays in production. Last but not least, AI technologies contribute to **energy management.** With the use of AI, it is possible to monitor energy consumption in real time and optimize it so that production processes run with minimal losses. AI can design modifications in the operation of equipment or production lines that reduce energy consumption and help meet the environmental goals of businesses. All these activities show that AI in production processes is not just about automation, but above all about intelligent decision-making based on data. Companies that implement AI gain the advantage of lower costs, higher quality, and greater flexibility to the market. A summary of the use of AI in production processes is shown in the following table (Figure 4).

Table 7. Activities using AI in production processes

Activity	Short description	Benefits
Predictive machine maintenance	Predict machine failures based on sensor data.	Minimized downtime, lower repair costs, higher reliability.
Qualitative control of products	Automated quality control using computer vision.	Higher product quality, fewer complaints, quick inspection.

Activity	Short description	Benefits
Optimization of production processes	Optimization of material flow, production times and resource consumption.	Lower production costs, reduced waste, higher productivity.
Robotics and Autonomous Systems	Robots with AI capable of flexibly changing tasks and processes.	Flexible production, faster introduction of new products.
Supply chain management	Prediction of material needs, optimization of inventory and logistics.	Efficient planning, lower inventory costs, smoother production.
Energy efficiency of production	Monitoring and optimization of energy consumption in production.	Save energy, reduce costs and meet environmental goals.

Source: own processing (2025)

Artificial intelligence is also increasingly used in the management and organization of corporate administrative processes (Muller et al., 2023). In this area, it is not only about automating routine tasks, but also about intelligent decision-making and improving management efficiency. In the **automation of administrative tasks (Robotic Process Automation – RPA),** AI takes over many routine activities such as processing invoices, registering documents, entering data into systems or processing email communication. This saves employees time, reduces errors, and allows them to focus on more strategic tasks. At the same time, it helps in **intelligent document management,** where AI systems can sort, analyze and archive large volumes of documents. They use natural language processing (NLP) technologies to recognize the content and meaning of documents, which speeds up their retrieval and circulation in the organization. The result is a smoother flow of information and better transparency of processes. AI tools also **support decision-making using data analytics**, as AI can process large amounts of data from different departments (finance, HR, purchasing, sales) and provide managers with recommendations based on analyses and predictions. This allows for more accurate resource planning, budget optimization, and faster response to changes in the environment. More advanced AI technologies can also create **virtual assistants for administration**. Chatbots and voice assistants help employees with common tasks such as processing simple requests or navigating internal systems. This improves the user experience and speeds up the resolution of everyday tasks. AI also helps to **manage compliance management**.

AI monitors legislative changes and automatically checks whether company documents and processes are compliant with current rules. It also helps to identify risks and prevent penalties. This is a key area for companies in regulated industries. Last but not least, the part of administrative management where AI helps is the **analysis and optimization of internal processes**. AI maps processes in the company, identifies their weak points and recommends improvements. It can point out the duplication of certain processes or identify time losses, thereby increasing the efficiency of the entire organization. These activities clearly show that AI in the administrative management of a business is not only about reducing costs, but also about increasing accuracy, transparency, and speed of decision-making. Companies that implement such solutions create a more efficient and flexible environment for management. A summary of activities (including benefits) where AI is used in administrative management is presented in the following table (Figure 5).

Table 8. Activities using AI in organisation of business administration processes

Activity	Short description	Benefits
Automation of administrative tasks (RPA)	Automation of routine tasks such as invoicing, record-keeping and data processing.	Time savings, fewer mistakes, employees can focus on more valuable activities.
Intelligent document management and workflow	Sorting and analyzing documents using NLP for efficient information circulation.	Faster document processing, better transparency and availability.
Supporting decision-making with data analytics	Analysis of data from different departments and suggestions for better decision-making.	More precise planning and strategic decision-making.
Virtual assistants for administration	Chatbots and assistants help with day-to-day administrative tasks.	Simplification of work, better user experience.
Compliance management	Checking the compliance of processes and documents with legislation.	Risk prevention, reduction of sanctions, compliance with regulations.
Analysis and optimization of internal processes	Identifying weaknesses in processes and proposing improvements.	Higher efficiency, less duplication and waste.

Source: own processing (2025)

In the field of business management, the use of artificial intelligence is of great importance – from strategic decision-making, through effective planning, to performance monitoring (Duan et al., 2019. Businesses use AI in business management for **strategic planning and prediction**, as AI can analyze a huge amount of internal and external data. Based on these, it creates predictions of market development and recommendations for long-term planning. This helps businesses to make more flexible strategies and better prepare for possible future scenarios. Following this, AI can also be helpful in **financial and risk management**. AI-based systems are used to model financial flows, detect risk factors, and design optimal investment decisions. They help detect irregularities in statements, prevent fraud, and maintain sound financial stability of the business. Since AI tools enable effective monitoring of key performance indicators (KPIs), it becomes a suitable aid in **performance management.** They can identify which departments or processes are lagging behind and recommend steps for improvement to managers. The result is more effective control and faster problem resolution. Thanks to simulations of various scenarios, it can offer managers several variants of solutions, which is a significant **support for decision-making (Decision Support Systems)** based on facts and data. By combining data analytics and machine learning, it provides so-called "intelligent recommendations" that facilitate strategic and operational decision-making. Since AI has great creative thinking, it is also a suitable tool for **innovation management and new product development**. AI analyzes market gaps, customer behavior, and technology trends to identify opportunities for innovation. It can simulate the success of new products before they are launched on the market. This helps businesses innovate faster and more efficiently. This has an equally great impact on the implementation of **knowledge management** in enterprises. AI helps to systematically collect, classify, and make available knowledge within an organization. It can search for relevant information from large databases and recommend it to employees when solving problems. This promotes know-how sharing and better decision-making across the company. All these activities show that AI in business management is not only a tool for automating data analytics, but above all a partner for strategic and innovative decision-making. Companies that use AI in management gain the ability to better adapt to a turbulent environment and stay in the market and build their market position. The main activities, including benefits, that companies use within business management are summarized in the following table (Figure 6).

Table 9. Activities using AI in management of enterprises

Activity	Short description	Benefits
Strategic planning and forecasting	Analysis of market trends and internal data for prediction and planning.	Better long-term strategies and preparedness for future developments.
Financial and Risk Management	Modeling of financial flows, detection of risks and fraud.	Financial stability, lower risk of losses and greater transparency.
Performance Management	Real-time KPI monitoring and recommending steps for improvement.	More efficient performance control and faster problem resolution.
Decision Support Systems	Simulate scenarios and provide intelligent recommendations.	Better decisions based on data and simulations.
Innovation management and new product development	Identifying market gaps and supporting the development of new products.	Faster innovation and higher success rate for new products.
Knowledge management and corporate knowledge management	Gathering and making knowledge available within the organization.	Better use of company know-how and more efficient cooperation.

Source: own processing (2025)

In the field of logistics, artificial intelligence is becoming increasingly important, as it helps companies reduce costs, speed up deliveries, and respond more flexibly to changes in the market. An example is **demand forecasting**, in which AI processes historical sales data, seasonal trends, economic indicators, and even external factors such as weather or geopolitical events (Wamba et al., 2023). Based on these, it can accurately predict future demand. This allows companies to better plan inventory, reduce excess inventory, and minimize the risk of outages. Companies also use AI technologies in logistics for **route and transport optimization.** AI systems can analyze real-time traffic situations, road conditions, and current orders. As a result, they can design the most efficient routes for drivers, saving time and fuel. At the same time, it is possible to use **automated warehouse management (smart warehousing),** which is an essential part of modern businesses. AI is used to control the movement of goods – from automatic sorting to coordinating robotic technologies that take care of handling shipments. AI optimizes storage according to the turnover of goods and can anticipate the need for replenishment in real time. A large use in logistics can also be seen in the **processes of shipment**

tracking & visibility. With the use of AI, it is possible to track goods throughout the journey to the customer. Algorithms can predict delays and suggest alternative solutions, increasing supply chain reliability and transparency. All of this is closely related to **supply chain resilience**, where companies also use AI technologies. AI can identify potential supply disruptions such as supplier issues, price fluctuations, or geopolitical conflicts. It warns managers in time and recommends alternative partners or supplier routes. This increases the resilience of the business to unexpected crises. As an extension in logistics, some companies use AI to increase the **energy and environmental efficiency of logistics (Green Logistics).** AI helps minimize the carbon footprint of logistics by designing fuel-efficient use, possibly even optimal vehicle loading. In this way, companies not only save costs, but also meet environmental goals and improve their reputation in the eyes of customers. All activities show that AI in logistics is crucial. Whether it's demand forecasting through efficient transport and warehouse management to increasing the resilience of supply chains. Companies that implement AI are able to deliver faster, cheaper and more sustainably, which in turn is reflected in the economic results of companies. A summary of the individual activities supported by AI technologies is provided by the following table (Table 10).

Table 10. Activities using AI in logistics

Activity	Short description	Benefits
Predictive demand planning	Analyze historical data, trends, and external factors to estimate future demand.	Better inventory planning, less overage and downtime.
Route and transport optimization	Selection of the most efficient routes based on the traffic situation and orders.	Fuel and time saving, faster delivery.
Automated warehouse management	Control of the movement of goods, use of robots and drones in warehouses.	Faster order fulfillment, lower storage costs.
Shipment Monitoring & Tracking	Real-time tracking of goods and prediction of delays.	Higher reliability and transparency of deliveries.
Risk management and supply chain resilience	Identification of supply problems and suggestion of alternative solutions.	Greater flexibility, resilience to crises and disruptions.
Energy and environmental efficiency	Optimizing fuel consumption and planning greener processes.	Lower costs, smaller carbon footprint and better reputation.

Source: own processing (2025)

Even in the field of ICT security, AI presents many opportunities to improve functioning. This is mainly because it can process huge volumes of data, quickly identify threats and respond to them faster than human experts (Buczak & Guven, 2016). Businesses are using AI in security processes, for example, to **detect anomalies and suspicious behavior** within ICT. AI systems can continuously monitor network traffic and user behavior. They use machine learning to identify unusual patterns that can signal a cyberattack or unauthorized access. Such detection is much faster and more accurate than traditional manual monitoring. It also provides **malware prevention and detection**, as AI can analyze files, apps, and email attachments based on their behavior, rather than just comparing them to known "signatures." Thanks to this, it can also detect new, previously unknown types of malware (so-called zero-day attacks), which classic antivirus programs would not be able to detect. The great use of AI can also be seen in **access control and authentication**. AI-based systems are used to recognize a user's face, voice or behaviour (e.g. the way of typing). Such biometric authentication increases the level of security and minimizes the risk of unauthorized access. AI is also very helpful in **predictive cybersecurity**, as it processes vast amounts of global threat data, tracks trends, and can predict what attacks may occur in the future. This allows companies to take precautionary measures before an attack even takes place. It can implement an **automated incident response,** because time is of the essence in an attack. AI can instantly isolate an infected device, block malicious traffic, or recommend steps for system recovery. This significantly reduces response time and, most importantly, reduces consequential damage. AI can also increase **phishing protection** by analyzing emails, messages, and websites to identify fraudulent attempts to obtain sensitive data. The systems can also detect subtle variations in the language, stylistics, or design of fake news that the user might overlook. Last but not least, AI helps ensure **security in the cloud and IoT**, which businesses are increasingly using. AI can monitor these environments, identify unusual activities, and prevent unauthorized access or data leaks, which are particularly vulnerable in these systems. These activities show that AI in the field of ICT security is not only a tool for responding to attacks, but above all for preventing and predicting them. As a result, businesses are better able to protect themselves against increasingly sophisticated cyber threats and reduce the risk of financial and reputational losses. A summary of these activities and the benefits is provided in the following table (Table 11).

Table 11. Activities using AI in ICT security

Activity	Short description	Benefits
Detection of anomalies and suspicious behavior	Monitoring network and user behavior to identify unusual patterns.	Quick detection of attacks, lower risk of intrusions.
Malware prevention and detection	Behavioral file analysis, detection of unknown threats.	Protection against zero-day attacks, higher level of security.
Access control and authentication	Use of biometrics (face, voice, behavior) to authenticate users.	Stronger protection against unauthorized access.
Predictive Cybersecurity	Forecast threats based on global data and trends.	Attack prevention, proactive protection of systems.
Automated incident response	Immediate isolation of infected devices and recommendations for recovery.	Reduced response time, less damage.
Protection against phishing and social engineering	Email and website analytics to detect fraud.	Fewer successful phishing attacks, higher user trust.
Security in the cloud and IoT	Monitoring of cloud services and IoT devices.	Protection of sensitive data, less risk of leaks and attacks.

Source: own processing (2025)

Artificial intelligence is increasingly changing the way businesses approach managed human resources and recruitment. AI can process large amounts of data, simplifying processes and making more objective decisions (Jatoba et al., 2022). A lot of use can be seen in **automated candidate pre-selection**, as AI can quickly analyze hundreds to thousands of resumes and social media profiles. Based on defined criteria (experience, education, skills), it selects candidates who best meet the requirements of the job position. This saves the HR department time and eliminates the risk of a suitable candidate going unnoticed. To make work more efficient, **chatbots are used to communicate with applicants**, which answer applicants' questions, provide information about positions and even conduct basic screening interviews. This way, the candidate receives immediate feedback and the HR team has more space to focus on more strategic tasks. At the same time, AI can perform **predictive analysis of candidate success**, especially based on historical data about previous employees. Thanks to them, AI can predict how likely it is that a particular candidate will be successful in a given position. It analyzes factors such as career progress, work results or personality traits. Companies are thus making more informed decisions. AI is used to objectify decisions in **bias detection**. AI can help minimize unconscious biases in the hiring process. By analyzing recruiters' decisions or setting algorithms so that they do not favor gender, age or nationality, a fairer approach to candidates is ensured. As part of the continuous improvement of the quality of the workforce, AI also helps in **optimizing internal employee learning and development**. AI tracks employee performance and suggests personalized training and development programs. This helps to create an environment where each worker can improve according to their needs and potential. A large use can also be observed in the **analysis of employee satisfaction and engagement**. Through the analysis of feedback, surveys or communication (e.g. emails or company chats), AI can detect the level of employee satisfaction, or signals of burnout or risk of leaving. This allows companies to implement measures before the problem gets worse. Similarly, its use can be seen in **workforce planning,** where AI predicts workforce needs based on trends in the company and the market. It can identify where it will be necessary to replenish capacities and where, on the contrary, there is a risk of a surplus of workers. These activities show that AI in HR is not just about automating routine tasks, but above all about improving the quality of decision-making, fairness, and long-term employee satisfaction. A summary of the individual activities of the use of AI in HRM is shown in the following table (Table 12).

Table 12. Activities of using AI in HRM

Activity	Short description	Benefits
Automated pre-selection of candidates	Analysis of CVs and profiles, filtering candidates according to requirements.	Time savings, higher selection accuracy, less risk of overlooking suitable candidates.
Chatbots for communication with applicants	Virtual assistants answer questions and perform basic screening.	Faster communication, better candidate experience, relieving the HR team.
Predictive analysis of candidate success	It predicts whether a candidate will be successful in a given position based on historical data.	Better recruitment decisions, lower turnover.

Activity	Short description	Benefits
Bias detection	Identification and elimination of biases in recruitment processes.	Fair selection, greater diversity of the workforce.
Internal Learning Optimization	Personalized recommendations for training and development programs.	Better talent development, increased employee motivation.
Satisfaction and engagement analysis	Monitoring feedback, burnout signals, and exit risk.	Prevention of departures, higher loyalty and employee satisfaction.
Workforce Planning	Prediction of workforce needs according to trends and company needs.	More efficient planning, better use of human resources.

Source: own processing (2025)

2.2.3 Barriers of using AI technologies in SME

Barriers slow down the adoption of AI. However, the biggest challenges do not relate to the technology itself, but to human capital, legislation and organizational change. Companies that can overcome these obstacles gain a significant competitive advantage.

One of the first obstacles is the high cost of implementing AI technologies. For small and medium-sized enterprises, the procurement of hardware, software and professional services is a major financial burden. For example, in retail, smaller e-shops often cannot afford to implement personalization algorithms at the level of giants such as Amazon. The consequence is a slowdown in innovation and a risk of loss of competitiveness. Another major barrier is the lack of relevant expertise. Although companies want to use AI, they do not have experts in data analytics or machine learning. In practice, this is manifested, for example, in production, where companies buy robotic systems, but they lack a team that would be able to fully set them up and integrate them. This leads to inefficient use of technology and low ROI. Incompatibility with existing systems is also a problem. Many businesses run on legacy ERP or CRM solutions that they can't easily connect with modern AI applications. In business, for example, old IT infrastructures complicate the deployment of chatbots or fraud detection tools. This results in additional integration costs and the risk of technological delays. Difficulties with data availability or quality are a major limitation. AI needs large-scale, high-quality datasets, but businesses often don't have them. In retail, they are unable to connect their customer databases, which hinders the development of predictive customer behavior systems. Weak data also means poor outputs and reduced trust in AI results. Companies are afraid that when using AI, they will face data leaks or violations of legislation (e.g. GDPR). An example is the HR area, where the use of AI in recruitment processes can lead to the collection of sensitive personal data. The impact can be not only legal, but also reputational. This is also related to the lack of clarity of the legal consequences. Businesses aren't sure who is responsible for the error caused by the AI system. In the case of autonomous vehicles, for example, the question arises as to who is at fault in an accident – the software manufacturer, the car manufacturer or the driver. This uncertainty can discourage businesses from deploying AI at scale. Another barrier is ethical issues. Businesses are concerned that the use of AI will be perceived as unethical – for example, when tracking employees or evaluating candidates based on algorithms. Such practices can lead to a loss of trust on the part of employees or customers. Finally, some companies still believe that AI is not useful for their business. A typical example is traditional industries, such as craft services or smaller family businesses, which do not see a direct benefit. However, this attitude can lead to long-term lagging behind competitors that are gradually implementing AI.

Table 13. Problems with AI technologies implementation in companies (% of all enterpises)

	2023	**2024**
the costs seem too high	2.97	3.34
a lack of relevant expertise	4.45	7.10
incompatibility with existing equipment, software or systems	3.13	4.15
difficulties with availability or quality of the necessary data	3.10	4.44
concerns regarding violation of data protection and privacy	2.75	4.89
a lack of clarity about the legal consequences	2.95	5.26
ethical considerations	1.43	2.36
artificial intelligence technologies are not useful for enterprise	1.29	2.7

Source: Eurostat (2025)

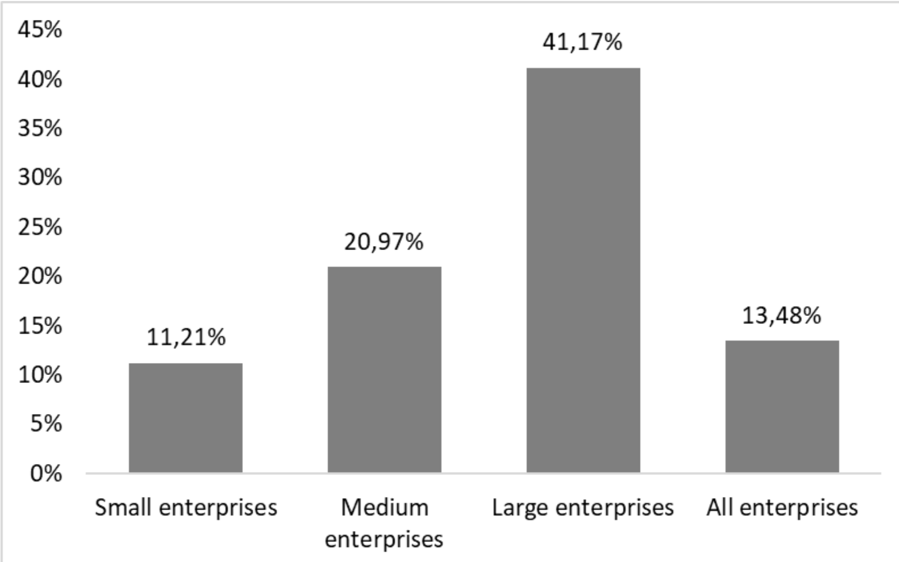
According to data from Eurostat, despite the great popularity of AI, there are also many barriers to the use of AI technologies in businesses. Between 2023 and 2024, barriers to the use of AI in businesses increased noticeably, shifting their nature from financial to legislative, organisational and knowledge challenges. While in 2023 the most frequently mentioned were costs or lack of expertise, already in 2024 it turns out that the biggest problem is the lack of qualified professionals, which has risen from 4.45% to 7.10%. Similarly, concerns about data protection and privacy breaches (from 2.75% to 4.89%) and legal ambiguities (from 2.95% to 5.26%) also increased significantly. Also interesting is the growth in the perception of I as a potentially "useless" technology, which has more than doubled, although the absolute values remain low. Overall, it turns out that while financial barriers remain relatively stable, businesses are increasingly facing challenges related to regulation, legal certainty, and the availability of human capital, which will be critical to the pace of AI adoption going forward.

2.2.4 Case Studies of AI Implementation in SMEs

Innovation is widely recognized as a key driver of economic growth and competitiveness, especially for SMEs. SMEs make up a significant part of the global economy, accounting for approximately 90% of enterprises and more than 50% of jobs worldwide. The ability of these enterprises to innovate is essential for their survival and growth, especially in an increasingly competitive and rapidly changing market environment (Iyelolu, 2024).

According to survey conducted by Eurostat (2025) in European Union (EU) countries, AI is used more by large businesses than by SMEs. AI was utilised by 11.21% of small businesses, 20.97% of medium-sized businesses, and 41.17% of large businesses in 2024. This gap could be explained, for instance, by the difficulty of integrating AI technology into a business, economies of scale (i.e., businesses with larger economies of scale can benefit more from AI), or costs (i.e., investment in AI may be more affordable for large organisations).

Figure 4. Enterprises in EU using AI technologies by size in 2024



Source: own processing based on Eurostat data (2025)

Although the use and adoption of AI technologies in SMEs is significantly lower than in a case of large enterprises, the volume of successful AI implementations is rapidly growing also in SME segment. In this chapter are presented 3 cases studies of successful AI implementation by SMEs operating in different segments (manufacturing, retail and services). The inclusion of these case studies in this chapter serves to complement the theoretical and analytical parts of the monograph with empirical evidence from real-world practice. While the preceding sections discuss the benefits, barriers, and areas of AI application in SMEs from a conceptual perspective, case studies provide a tangible illustration of these dynamics in practice. They enable a deeper understanding of the complex interplay between technological, organizational, and human factors shaping AI adoption. By examining diverse examples across manufacturing, retail, and service sectors, this chapter highlights both the measurable outcomes and the practical challenges SMEs face when implementing AI solutions. The insights drawn from these cases reveal common patterns, critical success factors, and lessons learned that can influence future research, managerial decision-making, and policy initiatives supporting digital transformation in SMEs.

2.2.4.1. Case Study 1: AI-Driven Quality Inspection in Textile Manufacturing

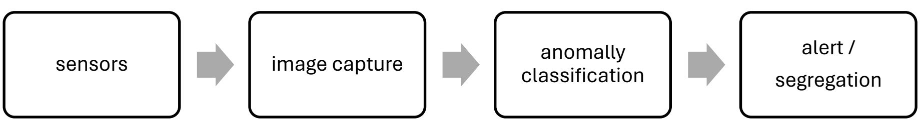
Background

The manufacturing sector represents one of the most promising areas for AI deployment in SMEs, particularly through predictive maintenance and quality control systems. A notable real-life example involves a Baltic sportswear manufacturer that collaborated with the technology company *EasyODM* to implement a computer-vision-based quality inspection system (EasyODM, 2024). The company faced recurring challenges in manual fabric inspection i.e. human fatigue and subjectivity often resulted in undetected defects, inconsistent quality, and unnecessary waste.

AI Solution and Implementation

To address these issues, *EasyODM* deployed a computer-vision (CV) system integrating high-resolution cameras and machine-learning algorithms trained on a dataset of both "flawless" and "defective" fabric samples. The implementation followed an incremental approach: the system was first tested on a single production line, where AI models learned to identify surface anomalies such as weaving faults and colour inconsistencies. Once the proof of concept demonstrated satisfactory performance, the company extended the solution across multiple production lines. The deployment did not require significant infrastructure changes, making it economically feasible for an SME context.

Figure 5. Computer-vision quality inspection workflow



Source: own processing (2025)

Outcomes

The AI system achieved significantly higher detection accuracy compared to manual inspection. As a result, the manufacturer reduced rework rates and waste, shortened inspection times, and improved overall process transparency (EasyODM, 2024). Beyond direct productivity gains, the system also improved employee satisfaction, as workers could shift their focus from repetitive inspection tasks to higher-value analytical or supervisory roles.

Barriers and Lessons Learned

Key implementation barriers included the need for high-quality image data for algorithm training and integration with existing production workflows. Moreover, employees initially expressed scepticism about machine decisions. These challenges were mitigated by validation using human participation and targeted employee training.

Case Study Relevance

This case illustrates that for manufacturing SMEs, AI adoption succeeds when combined with incremental integration, collaboration with technology providers, and organizational readiness for change.

2.2.4.2. Case Study 2: Conversational AI for Customer Engagement in an E-Commerce SME

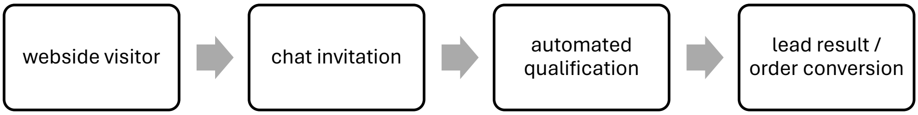
Background

AI technologies have rapidly transformed the retail and e-commerce sectors, offering tools for personalization, customer analytics, and automated communication. The company Pastreez, a French-based small online confectionery specializing in macarons, adopted AI-driven customer service via Tidio's chatbot platform (Tidio, 2025). As order volumes increased, the founders needed to maintain high-quality, responsive communication without expanding their workforce.

AI Solution and Implementation

Pastreez integrated a software as a service (SaaS) conversational AI solution on its Shopify website. The Tidio chatbot used AI-assisted message routing and predefined conversational flows to answer common queries, capture orders, and provide personalized product suggestions. The implementation was completed in less than a week, demonstrating the low technical barrier for SMEs using cloud-based AI tools. Unlike custom-built systems, the Tidio platform offered pre-trained models that could be fine-tuned using company-specific vocabulary and product data.

Figure 6. Flow diagram of chatbot implementation



Source: own processing (2025)

Outcomes

The introduction of conversational AI dramatically improved efficiency and conversion. According to Tidio’s case documentation, approximately 70% of chat interactions converted into orders, and the company secured new high-value clients such as Netflix, Google, and Visa through faster, more consistent communication (Tidio, 2025). Moreover, automating routine inquiries freed managerial time for strategic business development.

Barriers and Lessons Learned

The main challenges related to maintaining brand tone in automated responses and balancing automation with personal touch, which is an important issue for craft brands. Compliance with privacy regulations such as GDPR was also a consideration, requiring data handling policies to be reviewed.

Case Study Relevance

This case underscores the growing democratization of AI: even micro-SMEs can deploy AI using SaaS platforms without technical expertise. It also confirms that AI’s primary value in SMEs often lies not in technological sophistication, but in expanding human capacity and scaling personalized service efficiently.

2.2.4.3. Case Study 3: Intelligent Invoice Processing in Financial Administration

Background

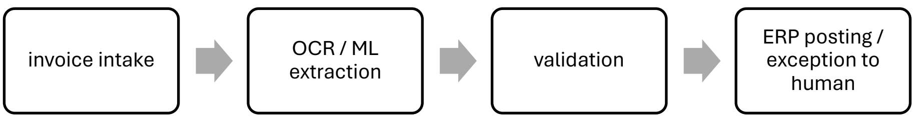
AI adoption in SME service functions, particularly finance and accounting, often takes the form of automation through machine learning (ML) and robotic process automation (RPA). A case reported by KGiSL Technologies

(2024) describes a mid-sized enterprise that modernized its invoice processing using AI-driven document understanding and workflow automation.

AI Solution and Implementation

Previously, the firm's finance department manually processed thousands of suppliers invoices each month, resulting in high error rates and long cycle times. The new system combined optical character recognition (OCR) and ML models to extract structured data from diverse invoice formats, while RPA bots validated entries and posted them into the enterprise resource planning (ERP) system. Human staff only reviewed exceptions flagged by the model. The implementation replaced a coordinate-based extraction approach with a cognitive model capable of learning from new invoice templates.

Figure 14: OCR and ML workflow for invoice processing



Source: own processing (2025)

Outcomes

The case study reports a reduction in error rates to 0.01 %, freeing over half of the full-time equivalent (FTE) capacity previously devoted to manual entry. The company achieved an estimated return on investment exceeding 150 % within one year (KGiSL, 2024). Employees were retrained to focus on supplier relations and financial analysis instead of data entry.

Barriers and Lessons Learned

Initial challenges involved data inconsistency and staff adaptation to new digital workflows. Success depended on process standardization and human oversight of the exception management process during the model learning phase.

Case Study Relevance

The case illustrates that the impact of AI on SMEs extends beyond cost savings (it promotes process transparency and organizational learning). It also reinforces a recurring pattern: SMEs benefit the most from deploying AI to automate structured, repetitive tasks that are resource-intensive but data-rich.

Together, these cases studies demonstrate how SMEs can successfully implement AI across manufacturing, retail, and administrative functions when these projects:

- Begin with clearly defined, narrow problems.
- Use accessible, vendor-supported technologies.
- Combine automation with human oversight.
- Treat AI adoption as an organizational learning process, not merely a technological upgrade.

Comparison of all 3 presented case studies from the perspective of *AI implementation area*; *Primary AI technology used*; *Key benefit*; and *Main barrier* is summarized in Table 14.

Table 14: Case Studies Comparison Summary

Case Study	1	2	3
Area of AI implementation	Manufacturing – quality inspection	Retail/e-commerce – customer engagement	Services/administrative – invoice processing
Primary AI technology used	Computer vision system	SaaS chatbot / AI live chat	Robotic process automation & optical character recognition and machine-learning models
Key benefit	Improved defect detection, faster processing	High conversion from enquiries, scalable customer service	Large time and cost savings, error reduction
Main barrier	Data / training, integration with production line	Maintaining brand voice, integrating AI into workflows	Variable data inputs, process redesign, staff training

Source: own processing (2025)

2.2.5. Future Trends and Opportunities for Using AI by SMEs

It is impossible to ignore the important contributions that AI has made in the current era of digitalisation. SMEs are open to implementing AI to improve their performance, reduce costs, increase effectivity, etc. Enterprises do, however, confront also difficulties in this process. Within this context, the following part of the chapter presents the future trends and opportunities of AI implementation that can have significant influence on the processes of SMEs in the near future.

Future Trends of Using AI by SMEs

AI has a lot of potential for SMEs in the future, providing creative ways to boost competitiveness and stimulate company expansion. A number of new phenomena have the potential to significantly alter the SME landscape as AI technologies develop. Natural language processing (NLP) developments, the emergence of AI-driven personalisation, the integration of AI with the Internet of Things (IoT), and the growing accessibility of AI through cloud computing and democratised AI tools are some of these themes (Iyelolu, 2024). These and other new trends and their possible effects on SMEs are outlined in the following section.

The development of AI-driven personalisation is one of the most important developments in AI for SMEs. Businesses may increase customer engagement and happiness by customising their goods, services, and marketing campaigns to each client's preferences thanks to personalisation technologies (Gentsch, 2018). As AI algorithms advance, they will be able to analyse enormous volumes of data and provide real-time, highly customised experiences. For example, AI can monitor consumer behaviour at several touchpoints and make remarkably accurate predictions about their needs and preferences. According to Davenport et al. (2020), SMEs may improve client connections, boost loyalty, and boost revenue growth with this degree of personalisation.

Natural language processing (NLP) developments are also expected to transform how SMEs handle internal procedures and engage with clients. NLP makes AI more approachable and user-friendly by enabling machines to comprehend, interpret, and react to human language. Chatbots and virtual assistants, who may respond to consumer questions, offer assistance, and even help with sales transactions, are powered by this technology. As NLP technologies advance, they will be better able recognise context and complexities in human communication, resulting in more organic and productive exchanges

(Iyelolu, 2024). Better customer service, lower operating expenses, and the capacity to expand customer support initiatives without appreciably adding staff are all benefits for SMEs.

Another new development that has major consequences for SMEs is the integration of AI with the Internet of Things (IoT). When paired with AI, the massive amounts of data generated by IoT devices can offer insightful information on a variety of corporate activities. Supply chain management, asset utilisation, and predictive maintenance can all be improved by using AI to analyse data from IoT sensors (Lee & Lee, 2015). AI-powered IoT solutions, for instance, may track equipment performance in real-time and spot any problems before they cause expensive downtime. This skill improves overall productivity and competitiveness by enabling SMEs to retain operating efficiency and lower maintenance expenses.

Another development that can boost SME innovation in the near future is the growing accessibility of AI through cloud computing and democratised AI tools. Without requiring large upfront expenditures in hardware and infrastructure, cloud-based AI platforms give SMEs access to robust AI capabilities (Marston et al., 2011). These platforms provide a variety of services that SMEs can use to improve their operations, such as data analytics tools and machine learning models. Additionally, SMEs with little technical skills may now adopt AI solutions thanks to the democratisation of AI technologies like pre-trained models and user-friendly AI development platforms. More SMEs can profit from AI-driven innovations as a result of this accessibility, which decreases the barriers to AI adoption (Smith & Anderson, 2014).

Additionally, ethical AI and responsible AI development are becoming significant themes in the field of AI. As SMEs use AI more frequently, it is critical to make sure that these technologies are created and used ethically, taking accountability, fairness, and transparency into account. SMEs may reduce the risks associated with biassed algorithms, comply with regulatory obligations, and develop trust with stakeholders and consumers by using ethical AI practices (Floridi et al., 2018). SMEs may use AI technologies responsibly and sustainably, promoting long-term success and societal advantages, by placing a high priority on ethical AI.

Several new trends that have the potential to significantly enhance creativity and competitiveness characterise the future of AI for SMEs. The SME landscape is about to change due to AI-driven personalisation, IoT integration, NLP developments, cloud-based and democratised AI tool accessibility, edge AI, and ethical AI practices. SMEs may unleash new prospects for growth, productivity, and customer engagement by following up with current trends and proactively incorporating AI into their operations (Iyelolu, 2024). SMEs that adopt these advancements will be well-positioned to prosper in the rapidly evolving, demanding marketplace as AI technologies continue to advance.

Opportunities and Future Outlook

SMEs can profit quite greatly from AI integration. Businesses frequently seek to grow and expand, and AI can be quite helpful in achieving these objectives (Baabdullah et al., 2021). AI is being used in many commercial fields, including sales, marketing, customer and employee engagement, and hiring. The potential for AI in the future is promising for SMEs given its quick rise in the business sector. The business is becoming more competitive because of the growing awareness and understanding of AI. According to Borges et al. (2021), this is a favourable trend that will assist change the status quo regarding AI integration. In addition, as more research and development is done in this field, the cost of AI is gradually decreasing. AI is probably going to become more stable in the future, which will result in the creation of complex solutions that companies can use efficiently. This will undoubtedly decrease the time, money, and effort organisations need to integrate AI and improve their performance (Onu & Mbohwa, 2021). Based on these indications, it can be concluded that SMEs will find it easier to integrate AI in the future, which will help them perform better and expand more effectively. The degree to which technical innovation, human capital development, and policy frameworks come together to produce an inclusive digital ecosystem will determine the future of AI adoption in SMEs. SMEs must implement forward-thinking strategies that improve adaptability, resilience, and innovation capability as the global economy grows more data-driven and interconnected (Senthilvelan, 2025). For SMEs aiming to overcome the digital divide and prosper in the digital age, the upcoming years offer both opportunities and challenges.

AI adoption and the whole process of digital transformation of the entire SME segment should go hand in hand with inclusivity. Therefore, governments and development organisations should guarantee that low-income and rural SMEs are not left behind because of financial limitations or inadequate infrastructure. Digital divide can be considerably reduced by policy frameworks that support digital inclusion, such as public broadband expansion, reasonably priced cloud access, and SME-focused incubators. Additionally, to enable equitable involvement in digital economies, digital literacy programs must be extended to marginalised communities (Andrew, 2025). Sustainable AI implementation and digital transformation of SMEs should be based on the collaboration between governments, businesses and academic institutions. By combining resources and knowledge, public-private partnerships (PPPs) can encourage innovation while also making sure that digital projects are in line with regional business realities. Under inclusive licensing arrangements, technology companies can supply SMEs with digital tools and training, and governments can encourage such partnerships with incentives and policy support. Good governance practices that address cybersecurity, data protection, and ethical technology use are necessary components of this process. Regulatory certainty guarantees fair competition in the market and enables SMEs to confidently embrace digital tools. To assist SMEs in tracking their development and benchmarking best practices, governments should create standardised frameworks for digital maturity assessments and certification programs. Policies for regional integration can also promote international digital cooperation and trade, especially in emerging markets.

AI integration has a lot of promise for SMEs because it may assist them in achieving their objectives. Multiple organisations have found AI to be a tremendous asset, and the technology's rapid research and development is proof that it will change enterprises in the future. Even though there are certain obstacles to AI integration for SMEs, such as expenses and technological difficulties, these are probably going to be decreased with further advancement. It is quite difficult for SMEs to implement AI due to the significant integration costs (Govori & Sejdija, 2023). Nonetheless, it has been observed that there is growing research and development in this area, which would improve the application of AI in SMEs. Therefore, as technology becomes more affordable and advanced, it is expected that AI will become more applicable throughout the SME segment in the future.

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2.3. Barriers to AI Implementation in European SMEs: A Comparative Review

Small and medium-sized enterprises (SMEs) account for the backbone of the European economy, yet they face a distinct set of opportunities and constraints when adopting artificial intelligence (AI) for business management. This work provides a coherent review of benefits and barriers of AI with a comparative lens on Germany (benchmark), Spain, Italy, Poland and Slovakia. Germany is used as a reference point because the literature repeatedly links its stronger compliance by design habits, denser integrator markets and closer ties with applied research to faster transitions from pilot to production in SMEs (OECD, 2021; European Parliament, 2024). The structure follows the project's requested outline. First part summarizes the applications most commonly recognized as beneficial by SMEs and the scientific community. The second part synthesizes barriers and challenges under fourteen headings, including skills, finance, data and infrastructure, technological complexity, legal obligations, culture, regional disparities, ethics and leadership, ending with practical strategies. Tables and figures are used sparingly to support, not replace, the narrative. We have prioritised the use of the most up-to-date and prestigious sources, supplemented by Eurostat statistics on the adoption of AI by businesses and the EU AI Act as a policy reference (Eurostat, 2024; European Parliament, 2024; OECD, 2021).

2.3.1. Applications of AI recognized as beneficial by SMEs and scientific community

2.3.1.1. Business Process Automation

Across Europe, the first wave of AI in SMEs typically targets repetitive, information – intensive processes – invoice capture and matching, purchasing approvals, stock reconciliation, warranty triage, schedule adherence and anomaly detection in bookkeeping. These tasks are costly because they depend on manual checks, scattered spreadsheets and unstructured communications. AI assisted automation – often a pragmatic combination of rules, classical machine learning and robotic process automation (RPA) – reduces cycle time and error rates while building audit trails that later simplify compliance reviews (OECD, 2021). In industrial SMEs, computer vision for quality checks and simple anomaly detectors on sensor streams help stabilize scrap and downtime without requiring a full "lights-out" factory (Masood

& Sonntag, 2020; Moeuf et al., 2018). Service bundle approaches – preintegrated connectors, configurable workflows and catalogued use cases– have proved particularly helpful to small firms because they compress search, integration and training costs (Gładysz et al., 2023). Recent practice oriented accounts confirm that lightweight assistants can standardize quoting, order capture and billing in commercial teams, freeing scarce managerial capacity for higher value work (Crockett et al., 2023). Even in basic sales operations, small interventions –such as AI supported product recommendation or stock alerts tied to *Enterprise resource planning (*ERP) data– have been associated with measurable reductions in rework and late deliveries (Giguashvili, 2024). More broadly, the literature is consistent on a sequence: digitize the workflow, improve the structure and timeliness of data at the point of work, then layer AI to accelerate and stabilize execution. Once that foundation is in place, firms can branch into forecasting, simulation and optimization that compound returns (Duan et al., 2019; OECD, 2021).

Automation of routine administrative and operational tasks is consistently reported as a primary, early stage benefit of AI in SMEs. Evidence points to process acceleration, fewer errors, and improved compliance when AI is applied to workflow orchestration, forecasting and quality control (OECD, 2021; Duan et al., 2019; Cubric, 2020). Recent case-oriented studies show that even lightweight AI (e.g., rules-augmented machine learning and conversational agents) can streamline sales, billing and inventory processes (Giguashvili, 2024). In a prescriptive framing, AI within the Technology–Organization–Environment (TOE) context amplifies operational efficiency insofar as data availability and managerial readiness are present (Badghish & Soomro, 2024). Across EU enterprises that already use AI, the two most common purposes are marketing/sales (34.08%) and business administration/management (27.51%), which encompasses process automation and administrative optimization (Eurostat, 2024). Platform-based service bundles further lower transaction and search costs for SMEs adopting modular AI building blocks (Gładysz et al., 2023). As one policy document stresses, SMEs need “simple, interoperable digital solutions” to unlock cumulative productivity gains (OECD, 2021, p. 19). Empirical reports describe notable reductions in cycle times and administrative burden after RPA plus AI deployments (Crockett et al., 2023; Vanessa et al., 2024).

2.3.1.2. Human Resource Management (HRM)

In HRM, AI supports requisition management, skills inference, candidate shortlisting, interview scheduling and onboarding, and it increasingly informs workforce planning and learning pathways. SMEs report benefits primarily through cycle time reductions and more consistent screening; when combined with training and documentation, these gains translate into fewer downstream issues in probation and performance management (Murire, 2024). However, HR is also a domain where trust and accountability are decisive: algorithms should make recommendations, not decisions, and documentation must clarify what criteria are used and which decisions remain human. Two complementary strands recur in the evidence. The first highlights hybrid competence development – combinations of analytical literacy with managerial and domain skills– as a precondition for sustained HR analytics (Hayajneh et al., 2022). The second links adoption success to organizational readiness factors such as leadership sponsorship, experimentation culture and data governance routines (Jöhnk et al., 2021). Country evidence underscores that internal competence building is a strong predictor of firm level AI adoption. Spanish SMEs, for example, show higher uptake where training and vendor empowerment are coupled with procurement (Huseyn et al., 2024). Because HR data are sensitive, European SMEs operate under strict privacy and nondiscrimination expectations. The EU's risk based approach codified in the AI Act places special emphasis on transparency and human oversight in employment contexts (European Parliament, 2024). When those safeguards are treated as part of the product –not an obstacle– HR analytics is more likely to be perceived as augmentation rather than opaque automation (OECD, 2021).

In HRM, AI supports candidate screening, skills inference, onboarding, and workforce planning, often reducing time-to-hire and improving matching quality (Singh & Pandey, 2024; Madanchian & Taherdoost, 2025; Murire, 2024). Evidence links analytics capabilities and πshaped skills –deep expertise in **two distinct areas** combined with a **broad, foundational understanding of many other fields**, enabling them to bridge disciplines, collaborate effectively, and solve complex, cross-functional problems in dynamic environments (Kronick, 2024)– to innovative performance, a relationship that is especially salient for SMEs with resource constraints (Hayajneh et al., 2022). Interview-based research on AI readiness also emphasizes leadership commitment, experimentation culture, and data governance as prerequisites for HR analytics at scale (Jöhnk et al., 2021; Li et al., 2021). Spanish evidence confirms that competence development –digital, analytical, and managerial– predicts AI uptake at the firm level (Huseyn et al., 2024). When applied responsibly, HRM AI supported can augment, rather than replace, human judgement in talent and performance management (OECD, 2021; European Parliament, 2024). However, benefits materialize only where SMEs articulate clear HR use cases, codify fairness and transparency safeguards, and invest in change management (Madanchian & Taherdoost, 2025; Singh & Pandey, 2024). As one review notes, organizational and technological factors co-determine adoption success, implying that HR benefits are contingent on governance maturity (Madanchian & Taherdoost, 2025, p. 6). Germany's emphasis on compliance by design and data protection has catalyzed more structured HR AI supported piloting relative to peers (Joswig & Kurz, 2025).

2.3.1.3. Customer Relationship Management (CRM)

AI-enabled CRM integrates interaction histories (emails, meetings, support tickets) with transaction data to improve lead scoring, opportunity prioritization, churn prediction and cross/upsell recommendations. SMEs that make predictive scores interpretable to sellers –"why this lead, now?"– report better adoption and more disciplined pipeline management (Baabdullah et al., 2021). In Business to Consumer (B2C) contexts, microsegmentation and journey analytics support personalized offers and cadence; in Business-to-Business (B2B), account level signals coordinate outreach across roles. The evidence is unambiguous that evergreen data hygiene—harmonized identifiers, maintained taxonomies, routine deduplication—is the technical debt that determines whether CRM-AI creates value or triggers fatigue (OECD, 2021). SMEs benefit from modular CRM add-ons with prebuilt models and connectors, provided they invest in training and define feedback loops so that the system learns from seller outcomes (Gładysz et al., 2023). Because CRM touches personal data and often triggers automated decisions about pricing or eligibility, transparency and consent practices matter for long-term acceptance (Crockett et al., 2023; European Parliament, 2024). Spanish evidence indicates that firms with internal capacity to steward data and challenge vendor defaults extract more value from CRM-AI deployments (Huseyn et al., 2024).

AI-embedded CRM systems help SMEs integrate demand signals, personalize offers, and prioritize leads using predictive scoring (Baabdullah et al., 2021; Badghish & Soomro, 2024). Evidence shows that AI-enabled B2B practices enhance relationship quality and, ultimately, sales outcomes, provided that data stewardship and change management are in place (Baabdullah et al., 2021; OECD, 2021). Conversational AI reduces response times and surfaces next best actions for account managers (Ridho, 2023; Crockett et al., 2023). Spanish SMEs exhibit stronger CRM impacts when internal competencies complement vendor solutions (Huseyn et al., 2024). Studies also flag trust and transparency as requisites for sustained CRM value realization (Crockett et al., 2023; OECD, 2021). European SMEs report that accessible, pre-integrated CRM-AI modules lower adoption frictions (Gładysz et al., 2023; Vanessa et al., 2024). As summarized by one review, “AI can intensify customer intimacy, but only where data quality and consent practices are robust” (Cubric, 2020, p. 8). This aligns with EU risk based obligations around transparency and human oversight in customer-facing AI (European Parliament, 2024).

2.3.1.4. Customer support and loyalty

Customer service is a natural early use case for SMEs because demand is volatile and response time is highly salient. Chatbots and virtual assistants triage routine queries, retrieve knowledge base content and escalate when necessary, lowering average handling time and improving first contact resolution (Ridho, 2023). Generative models now assist in drafting replies, summarizing tickets and updating FAQs, but they require protection to prevent fabrication and to respect privacy (Crockett et al., 2023). Responsible service automation follows three principles: clearly signal when customers are interacting with automation; provide an easy path to a human agent; and log decisions to support audit and continuous improvement (OECD, 2021). Under the EU AI Act, transparency duties and record keeping are not optional; they are preconditions for deploying customer-facing systems at scale (European Parliament, 2024). Where these elements are present, firms report not only cost savings but also more consistent discourse and better reuse of institutional knowledge –effects that strengthen loyalty over time (OECD, 2021).

SMEs deploy chatbots and virtual assistants to extend support hours, triage requests, and standardize service quality (Ridho, 2023; Crockett et al., 2023). Evidence suggests measurable reductions in average handling time and increases in first contact resolution when conversational systems are integrated with knowledge bases (Ridho, 2023; Vanessa et al., 2024). Generative

AI has accelerated content authoring for FAQs and service scripts, yet requires careful guardrails to avoid hallucinations and privacy violations (European Parliament, 2024; OECD, 2021). Trustworthiness –explainability, security, and robust testing– emerges as a core enabler of loyalty impacts (Crockett et al., 2023; OECD, 2021). As a practical guideline argues, SMEs need pragmatic, auditable AI methods for customer-facing use cases (Crockett et al., 2023, p. 781). Aligned incentives and clear escalation to human agents remain crucial to preserve customer satisfaction (OECD, 2021; Cubric, 2020). In digitally advanced contexts, support analytics feed back into product improvement cycles (Gładysz et al., 2023; Badghish & Soomro, 2024). Overall, the loyalty effect depends on service design, data governance, and user acceptance (OECD, 2021; Vanessa et al., 2024).

2.3.1.5. Marketing and sales optimization

AI helps SMEs target audiences, test creative variants, optimize channel mix and adjust pricing or promotions. The pragmatic playbook emphasizes short, well defined experiments with clear metrics, so that teams reallocate budgets based on evidence rather than inertia (Chaudhuri et al., 2022). Generative models reduce content production bottlenecks, especially for localization and product descriptions, but require quality assurance and style governance to prevent drift (Crockett et al., 2023). Studies link the payoffs from AI-augmented marketing to the maturity of digital infrastructure and analytics capabilities; when data flows seamlessly from websites, marketplaces and point of sale systems, SMEs can iterate faster and at lower cost (Polas et al., 2022; Duan et al., 2019). Because many European SMEs operate on thin margins, pricing and promotion analytics are high leverage: combining seasonality, inventory and competitive signals with human oversight stabilizes returns without eroding trust (Baabdullah et al., 2021; OECD, 2021). At sector level, adoption intensity is higher in information and communication services than in construction or accommodation, which reflects structural differences in digital intensity (Eurostat, 2024).

AI enhances targeting, pricing, and campaign optimization via pattern detection and rapid experimentation (Chaudhuri et al., 2022; Duan et al., 2019). For AI-adopting EU firms, marketing/sales is the most cited purpose (34.08%), followed by administration/management (27.51%) and production (Eurostat, 2024). SMEs report uplift in conversion and average order value when integrating predictive models into marketing stacks (Baabdullah et al., 2021; Vanessa et al., 2024). Change management is a recurring determinant of gains, especially in traditional sectors (Lemos et al., 2022; OECD, 2021). Lightweight generative AI accelerates creative testing and content localization, but demands stringent quality assurance (European Parliament, 2024; Crockett et al., 2023). Evidence from emerging market SMEs stresses the interplay between digital infrastructure and market agility (Polas et al., 2022), a lesson that transfers to lagging EU regions (Hoffmann & Nurski, 2021). Platformized AI service bundles reduce integration time and support omnichannel consistency (Gładysz et al., 2023). In sum, marketing ROI depends on data quality, responsible personalization, and organizational learning rates (OECD, 2021; Cubric, 2020).

2.3.1.6. Strategic decision making support

The strategic contribution of AI is less about spectacular predictions and more about quietly improving the cadence and quality of managerial decisions. Forecasting demand, anticipating supplier failure, prioritizing capital projects, and aligning staffing to workload variability all benefit from repeatable, data driven routines (Duan et al., 2019). Research on organizational AI readiness emphasizes leadership sponsorship, experimentation culture and governance routines as prerequisites for moving from dashboards to decision support (Jöhnk et al., 2021). SMEs that link AI initiatives to explicit goals – margin protection, working capital reduction, customer lifetime value– report clearer trade-offs and faster learning cycles (Peters et al., 2024). From a policy perspective, interoperability standards and a risk based regulatory baseline reduce uncertainty and help SMEs adopt decision support responsibly (OECD, 2021; European Parliament, 2024).

AI contributes to managerial decision making by augmenting forecasting, scenario analysis, and risk detection (Duan et al., 2019; OECD, 2021). Studies point to stronger effects where SMEs cultivate analytics capabilities, modular data pipelines, and leadership that tolerates experimentation (Hayajneh et al., 2022; Jöhnk et al., 2021). Frameworks emphasize aligning AI with strategic priorities and measurable key performance indicator (KPI), not technology push (Hussain & Rizwan, 2024; Badghish & Soomro, 2024). As one review notes, AI creates value “when embedded into routines of sensing, seizing and transforming” rather than as standalone pilots (Chaudhuri et al., 2022).

German SMEs tend to formalize governance for data protection and compliance earlier in the life cycle, easing board level acceptance (Joswig & Kurz, 2025). Spanish evidence highlights competence development as the hinge variable for strategy level benefits (Huseyn et al., 2024). OECD guidance underlines the importance of interoperability and standards to scale decision support responsibly (OECD, 2021). The EU AI Act codifies risk based obligations that, when anticipated, can make strategic AI more sustainable (European Parliament, 2024).

2.3.1.7. Summary and comparative perspective

Across the literature, realized benefits from AI adoption in European SMEs cluster around process efficiency, customer-facing personalization, and decision support –provided clean data and basic governance are in place (OECD, 2021; Eurostat, 2024; Cubric, 2020). Eurostat's 2024 release confirms uptake expanded across Member States but remains uneven: Poland recorded one of the lowest overall shares (5.9%), Germany and Spain sit closer to the EU average, and Italy and Slovakia trail below it (Eurostat, 2024). Germany's benchmark status reflects earlier institutionalization of privacy and quality assurance, denser integrator markets, strong ties between applied research and industry, and more structured vendor-management and compliance practices, which shorten the path from pilot to production (OECD, 2021; Joswig & Kurz, 2025). Spain generally occupies a mid-field position, with momentum where competence development accompanies procurement—particularly in CRM and marketing (Huseyn et al., 2024; Baabdullah et al., 2021). Italy and Slovakia show progress but face persistent gaps in digital skills and ecosystem density, underscoring the need for targeted capability building and integration support (Agostini & Nosella, 2019; Zavodna et al., 2024). Poland's lag aligns with foundational readiness constraints –digital infrastructure and skills– and more limited access to specialized advisory services (Hoffmann & Nurski, 2021; OECD, 2021). Across all five countries, durable impact depends less on acquiring tools than on converting pilots into operating routines –codified roles, metrics, and governance-underpinned by trustworthy AI and effective change management; readiness, governance maturity, and the ability to operationalize beyond pilots remain the decisive levers (Crockett et al., 2023; OECD, 2021; European Parliament, 2024; Gładysz et al., 2023; Jöhnk et al., 2021; Hussain & Rizwan, 2024).

Table 15. Qualitative position of SME AI use relative to the EU average

Country	Position vs EU average	Indicative strengths/needs
Germany	At/above	Compliance-by-design; integrator density
Spain	Near	CRM/marketing momentum; competence focus
Italy	Below	Digital-skills gaps; ecosystem dispersion
Slovakia	Below	Pilot-heavy; integrator reliance
Poland	Low	Foundational readiness constraints

Source: Eurostat (2024); OECD (2021); country-level studies cited in text.

Table 16. AI use in EU enterprises by size class

Enterprise size	Share using AI (%)
All enterprises	13.48
Small (10–49)	11.21
Medium (50–249)	20.97
Large (250+)	41.17

Source: Eurostat (2024)

2.3.2. Barriers and challenges for AI implementation in SMEs

2.3.2.1. Prerequisites for successful AI use in SMEs

The literature converges on a multidimensional notion of “AI readiness” that blends technical and organizational foundations. Technically, SMEs require reliable connectivity, interoperable applications and minimally adequate data capture so that models receive timely, structured inputs. Organizationally, executive sponsorship, cross functional collaboration and iterative delivery practices are needed to turn proofs of concept into operational services (OECD, 2021; Jöhnk et al., 2021). Governance by design-privacy, security, role based access, documentation and human oversight-reduces rework and accelerates audits. The EU’s risk based baseline codifies these expectations and provides a shared vocabulary for buyers and vendors (European Parliament, 2024; OECD, 2021). Because SMEs often learn by doing, pragmatic maturity grids and gating criteria help teams decide when to move from discovery to pilot and from pilot to production, preventing the "prototype purgatory" that drains resources without building capability (Hussain & Rizwan, 2024).

The literature converges on foundational prerequisites: clear business use cases, sufficient data quality, interoperable infrastructure, and governance for security, privacy and fairness (OECD, 2021; Duan et al., 2019; Cubric, 2020). Readiness involves leadership, cross functional collaboration, and iterative delivery methods to translate pilots into operations (Jöhnk et al., 2021; Hussain & Rizwan, 2024). In Europe, standards and a risk based regulatory environment provide a stable frame for responsible scaling (European Parliament, 2024; OECD, 2021). Germany's compliance first posture illustrates how legal clarity can function as an enabler rather than a deterrent when embedded early (Joswig & Kurz, 2025). Spanish and Central European evidence highlights the centrality of competence development and vendor integration capacities (Huseyn et al., 2024; Zavodna et al., 2024). Platforms that bundle services and support simplify SME adoption journeys (Gładysz et al., 2023). Without these prerequisites, benefits remain isolated to pilots and do not scale (OECD, 2021; Hoffmann & Nurski, 2021). In short, readiness is both technical and organizational, and must be measured and managed explicitly (Hayajneh et al., 2022; Jöhnk et al., 2021).

2.3.2.2. Knowledge and skills gap; talent shortages

Skills shortages are the most frequently cited barrier to SME AI adoption, and the binding constraint extends well beyond data science to include data engineering, Machine Learning Operations (MLOps), product management, and change leadership—roles that translate models into reliable services (OECD, 2021). These gaps delay implementation and heighten dependency on external vendors, yielding short-term gains at the expense of organizational learning and bargaining power (OECD, 2021; Hoffmann & Nurski, 2021). Evidence links hybrid, **π-shaped** competences –analytical literacy combined with domain and managerial skills-to innovation gains and to better outcomes in small firms where individuals wear multiple hats (Hayajneh et al., 2022). Country evidence from Spain indicates that competence pathways tied to concrete use cases and reinforced through vendor enablement and training are primary determinants of adoption (Huseyn et al., 2024). Leadership readiness and empowered champions can partially offset skill constraints by orchestrating internal learning and selective outsourcing (Jöhnk et al., 2021; Hussain

& Rizwan, 2024). Cross-continental analyses concur that skills and change management remain the most cited impediments (Yusuf et al., 2024; OECD, 2021). National differences matter: Germany’s stronger compliance and data-protection talent pool reduces perceived risk and enables more controlled experimentation, whereas Italy and Slovakia face thinner local talent markets and slower diffusion of advanced digital skills (Joswig & Kurz, 2025; Hoffmann & Nurski, 2021; Zavodna et al., 2024). As one review puts it, “skill scarcity is the bottleneck through which all other constraints are felt” (OECD, 2021, p. 63).

2.3.2.3. Financial and resource constraints

Resource constraints are structural for SMEs and shape every phase of the AI lifecycle – from data preparation and integration through deployment, monitoring, and iterative improvement. Total cost of ownership is routinely underestimated because hidden components –integration and data labelling, documentation, retraining, security hardening, monitoring, compliance, and audits– surface late, delaying implementation and increasing reliance on external vendors (OECD, 2021; Crockett et al., 2023; Hoffmann & Nurski, 2021). In response, SMEs tend to prioritize bounded, high-payback use cases, adopt modular services, and leverage platform bundles that compress integration effort and time-to-value (Gładysz et al., 2023). **Technology-Organization-Environment (TOE)** based studies corroborate that expected performance, cost, and competitive pressure jointly predict adoption, with financing frequently the binding constraint (Badghish & Soomro, 2024). A realistic financing plan therefore budgets for operations –not just prototypes– covering monitoring, incident response, governance, and periodic retraining (Hoffmann & Nurski, 2021; OECD, 2021).

Ecosystem conditions modulate these constraints. In more mature settings, public programs and industry associations mitigate risk via advisory services, shared infrastructure, and templates; Germany’s denser network of integrators and programs lowers per-project risk and improves access to capital, whereas pilot studies in parts of Central Europe highlight limited targeted funding and advisory support (OECD, 2021; Joswig & Kurz, 2025; Zavodna et al., 2024). Country evidence suggests that competence-centric strategies – visible in Spain– help SMEs prioritize cost-effective use cases with fast payback, but without sustained resources for operations, many implementations stall before reaching scale (Huseyn et al., 2024; Hoffmann & Nurski, 2021; OECD, 2021; Gładysz et al., 2023).

2.3.2.4. Digital infrastructure and data quality limitations

Even basic AI depends on data that are timely, accurate, and well structured; in many SMEs, however, information remains fragmented across legacy systems, spreadsheets, and email, with inconsistent identifiers and missing metadata –raising integration costs and degrading model performance (OECD, 2021). A pragmatic route is to standardize capture at the point of work, institute master-data governance for customers, products, and suppliers, and adopt minimum viable lineage and quality checks; without such improvements, downstream benefits remain limited (Duan et al., 2019; OECD, 2021). Weak connectivity and fragmented applications further impede training and integration, and data-governance basics –lineage, consent, access control – are often underdeveloped (OECD, 2021; Crockett et al., 2023). Eurostat's 2024 figures show AI use is higher in information and communication industries than in low-intensity sectors, underscoring the compounding returns from foundational IT investments (Eurostat, 2024; Polas et al., 2022). Platformized tooling can help standardize pipelines and metadata practices, accelerating time-to-value for smaller firms (Gładysz et al., 2023).

Country conditions shape how quickly firms can scale once the basics are in place. Germany's rigorous data-protection and security practices can raise initial overhead yet ultimately facilitate scaling because controls are institutionalized earlier (OECD, 2021; Joswig & Kurz, 2025). Spain's competence-driven path places data stewardship at the center of capability building, supporting CRM and customer-facing use cases (Huseyn et al., 2024). By contrast, Italy, Poland, and Slovakia show greater variability in basic digital intensity and infrastructure, reflected in lower overall AI uptake and a larger need for foundational upgrades before advanced applications can pay off (Hoffmann & Nurski, 2021; Eurostat, 2024).

2.3.2.5. Technological complexity of AI and implementation in business management

AI implementation complexity for SMEs spans model selection and lifecycle management –versioning, drift, monitoring, incident response–, pipeline engineering, and integration with legacy transactional systems. In heterogeneous toolchains, ownership boundaries blur and responsibilities across vendors, IT, and business units can be unclear (OECD, 2021; Duan et al., 2019). SMEs also cite vendor-lock-in risks, opaque pricing, and uncertain performance guarantees (Crockett et al., 2023; Vanessa et al., 2024). Recommended mitigations include narrowing scope to high-leverage, well-bounded use cases with modest data requirements; defining explicit acceptance criteria and service-level objectives; and resourcing monitoring and retraining before go-live (Hussain & Rizwan, 2024; Badghish & Soomro, 2024). Where local integrator markets are thin, peer networks, platformized tooling, and public–private initiatives can supply implementation know-how and standardize pipelines and metadata practices (Gładysz et al., 2023).

Country evidence underscores organizational enablers. German SMEs often progress through staged pilots with audit trails and clear acceptance gates; Spain’s experience points to internal competences as the key buffer against complexity; and Slovak pilot studies emphasize the need for integrator support in industrial SMEs (Joswig & Kurz, 2025; Huseyn et al., 2024; Zavodna et al., 2024). In all contexts, change management must run in parallel to align processes, roles, and incentives with AI outputs, and maturity in MLOps and governance ultimately separates sustained adopters from stalled pilots (OECD, 2021; Lemos et al., 2022; Jöhnk et al., 2021).

2.3.2.6. Scalability and maturity of AI

SMEs frequently fall into the **“pilot trap”** –proofs of concept that never clear reliability, cost, or compliance thresholds for production. Escaping it requires treating AI as a managed product: standardized pipelines, robust MLOps, explicit documentation, and clear service levels, plus monitoring and feedback loops baked in from day one (OECD, 2021; Cubric, 2020; Hussain & Rizwan, 2024; Crockett et al., 2023). Compliance obligations –traceability, human oversight, and record-keeping– should be **designed in** to avoid costly refactoring later (European Parliament, 2024). Ecosystem conditions matter: in denser settings with strong integrators and associations, shared norms and templates reduce ambiguity and accelerate the jump from pilot to production; Germany's structured compliance culture is a case in point, whereas resource-constrained SMEs elsewhere struggle to finance ongoing operations (OECD, 2021; Joswig & Kurz, 2025; Hoffmann & Nurski, 2021). Where available, platform bundles and external MLOps support compress time-to-scale (Gładysz et al., 2023; Vanessa et al., 2024).

Sector heterogeneity is substantial: information/communication and professional services lead, while construction and accommodation lag, reflecting differences in digital intensity and operational readiness (Eurostat, 2024). Across contexts, **competence investments –**from data stewardship to product and operations skills– consistently correlate with maturity progression; without them, AI remains a set of isolated tools rather than a scalable capability (Huseyn et al., 2024; Hayajneh et al., 2022; OECD, 2021; Duan et al., 2019).

2.3.2.7. Dependence on external providers

Vendor dependence is a double-edged sword for SMEs: external providers deliver speed and expertise, yet they can create lock-in and knowledge asymmetries via proprietary formats, opaque pricing, and non-portable models (OECD, 2021; Hoffmann & Nurski, 2021). Trustworthy-AI guidance and the EU's risk-based regime stress transparent performance reporting, safe defaults, auditability, and documented limitations (Crockett et al., 2023; European Parliament, 2024). Good contracting practice should therefore require clear service-level objectives, change-control processes, data portability and exit clauses; in parallel, SMEs ought to retain stewardship of critical data assets, build minimal in-house capability to interpret and challenge vendor claims, and prefer open standards and modular architectures. Platform ecosystems can also mitigate integration costs while preserving optionality, especially when paired with vendor diversification (Gładysz et al., 2023; OECD, 2021; Hussain & Rizwan, 2024).

Country conditions shape exposure to these risks. Germany's denser integrator landscape improves bargaining power and quality assurance. Spain and Italy report heavier reliance on turnkey solutions, making capability building central to reduce dependency. and Central-European pilot evidence points to gaps in local integrator availability, particularly for industrial SMEs (OECD, 2021; Huseyn et al., 2024; Agostini & Nosella, 2019; Zavodna et al., 2024). Across contexts, contracting for portability and explicit Service Level

Objectives (SLOs), using platform bundles to standardize pipelines, and developing internal data stewardship are the practical levers to curb lock-in while keeping time-to-value low (OECD, 2021; Crockett et al., 2023; Gładysz et al., 2023).

2.3.2.8. Legal challenges

The EU AI Act establishes a risk-based framework with obligations proportional to system purpose and risk level, placing particular emphasis on transparency, documentation, and meaningful human oversight-especially for high-impact applications (European Parliament, 2024). Compliance interacts with data-protection and sectoral rules from the outset, shaping design choices, procurement, and operating models. German SMEs face especially stringent expectations around data processing and data-center governance (OECD, 2021; Joswig & Kurz, 2025). In practice, SMEs should classify use cases, maintain technical documentation, and log relevant events so accountability lines are clear; customer-facing systems must ensure transparency, record-keeping, and human oversight (OECD, 2021; European Parliament, 2024; Crockett et al., 2023).

Operationalizing compliance-by-design reduces scaling delays because controls and evidence are embedded rather than retrofitted. and guidance and platformized tooling make costs more predictable and help standardize practices (OECD, 2021; Gładysz et al., 2023). Benchmark ecosystems increasingly use procurement templates, **Data Protection Impact Assessments (**DPIAs) and model-risk inventories. Spain’s competence literature stresses regulatory literacy as part of adoption pathways (OECD, 2021; Joswig & Kurz, 2025; Huseyn et al., 2024). While SMEs report compliance uncertainty as a barrier, clarity ultimately lowers long-run risk –so regulation functions both as a constraint and a coordination mechanism for trustworthy AI (Hoffmann & Nurski, 2021; European Parliament, 2024).

2.3.2.9. Organizational culture as a barrier

Culture shapes risk tolerance, learning behavior, and the willingness to change routines; in many SMEs, scarce managerial bandwidth fosters “firefighting” that deprioritizes capability building and experimentation, reinforcing siloed decision-making and risk aversion (OECD, 2021; Cubric, 2020).

Evidence consistently links successful implementation to leadership behaviors that set the tone for learning –clear communication, empowered champions, and tolerance for iterative cycles– paired with resourced change management embedded in project plans (Jöhnk et al., 2021; Murire, 2024). Practical levers include celebrating quick wins, aligning incentives to the use of AI outputs, and nurturing communities of practice and peer-learning forums to diffuse tacit know-how; without such cultural alignment, technical investments underperform (OECD, 2021; Vanessa et al., 2024; Duan et al., 2019).

Country evidence points to distinctive pathways. Germany's culture of process discipline supports staged roll-outs and quality gates. Spain shows stronger uptake when training is embedded into everyday workflows. and Slovak pilot studies highlight the importance of managerial support networks for sustaining adoption (Joswig & Kurz, 2025; Huseyn et al., 2024; Zavodna et al., 2024). Yet across contexts, change-management practices remain under-resourced in SMEs, making leadership sponsorship and structured learning routines the decisive counterweights to cultural resistance (OECD, 2021; Hoffmann & Nurski, 2021).

2.3.2.10. Inequality across regions and sectors

AI adoption across Europe is uneven. Eurostat shows stark sectoral differences-information/communication and professional services lead, while construction and accommodation lag– mirroring underlying variation in digital intensity (Eurostat, 2024). Regional disparities map to infrastructure quality, ecosystem density, and talent availability. Central and Eastern European SMEs often face thinner integrator markets and less access to advisory support, which helps explain lower adoption levels in Poland and Slovakia (Hoffmann & Nurski, 2021; Eurostat, 2024; Zavodna et al., 2024). Italy remains below the EU average, with structural digital-skills gaps frequently cited, while Spain sits nearer the EU mean with substantial variation by sector; Germany maintains a relatively stronger position across manufacturing and business services (OECD, 2021; Hoffmann & Nurski, 2021; Huseyn et al., 2024; Joswig & Kurz, 2025). Cross-continental perspectives reinforce that SMEs' AI use largely tracks pre-existing inequalities in infrastructure and skills (Yusuf et al., 2024; Polas et al., 2022).

Addressing these disparities requires **place-based policies**, **sector-specific playbooks**, and **shared infrastructure** that create viable on-ramps for late adopters; platform-based support can further standardize integration and reduce costs for SMEs (OECD, 2021; Gładysz et al., 2023).

2.3.2.11. Ethics, trust and acceptance of AI

Trustworthiness is foundational for value creation in customer and employee-facing AI: SMEs must address explainability, **fairness**, robustness, privacy, and security, supported by transparent user communication, meaningful human oversight, and clear escalation paths to human agents (Crockett et al., 2023; OECD, 2021; Ridho, 2023). The EU AI Act codifies requirements such as transparency, record-keeping, and human oversight –especially for higher-risk and certain generative uses– so model-risk management (bias testing, performance monitoring, incident handling) should be designed in from the start to build confidence and avoid costly retrofits (European Parliament, 2024; OECD, 2021). Ethical risk management reduces reputational exposure and improves long-term ROI, while realistic user expectations and plain-language disclosures are critical to sustained acceptance (OECD, 2021; Cubric, 2020; Crockett et al., 2023).

Context matters. Cultural acceptance correlates with digital literacy and training, and competence-building programs raise adoption odds (Huseyn et al., 2024; Vanessa et al., 2024). German SMEs report fewer privacy blockers thanks to stronger internal compliance capabilities; by contrast, resource constraints in Italy and Slovakia amplify concerns about bias, accountability, and ongoing assurance (Joswig & Kurz, 2025; Hoffmann & Nurski, 2021; Zavodna et al., 2024). Across settings, clear governance, auditable practices, and human-in-the-loop safeguards remain the practical levers for trustworthy, durable deployment (OECD, 2021; European Parliament, 2024).

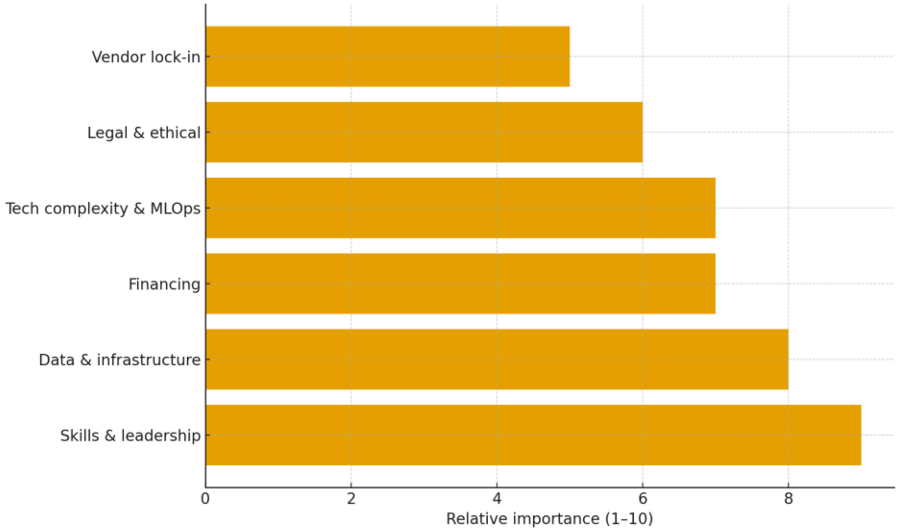
2.3.2.12. Leadership as barrier or facilitator

Leadership is the cross-cutting lever that determines whether AI becomes a managed capability or remains a set of isolated tools. Effective leaders link AI to measurable business outcomes, shape prioritization and funding, allocate budget for data stewardship and talent, enforce governance and quality gates, and set cadences for review, learning, and responsible experimentation –unlocking compounding gains when they also invest in people and processes (Jöhnk et al., 2021; OECD, 2021; Hayajneh et al., 2022; Hussain & Rizwan, 2024). Country evidence illustrates the point: in Germany, leadership often institutionalizes compliance and quality controls that improve scalability; in Spain, leadership support for competence development raises adoption odds; whereas in Poland, Italy, and Slovakia, leadership gaps frequently manifest as underfunded data stewardship and fragmented pilots that stall at proof-of-concept (Joswig & Kurz, 2025; Huseyn et al., 2024; Eurostat, 2024; Hoffmann & Nurski, 2021; Cubric, 2020). Responsible leadership also reduces ethical risk and strengthens stakeholder trust, without which initiatives fragment and fail to reach operational impact (OECD, 2021; Crockett et al., 2023).

2.3.2.13. Hierarchy of barriers and timing in a comparative perspective

Short-term constraints surface first as **skills gaps**, **data-quality issues**, **vendor dependence**, and in some cases **unclear use cases**; over the medium term, barriers shift toward the **costs of scaling –m**onitoring, retraining, and governance– along with **compliance process maturation** under the EU AI Act and **organizational change saturation** as multiple initiatives compete for attention (OECD, 2021; Hoffmann & Nurski, 2021; European Parliament, 2024; Hussain & Rizwan, 2024; Huseyn et al., 2024; Crockett et al., 2023). A pragmatic hierarchy observed across European SMEs places **(1) skills and leadership** at the top, followed by **(2) data and infrastructure**, **(3) financing**, **(4) technological complexity/MLOps**, **(5) legal and ethical assurance**, and **(6) vendor lock-in** (OECD, 2021; Hoffmann & Nurski, 2021; Cubric, 2020; Eurostat, 2024).

Figure 15. Relative importance of key SME AI barriers



Note: Summary emphasis synthesized from OECD (2021) and Hoffmann & Nurski (2021), cross-checked with country evidence.

Country differentiation tracks ecosystem characteristics. **Germany** benefits from compliance-by-design norms and higher integrator density and early integration of data protection and AI governance mitigates downstream risks and aids scale-up (OECD, 2021; Joswig & Kurz, 2025). **Spain** tends to progress where competence building accompanies CRM/marketing deployments, with skills pathways tied to concrete use cases (Huseyn et al., 2024). **Italy** shows structural digital-skills gaps and below-average adoption. **Slovakia** remains pilot-heavy with integrator shortages and **Poland** records the lowest overall uptake, reflecting foundational capability gaps (Eurostat, 2024; Hoffmann & Nurski, 2021; Zavodna et al., 2024; Agostini & Nosella, 2019). Platform-based, modular bundles can compress adoption frictions and preserve optionality (Gładysz et al., 2023). Across contexts, coordinated **capability building** and **governance** are the decisive levers for moving beyond pilots into reliable, scaled services (OECD, 2021; Hussain & Rizwan, 2024).

2.3.2.14. Strategies and recommendations for overcoming barriers

A pragmatic playbook for European SMEs combines seven mutually reinforcing steps. **(1) Capability pathways:** anchor training in concrete use cases and invest in hybrid, **π-shaped** roles (analytical literacy plus domain and managerial depth), embedding **regulatory literacy** so teams can make informed trade-offs (Hayajneh et al., 2022; Huseyn et al., 2024; OECD, 2021). **(2) Data foundations:** treat data governance as a product –data lineage and quality checks, formal consent and access controls, standardized capture at source, maintained taxonomies – and pair this with interoperable architectures and standardized pipelines (OECD, 2021; Crockett et al., 2023; Duan et al., 2019). **(3) De-risk first deployments:** start with bounded, high-ROI use cases; require vendor transparency on model limits and **portability clauses**; set acceptance criteria plus monitoring and retraining plans **before** go-live (Crockett et al., 2023; Hussain & Rizwan, 2024; Gładysz et al., 2023). **(4) Finance for scale:** budget for the full lifecycle-integration, monitoring, incident response, retraining, audits, and compliance – and leverage vouchers, advisory programmes and platform ecosystems (OECD, 2021; Hoffmann & Nurski, 2021). **(5) Governance-by-design:** operationalize the EU AI Act through procurement templates, risk classification, record-keeping and meaningful human oversight, embedding DPIAs and model-risk inventories into procurement and delivery (European Parliament, 2024; OECD, 2021; Joswig & Kurz, 2025). **(6) Ecosystem partnerships:** cultivate local integrators, peer networks and academia-industry links; deploy sector-specific playbooks and place-based programmes-especially salient for Poland, Italy and Slovakia– to diffuse tacit know-how and address regional gaps (Zavodna et al., 2024; OECD, 2021; Vanessa et al., 2024; Gładysz et al., 2023). **(7) Leadership operating model:** define vision, metrics and review cadences; reward data-informed decisions; scale patterns that work and sunset those that do not, thereby avoiding the pilot trap (Jöhnk et al., 2021; Peters et al., 2024; OECD, 2021; Hussain & Rizwan, 2024). Sequenced in this way – and tailored to baseline differences in adoption – these steps help convert pilots into reliable, trustworthy AI capabilities while keeping time-to-value low (OECD, 2021; Gładysz et al., 2023; Eurostat, 2024).

Table 17. Country–barrier emphasis (qualitative synthesis)

Country	Skills	Data/Infra	Financing	Complexity /MLOps	Legal/ Ethical	Vendor dep.
Germany	Medium	Medium	Medium	Medium	High	Medium
Spain	Medium	Medium	Medium	Medium	Medium	Medium
Italy	High	High	Medium	Medium	Medium	Medium
Poland	High	High	High	Medium	Medium	High
Slovakia	High	High	High	Medium	Medium	High

Scale: Low/Medium/High, synthesized from country-level evidence referenced in the narrative.

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2.4. Policies to support AI deployment in Europe

One of the most important challenge in the development of future world is the elaboration and inplemantation of Artificial Inteliigence (AI). This problem can be solved by cooperatiom between countries in the areas of technology and science. Europe which is known as the best developed region of the world has to meet this problem and to develop its economy in a changing and more competitive world.

Europe to be more competitive than China, USA and other countries has to spend money on AI. Such activities require constant suport of AI and spending funds from national and European budget.

The purpose of this article is to learn about policies that support the implementation of artificial intelligence in Europe. Artificial intelligence (AI) plays a fundamental role in economic, technological and social transformation. In Europe, AI implementation is considered an opportunity to increase the competitiveness of the economy, improve public services and strengthen digital sovereignty. However, in order to achieve these goals, the European Union and member states should pursue coherent and ambitious public policies that support the development and implementation of AI. Sources used in the article were legal acts and websites.

2.4.1. Laws, regulations, plans to implement artificial intelligence in Europe

In 2018, the European Commission announced the European Strategy on Artificial Intelligence (updated in 2021) as the “Coordinated Plan on Artificial Intelligence.” Member states (within the European Industry and AI Digitization Group), Norway, Switzerland and the European Commission developed the plan in a series of meetings between June and November 2018. During these meetings, the member states and the Commission identified a series of joint actions to increase investment, collect data (the “raw material” used by AI), foster talent and ensure trust – actions based on the European strategy. Priority areas of public interest were identified, such as healthcare, transportation and mobility, safety, security and energy, as well as important economic sectors such as manufacturing and financial services. This communication outlines its main goals and initiatives. (Communication from the Commission to the European Parliament, 2018). All other member states have developed their national IS strategies by mid-2019, building on work done at the

European level. These strategies defined investment levels and implementation measures. Member states and the European Commission agreed on common indicators to monitor the introduction and development of AI in the Union and the level of effectiveness of existing strategies, using the "AI-Watch" developed by the Commission's Joint Research Center.

However, Europe has lagged behind when it comes to private investment in AI.

For this reason, the European AI strategy has set ambitious but realistic goals like: EU-wide public and private investment in AI must be increased to a target of €20 billion per year over the next decade.

As a first step, the Commission intended to increase investment in AI under the Horizon 2020 research and innovation framework program to €1.5 billion between 2018 and 2020, an amount that represented a 70% increase over the period covering 2014-2017. This would give the Union the opportunity to further increase its efforts over the next decade, with investment levels gradually approaching €20 billion a year. This would correspond to an annual investment of €7 billion by the public sector (member states and the Commission), which would be comparable to other continents. The Commission has proposed that the Union invest at least €1 billion a year in AI from Horizon Europe and Digital Europe in the next programming period 2021-2027. Member states have taken these targets into account and agreed that ambitious action is needed and that efforts should be stepped up at the national level. Coordinated efforts in the public sector will help boost private investment. While public investment plays an important role, it is an equally important responsibility of regulators to eliminate obstacles arising from fragmented markets. Products and services are increasingly interconnected and digitized. In this context, it is of utmost importance to avoid market fragmentation in strategic sectors such as artificial intelligence, including by strengthening key growth drivers (e.g., uniform standards and high-speed communications networks). A true digital single market will make it easier for companies to expand their operations and trade across borders, thereby increasing investment.

Further steps have been taken toward a European public-private partnership on AI and increased funding for start-ups and innovative small and medium-sized enterprises. The Commission brought together companies and research organizations to develop a joint strategic research agenda on AI, identify priorities in line with market demand, and encourage information sharing across sectors and borders. The private sector committed through this contractual partnership to specific and substantial investments in AI. The partnership built on existing robotics and big data partnerships, corresponding to an investment of €4.4 billion, most of which (€3.2 billion) came from industry. The Commission has provided start-ups and innovators working on AI and blockchain (blockchain) technology with resources to help them develop their businesses. An initial amount of €100 million was mobilized in 2020, which was supplemented by the participation of interested national development banks and other institutions. As a result, this has helped prepare for increased access to AI financing under the InvestEU program starting in 2021. At the same time, the European Commission has made progress on the establishment of the European Innovation Council and has supported cutting-edge technologies and the most innovative start-ups. In response to the European Council's call in June 2018, a new pilot initiative has been launched in early 2019, which will include support for the next generation of human-centered AI technologies.

The member states and the Commission aim to increase national research capabilities and bring them to critical mass through more closely linked networks of European AI research centers of excellence. The goal is to foster collaboration among Europe's top research teams so that, by combining their strengths, they can more effectively grapple with important scientific and technological challenges in AI. Bringing cutting-edge AI applications to market requires real-world experiments and research. As part of the implementation of the digitization strategy for European industry, adopted in 2016, the Commission is already supporting pilot programs and large-scale experiments conducted in areas such as smart agriculture, smart cities, and autonomous and connected net.

To optimise investment and avoid duplication of effort, the Commission has proposed the creation of a number of large-scale reference research centres accessible to all actors in Europe, using up to €1.5 billion from the AI part of the proposed Digital Europe programme, building on existing centres of excellence in Member States. Examples of research centres being developed by Member States include cross-border testing of autonomous and connected driving and real-world experiments in the field of smart hospitals. For connected and autonomous mobility, the identification of such research centres and the tests themselves will be coordinated first by the joint EU-wide platform referred to in the EU's future mobility strategy, and secondly by the relevant partnership to be established under the "Horizon Europe" programme.

It is equally important to support the widest possible use of AI by economic operators, in particular start-ups and small and medium-sized enterprises. By raising public awareness and sharing the latest scientific advances and proven modern technologies developed in Europe, every business – regardless of size and technological sophistication – as well as the public sector will be able to benefit from the opportunities offered by this digital technology. The proposed new Digital Europe programme provides for joint investments by Member States and the Commission in digital innovation hubs across Europe, including through Cohesion Fund resources. This programme will further facilitate the dissemination of AI capabilities across Member States and will be linked to an "AI-on-demand" platform.

Technological changes will entail, in particular, changes in the skills required of employees, which will necessitate many employees to upgrade their qualifications. Therefore, greater emphasis should be placed on lifelong learning. One particular aspect of the changes concerns those employees who will actually design and implement future AI-based solutions. Almost all Member States are facing a shortage of ICT specialists, with over 600,000 digital expert positions currently unfilled. Talented researchers and promising start-ups often receive attractive offers from abroad, for example, in 2017, 240,000 European citizens were working in Silicon Valley, many of whom had come to the US to take up specific jobs in the technology sector. Europe must have the capacity to train, attract and retain such talent, promote entrepreneurship and increase diversity and gender balance in this context. The issue of skills should also be included in national AI strategies, which were to be published by mid-2019. These strategies focus on AI-relevant skills in the formal education cycle, including vocational training and higher education, and on ways to increase opportunities for masters and doctoral students in the field of AI. The Commission will support those with master's or doctoral degrees in AI through proposed closer cooperation between centres of scientific excellence in AI and, more broadly, between EU research and innovation programmes. Support for interdisciplinarity will be provided by encouraging the combination of academic degrees, e.g. in law or psychology and AI. Digital skills that promote the development and use of AI should also be included in curricula across all areas of education and training. As technological advances often have a radical impact on reality, policymakers will develop strategies to deal with changes in employment so that these changes promote social inclusion, as the pace at which some occupations disappear and others emerge is likely to accelerate with changes in business models and the ways in which different jobs or tasks are performed. This may require changes to existing labour market and social protection arrangements to support labour market transitions.

The development of AI requires enormous amounts of data. Machine learning, which is one type of AI, involves identifying patterns in available data and then applying this knowledge to new data. The larger the data set, the better AI can learn and find even very subtle connections in the data. Once trained, algorithms can correctly classify objects they have never seen before, and will increasingly do so with greater accuracy than humans. Access to data is therefore a key component of a competitive AI environment, and the EU should facilitate this access while fully respecting the principles of personal data protection.

The further development of AI requires an efficient data ecosystem built on trust, data availability and adequate infrastructure. The General Data Protection Regulation (GDPR) provides the basis for trust in the single data market. (Rozporządzenie Parlamentu Europejskiego i Rady (UE) 2016/679 z dnia 27 kwietnia 2016 r. w sprawie ochrony osób fizycznych w związku z przetwarzaniem danych osobowych i w sprawie swobodnego przepływu takich danych oraz uchylenia dyrektywy 95/46/WEhttps://Rozporządzenie%20Parlamentu%20Europejskiego%20i%20Rady%20(UE)%202016_679%20z%20 dnia%2027%20kwietnia%20.pdf., access on 18.06.2025).

This Regulation has established a new global standard with a strong focus on the rights of individuals, reflecting European values, and is an important element in ensuring trust in AI. This trust is particularly important when processing healthcare data in AI-based applications. The Commission encouraged the European Data Protection Board to develop guidelines on the processing of personal data in the context of research. This facilitated the development of large cross-border scientific data sets that can be used for AI purposes. The entry into force of the Regulation on the free flow of non-personal data in 2019 has helped to "unlock" data, in particular machine-generated data, and has made it much easier for businesses to operate across borders within the Union. An open approach to international data flows will be maintained, in full compliance with EU data protection rules and in line with existing legal instruments, including free trade agreements. The agreement on the revision of the Public Sector Information Directive has increased the amount of data available for innovation. The creation of common European data spaces in a number of areas, such as manufacturing or energy, has created important resources for European innovators and businesses. The aim of these common European data spaces is to aggregate data, both for the public sector and data exchanged between businesses, across Europe and make it available for AI training on a scale that has enabled the development of new products and services. The European Commission also contributes large amounts of data and information on Earth observation obtained through its flagship initiative, the Copernicus programme. AI applications in healthcare are particularly promising. In 2020, the European Commission, in cooperation with Member States, supported the development of a common database of health images (based on voluntary data sharing by patients) through the Horizon 2020 programme. This database was initially dedicated to the most common forms of cancer and now uses AI to improve the quality of diagnosis and treatment. It currently operates in accordance with all necessary regulatory, safety and ethical requirements. AI tools are crucial for the future functioning of public administration. Member States and the European Commission have discussed areas where joint procurement of AI-based solutions is possible, including cybersecurity, as well as issues specific to the public sector. Particular legal and ethical challenges arise, for example, when using AI in the areas of security and law enforcement. It should be noted that public authorities are required to act in accordance with the law, that they must justify their decisions, and that their actions are subject to judicial review by administrative courts. In addition, adequate computing power is necessary for data processing. The European High Performance Computing Joint Undertaking (EuroHPC) pools resources to develop next-generation supercomputers for big data processing and AI training. In this context, cooperation with Member States and industry in the field of microelectronic components and circuits, and the European Processor Initiative, which aims to develop low-power processor technologies for high-performance computing, data centres and autonomous vehicles, are key to creating an independent and innovative European ecosystem for high-end chip design.

There is a need to better understand how AI can impact security in the following three dimensions: how AI could positively contribute to achieving security sector objectives; how AI technologies can be protected from attacks; and how any misuse of AI for harmful purposes should be addressed. As the capabilities and vulnerability of AI applications grow in many areas of the digital economy and society, such as autonomous mobility or preventing power outages, it is very important to establish cybersecurity requirements for AI. The use of AI in weapon systems has the potential to fundamentally change the nature of armed conflict and therefore raises serious concerns and questions. The Union intends to continue to emphasise that international law, including international humanitarian law and human rights law, is fully applicable to all weapon systems, including autonomous weapon systems, and that states remain responsible for the development and use of these systems in armed conflict. The EU continues to take the position that human control must be maintained over all decisions to use lethal force and that it must be incorporated into all parts of the life cycle of any weapon system.

13 June 2024 The Artificial Intelligence Act (AI Act) was published in the Official Journal of the European Commission (Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024). This key document sets out the regulatory framework for the development, implementation and use of artificial intelligence within the European Union. The Ministry of Digital Affairs is already working on a draft law that will allow the AI Act to be applied in Poland. The AI Act aims to ensure the safe and ethical use of artificial intelligence technology, taking into account citizens' rights and supporting technological innovation. The new regulations include, among other things, requirements for algorithm transparency, labelling of AI-generated content, and rules for managing the life cycle of AI systems. AI systems on the European market will have to meet specific norms and standards, which will translate into a high level of protection for citizens' and consumers' rights, as well as increased public confidence in new technologies. The regulations cover various important areas of practical AI applications, such as healthcare, transport, education and the labour market. The use of AI by the public sector, including the police, the electoral process and the courts, will be subject to particular scrutiny. This is the world's first comprehensive piece of legislation regulating AI. The new regulations define the obligations of suppliers and users depending on the level of risk posed by artificial intelligence. Although many AI systems pose minimal risk, they must still be assessed. European legislators have proposed classifying AI based on the following risk levels:

a. Unacceptable risk (e.g. systems that manipulate behaviour, social scoring) – manipulation of people or specific vulnerable groups: for example, voice-activated toys that encourage children to engage in dangerous behaviour. Scoring (point classification) of citizens: classification of people based on their behaviour, socio-economic status or personal characteristics, biometric identification and categorisation of individuals, real-time and remote biometric identification systems such as facial recognition. Certain exceptions may be permissible for law enforcement purposes.

Real-time remote biometric identification systems will be permitted in a limited number of serious cases, while systems with significant delays will be allowed to be used to prosecute serious crimes, but only with the consent of a court.

b. High risk (e.g. AI in recruitment, education, the judiciary) – requires strict requirements for transparency, oversight and security. These are divided into two categories:

   1) Artificial intelligence systems used in products covered by EU product safety regulations. These include toys, aviation, cars, medical devices and lifts.

   2) Artificial intelligence systems belonging to eight specific areas that will have to be registered in the EU database:

      – Management and operation of critical infrastructure.
      – Education and vocational training.
      – Employment, workforce management and access to self-employment.
      – Access to and use of basic private services and public services and benefits.
      – Law enforcement.
      – Migration, asylum and border control management.
      – Assistance with legal interpretation and application of the law. All high-risk AI systems will be assessed before being placed on the market and throughout their life cycle. Citizens will have the right to lodge complaints about artificial intelligence systems with designated national authorities.

c. Limited risk – transparency obligation (e.g. audio, images, text, videos, etc.), i.e. generative artificial intelligence (e.g. ChatGPT), has not been identified as presenting a high level of risk. However, it must comply with EU transparency and copyright requirements by:

   – Disclosure that the content was generated by artificial intelligence.
   – Designing the model so that it does not generate illegal content
   – Disclosure that the content was generated by artificial intelligence.

- Designing the model so that it does not generate illegal content.
- Publishing summaries of copyrighted data used to train artificial intelligence systems.

d. minimal risk – no restrictions.

Compliance requirements: Technical documentation, human oversight, data quality. Gradual entry into force – full implementation by 2026. The European AI Board (EAIB) will be responsible for coordinating enforcement and oversight. The AI Act enforces responsible system design, which can increase public trust. At the same time, it imposes obligations on AI providers, which can be challenging for SMEs – hence the need for policies to support adaptation. Such AI regulation enables research and exempts researchers from regulation until the product is placed on the market. It enables support for start-ups/SMEs through Contact Points (‘Service Desk’) and the EU AI Office. The Parliament has set up a working group to oversee the implementation and enforcement of the AI Act. The group cooperates with the European Commission's European Artificial Intelligence Office, which was set up to clarify the key provisions of the Act. This Act is to be fully applicable 24 months after its entry into force. Some of its provisions are to be complied with earlier (the ban on unacceptable artificial intelligence systems came into force on 2 February 2025). Codes of conduct will apply nine months after entry into force, provisions on general-purpose artificial intelligence, which must comply with transparency requirements, will apply twelve months after entry into force, and high-risk AI systems will have more time to meet the requirements imposed on them, as they will come into force 36 months after the act enters into force.

2.4.2. Plans, support programs, and funding

2.4.2.1. „Horizon Europe” programme

On 1 January 2021, the “Horizon Europe” programme was launched (Regulation (EU) 2021/695 of the European Parliament and of the Council of 28 April 2021 establishing Horizon Europe…,2021). It is the EU's largest research and innovation programme with a budget of €95 billion. It supports, among other things, research into AI, its applications and ethical aspects. Under the Horizon Europe and Digital Europe programmes, the EU has invested at least €1 billion per year in AI for 2021–2022, reaching this level of funding. The “Horizon Europe” budget for AI research and development amounted to €2.6 billion for 2021–2022.

Examples of initiatives:

1. Funding research projects on AI (e.g. robotics, machine learning)
2. Promoting cooperation between science, business and the public sector
3. Developing common European data spaces (e.g. for health, energy, industry).
4. AI: Supporting research on AI, robotics, algorithm development and AI implementation in industry

2.4.2.2. „The Digital Europe” Programme

The programme comprises five separate but interdependent specific objectives. Although individual actions under the programme relate to a single specific objective, the objectives should not be viewed in isolation but rather as the main element of a coherent package. Support is needed for small and medium-sized enterprises (SMEs) that want to digitally transform their production processes. Such support will enable SMEs to contribute to the development of the European economy through the efficient use of resources. A key role in the implementation of the Programme should be entrusted to European digital innovation hubs, which should support the large-scale uptake of advanced digital technologies by industry, in particular SMEs and other entities employing up to 3,000 people (mid-cap companies), public organisations and academia. To take full advantage of the opportunities offered by the ‘digital single market’, which are financed from other sources, the centres financed under the Programme should be called European Digital Innovation Hubs. European Digital Innovation Hubs should serve as access points to the latest digital solutions, including HPC, AI, cybersecurity and other existing innovative technologies, such as key enabling technologies, also available in fab labs or city labs. The European Union has allocated EUR 7.5 billion from its budget for the implementation of this programme in the period 2021-2027. Member States may, through a competitive and open procedure, designate as candidates entities that already function as digital innovation hubs in the context of the initiative on the digitisation of European industry.

European Digital Innovation Hubs shall develop appropriate synergies with relevant activities funded under „Horizon Europe” – the Horizon Europe

Framework Programme for Research and Innovation established by Regulation (EU) 2021/695 of the European Parliament and of the Council (hereinafter referred to as the „Horizon Europe programme”) or from other research and innovation programmes, with the European Institute of Innovation and Technology (EIT) established by Regulation of the European Parliament and of the Council, in particular its Digital Knowledge and Innovation Communities, as well as with established networks such as the European Enterprise Network or InvestEU Advisory Hubs, established in accordance with Regulation (EU) 2021/523 of the European Parliament and of the Council. European Digital Innovation Hubs should act as coordinators bringing together industry, businesses and public authorities that need new technological solutions with companies, in particular start-ups and SMEs, that have ready-to-market solutions. In accordance with Article 197(2)(c) of the Financial Regulation, which allows entities that do not have legal personality under the applicable national law to participate in calls for proposals, a consortium of legal entities may be selected as a European Digital Innovation Hub, provided that the representatives of those entities are authorised to enter into legal commitments on behalf of the entity concerned and that those entities provide guarantees for the protection of the Union's financial interests equivalent to those provided by legal persons.

In order to achieve maximum flexibility throughout the entire implementation period of the Programme and to generate synergies between the components of the Programme, each specific objective may be achieved through any instrument available under the Financial Regulation. The mechanism used to implement the Programme is direct management and indirect management, where it is necessary to combine EU funding with other sources of funding or where the implementation of the Programme requires the creation of jointly managed structures.

In order to ensure the effective allocation of Union budgetary resources, it is necessary to ensure that all actions under the Programme have European added value and are complementary to Member States' actions, while striving for consistency, complementarity and synergy with funding programmes supporting closely related policy areas. While, for actions managed directly and indirectly, the relevant work programmes are the tool for ensuring consistency, cooperation should be established between the Commission and the relevant authorities of the Member States to ensure consistency and complementarity in relation to measures managed directly or indirectly or measures subject to shared management, ensuring compliance with the applicable provisions of the Regulation of the European Parliament and of the Council laying down common provisions on the European Regional Development Fund, the European Social Fund Plus, the Cohesion Fund, the Just Transition Fund and the European Maritime, Fisheries and Aquaculture Fund, as well as the financial provisions for those funds and for the Asylum, Migration and Integration Fund, the Internal Security Fund and the Instrument for Financial Support for Border Management and Visa Policy (hereinafter referred to as the „Common Provisions Regulation for 2021-2027"). The Union's potential in HPC and related data processing should ensure wider use of HPC in industry and, more generally, in areas of public interest, in order to exploit the unique opportunities that supercomputers offer society in areas such as healthcare, the environment and security, as well as industrial competitiveness, in particular for SMEs. The acquisition of world-class supercomputers would secure the Union's supply chain and help to leverage services for simulation, visualisation and prototyping, while ensuring that HPC systems comply with the Union's values and principles. Support for Union intervention in the field of HPC has been expressed by the European Parliament and the Council. Furthermore, between 2017 and 2018, 22 Member States signed the European Declaration on EuroHPC , a multilateral intergovernmental agreement in which they committed to working with the Commission to build and deploy state-of-the-art HPC infrastructure and data processing systems in Europe, which would be accessible across the Union to the scientific community and to public and private partners. As set out in the impact assessment accompanying the Commission's proposal for a Council Regulation establishing the European High Performance Computing Joint Undertaking, in order to achieve the specific objective of high performance computing, the most appropriate means of implementation was considered to be a joint undertaking, which should in particular coordinate Union and national strategies and investments in HPC infrastructure and research and development activities, pool financial resources from public and private sources, and protect the economic and strategic interests of the Union. In addition, national competence centres for large-scale computing within the meaning of Council Regulation (EU) 2018/1488 (18) will provide HPC services to industry, including SMEs and start-ups, academia and public administrations. Developing AI capabilities is a key factor in supporting the digital transformation of industry, services and the public sector. More and more autonomous robots are being used in factories, deep-sea operations, homes, cities and hospitals. Commercial platforms using AI have moved from the testing phase to practical applications in healthcare and the environment.

All major car manufacturers are developing autonomous cars, and machine learning techniques are an integral part of all major internet platforms and applications that use large data sets. It is crucial that Europe joins forces at all levels to become internationally competitive. Algorithm libraries can include a large collection of algorithms, including simple solutions such as classification algorithms, neural network algorithms, and planning and reasoning algorithms. They can also include more advanced solutions such as speech recognition algorithms, navigation algorithms embedded in autonomous devices such as drones or autonomous cars, and AI algorithms embedded in robots to enable them to interact with and adapt to their environment. Algorithm libraries should be made readily available to everyone on fair, reasonable and non-discriminatory terms.

In its resolution of 1 June 2017 on the digitisation of European industry, the European Parliament highlighted the impact of language barriers on industry and the digitisation of industry. In this context, the development of large-scale language technologies based on artificial intelligence, such as machine translation, speech recognition, analysis of large text data sets, as well as dialogue and question-answering systems, is essential for preserving linguistic diversity, ensuring social inclusion and enabling communication between humans and between humans and machines.

AI-based products and services should be user-friendly, compliant with the law by default, and provide consumers with greater choice and more information, in particular regarding the quality of products and services. The availability of large data sets and testing and experimentation facilities is essential for the development of AI, including language technologies. In its resolution on the digitisation of European industry, the European Parliament emphasised the importance of a common European approach to cybersecurity and recognised the need to raise awareness. It recognised ensuring cyber resilience as a fundamental responsibility of business leaders, as well as European and national decision-makers involved in industrial and security policy, and taking security and privacy into account at the design stage and as a default option.

2.4.2.3. "European High-Performance Computing Joint Undertaking, EuroHPC JU" Programme

The European High-Performance Computing Joint Undertaking (EuroHPC JU) is a public-private partnership in the field of high-performance computing (HPC) that enables the pooling of resources at the European Union level with those of participating countries. EuroHPC JU) – a public-private partnership in the field of high-performance computing (HPC), enabling the pooling of resources at the European Union level with those of participating EU Member States and participating countries associated with the Horizon Europe and Digital Europe programmes, as well as private stakeholders. The project has two main objectives: to develop a pan-European supercomputing infrastructure and to support research and development activities (https://cc.eurohpc.pl/index.php/en/euro-hpc-ju-en/ access on 10.06.2025 r). In June 2016, EU leaders meeting at the European Council called for greater coordination of EU action on high-performance computing as part of a broader EU strategy for the digital single market. In March 2017, a declaration was announced in Rome, initially signed by seven EU Member States (France, Germany, Italy, Luxembourg, the Netherlands, Portugal and Spain), committing themselves to increasing European computing power. In June 2018, the EU Council approved the European Commission's proposal to establish the EuroHPC JU. On 3 July 2018, the European Parliament voted in favour of the Commission's proposal to establish the programme, and the proposal was formally adopted by the EU Council on 28 September 2018. The EuroHPC JU is jointly funded by its members and has a budget of approximately €7 billion for the period 2021-2027. EuroHPC has selected seven locations for the construction of new data centres for artificial intelligence infrastructure: BSC AIF in Barcelona, IT4LIA in Bologna, LUMI AIF in Kajaani, Meluxina-AI in Bissen, MIMER in Linköping, HammerHAI in Stuttgart, and Pharos in Athens. On 11 February 2025, during the AI Action Summit, European Commission President Ursula von der Leyen announced the InvestAI initiative worth €200 billion, including the creation of a €20 billion fund for the construction of data centres. The initiative was announced three weeks after US President Donald Trump announced the Stargate project. As part of the InvestAI initiative, the EU AI Champions initiative was announced, bringing together more than 60 European companies that have committed to investing €150 billion in AI. The EU has committed to allocating €50 billion to support the initiative. The fund plans to build up to five large data centres, referred to as AI gigafactories, with a minimum of 100,000 GPUs at each location. In June 2025, the Baltic AI GigaFactory initiative was announced, created by a consortium of the Baltic countries and Poland. In March 2025, six additional data centre locations were announced. Locations other than AI gigafactories will have up to 25,000 GPUs. These are: AI:AT in Vienna, BRAIN++ in Sofia, AI2F in France, JAIF in Jülich, PIAST in Poznań, and SLAIF in Maribor. Access to AI Factories for 2025 is available free of charge for AI start-ups.

2.4.2.4. The DARE Project

In March 2025, EuroHPC launched the 6-year DARE (Digital Autonomy with RISC-V in Europe) project to work on integrated circuits based on the RISC-V processor. The project envisages the creation of three processor designs, each developed by a separate company: a vector computing accelerator, a chip for AI model inference, and a general-purpose processor for HPC computing. This project has received funding from the European High-Performance Computing Joint Undertaking (JU) under grant agreement No 101101903. The JU receives support from the Digital Europe Programme and Germany, Bulgaria, Austria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, Greece, Hungary, Ireland, Italy, Lithuania, Latvia, Poland, Portugal, Romania, Slovenia, Spain, Sweden, France, Netherlands, Belgium, Luxembourg, Slovakia, Norway, Türkiye, Republic of North Macedonia, Iceland, Montenegro, Serbia.

2.4.2.5. Coordinated Plan on Artificial Intelligence

Updated and expanded „Coordinated Plan on Artificial Intelligence” (The Coordinated Plan for Artificial Intelligence), first adopted by the European Commission in 2018, was updated in 2021 and expanded in 2024 as a key element of the European AI strategy. Its main objective is to ensure that Europe becomes a global leader in trustworthy and sustainable artificial intelligence, in line with EU values.

The main objectives of the 2021 „Coordinated Plan on AI" (and its extension in 2024):

- Increasing investment in AI across the EU
- Mobilising at least €20 billion per year for public and private investment in AI.
- Supporting start-ups, SMEs and industrial projects using AI.
- Developing funding programmes through Horizon Europe, Digital Europe, and Recovery and Resilience Facility (Previous financing targets (set in the 2018 and 2020 Plans) assumed €20 billion per year from the public and private sectors, achievable within a decade. By September 2023, through Recovery and Resilience Facility (RRF) € 4.4 billion have already been allocated to AI projects in the EU.
- Building strategic AI capabilities and infrastructure
- Creating AI Excellence Centres and Test and Experimentation Facilities (TEFs).
- Developing common data spaces in key sectors (health, mobility, energy).
- Expanding high-performance computing (HPC) for advanced machine learning.
- Increasing the implementation of AI in the economy and the public sector by promoting the use of AI in sectors such as healthcare, agriculture, transport and public administration.
- Supporting the digitalisation of businesses, especially SMEs.– Budowa strategicznych zdolności i infrastruktury AI
- Facilitating the implementation of AI in compliance with regulations, including the Artificial Intelligence Act (AI Act).
- Developing and attracting AI talent in Europe by investing in education, training and reskilling in AI.
- Creating a European AI talent ecosystem (e.g. doctorates, postgraduate courses, exchange programmes).
- Encouraging professionals to work in Europe and preventing brain drain.
- Ensuring ethical, trustworthy and secure AI by implementing a legal framework for AI: AI Act, compliance with human rights and EU principles, supporting the development of trustworthy AI in line with the values

of democracy, privacy and transparency, and strengthening AI oversight and accountability mechanisms.

– Strengthening international cooperation and the EU's position in AI by promoting a global standard for AI based on EU values, cooperation with non-EU countries and international organisations (OECD, UN, G7), as well as joint research and regulatory projects with international partners.
– Integration with the AI Act: The plan provides operational support for the practical implementation of AI legislation

2.4.2.6. AI Innovation Package & GenAI4EU

In 2024, initiatives such as GenAI4EU were launched, with approximately €700 million earmarked for competitions in Horizon Europe and Digital Europe for 2025. This programme gives start-ups access to supercomputers and AI Factories. It supports the development of generative AI through collaboration between start-ups, industry and the public sector. The programme has supported the development of ‘AI factories’: €2.1 billion for EuroHPC JU in 2024, plus an additional €100 million for start-up incubation through InvestEU, generating a total of around €3 billion in public funding by 2027. Researchers, innovators, industrial companies and others applying for these EU funding opportunities will become part of GenAI4EU. This is a flagship initiative of the European Commission to support the development and deployment of generative AI solutions in European industrial ecosystems. Specific sectors – manufacturing, robotics, health, energy, agri-food, mobility, and aerospace – are aligned with the sectors identified in the EU industrial strategy and the Draghi report. GenAI4EU will support the transformation pathways outlined in these strategies by stimulating innovation, improving production and supporting sustainable growth in these sectors through the tailored adoption of generative artificial intelligence. This initiative will promote the development of large, open innovation ecosystems that encourage collaboration between AI developers – including start-ups and scale-ups – and strategic European industrial players and the public sector. As such, GenAI4EU contributes to the European Commission's overarching goals of increasing competitiveness and economic growth, as set out in the AI Action Plan for the continent presented in April 2025. GenAI4EU aims to increase the use of artificial intelligence by EU companies, which currently stands at only 13.5%. This demonstrates the significant potential for growth, innovation and competitiveness through the wider use of artificial intelligence. The future Apply AI strategy will set out how the European Commission plans to close this gap, building on initiatives such as GenAI4EU to deliver AI solutions „Made in Europe”. This initiative is based on the „AI Boost” project under the Horizon Europe programme (2023), under which four winners developing large artificial intelligence models were awarded €1 million and 8 million GPU hours. It also builds on support under the „Digital Europe” programme for open, multilingual large language models through OpenEuroLLM. Researchers, innovators, businesses and other interested organisations can find extensive EU funding opportunities to join forces to develop and deploy generative artificial intelligence in strategic sectors in Europe under the GenAI4EU flagship initiative. This initiative now exceeds the initial commitment of €500 million announced in the AI Innovation Package in January 2024, with nearly €700 million in funding planned under Horizon Europe, the Digital Europe Programme and the European Innovation Council. For example, researchers can receive EU funding of between €15 million and €17 million to use multimodal data to develop generative artificial intelligence in biomedical research, including through the transition to predictive and personalised medicine. This specific GenAI application helps industry competitiveness but also increases the effectiveness of treatment. The European Commission has launched the first wave of EU funding opportunities to integrate generative artificial intelligence (AI) into Europe's strategic sectors and maintain their competitive advantage. Horizon Europe Cluster: Group 1 (Health), Group 3 (Civil Security for Society), Group 4 (Digital Technologies, Industry, Space), Group 5 (Energy), Group 5 (Mobility), Group 6 (Agri-Food Products) (Invest AI & AI Continent Action Plan (Communication from the Commission to the European Parliament, the Council, The European Economic and Social Economic Committee and the Committee of the Regions, 2025)https://AI_Continent_Action_Plan_COM2025165_xL60HMmdrCHe7gEeVGS40RlUug_114523.pdf, access on 12.06.2025 r.).

The most important measures envisaged in the plan for the continent AI involves the use of the InvestAI initiative, which will allocate €200 billion to AI investments, to increase the EU's capabilities in this area by supporting initiatives in five main areas (combining public, Member State and private funding) for the development of a massive AI infrastructure in Europe. Advanced AI models require investment, infrastructure and cooperation. The EU plan will combine these elements to help European companies achieve the best possible results in the field of AI. For this purpose:

1. At least 13 AI factories will be established across Europe, using our world-leading supercomputer network. These factories will support start-ups, industry and researchers in developing cutting-edge AI models and applications.
2. At least five AI gigafactories, large-scale facilities with enormous computing power and data centres, will be established. They will enable the training of complex AI models on an unprecedented scale. This initiative requires both public and private investment. It will enable the EU to become a leader in pioneering AI models.
3. A bill on cloud and AI development will be presented, aimed at stimulating private sector investment in the expansion of cloud computing and data centres. The aim is to at least triple the computing capacity of EU data centres over the next 5–7 years, with priority given to sustainable data centres. Large sets of high-quality data are essential for the development and training of AI models. This objective is to be achieved through: a planned strategy for a European Data Union, which will facilitate the creation of a true internal market for data and enable the scaling up of AI development across the EU; and data labs in AI factories, which will collect and systematise high-quality data from various sources. This will provide researchers and developers with the tools they need to innovate. EU companies and EU countries should be supported in implementing the AI Act. Guidelines on this have already been published and a code of conduct is in preparation. An AI Act support centre will soon be operational, serving as a central point of contact for companies seeking information and guidance. The following proposals were announced at the AI Action Summit 2025:
    1. Investing € 200 billion (of which 50 billion from the EU and € 150 billion from the private sector through the AI Champions initiative);
    2. Building up to five AI 'gigafactories' (centers with 100,000 GPUs) and support for AI Factories;
    3. Establishing the InvestAI Facility and AI Skills Academy (to be launched in 2025) for training and talent exchange.

2.4.3. Support for innovation and scale-ups

Europe must leverage its science, innovative SMEs, and startups to compete in global markets increasingly defined by new technologies. This is why the European Commission established the European Innovation Council (EIC) to support groundbreaking ideas that are high risk, transform science into new business, and facilitate the market expansion of innovators shaping the future. By supporting the most promising European innovators—entrepreneurs from small and medium enterprises in realizing their projects, the European Innovation Council aims to implement the principles of the European Green Deal, shape an economy that works for people, and prepare Europe for the digital age. The goal of the European Innovation Council is to place Europe at the forefront of innovators who are creating new markets, particularly by integrating physical and digital products as well as services based on new technology business models. The task of the EIC is to fill the funding gap for innovative start-up companies and SMEs. A strategy has been dedicated to this, under which a public-private fund specializing in initial public offerings for SMEs has been established. The EIC is intended to complement the support of member states for innovation. Approximately €10 billion have been allocated for the development of breakthrough technologies (including AI) for startups and SMEs. The EIC provides direct support for innovators through the following funding instruments:

1. Pathfinder – for early stages of R&D work;
2. Transition – for further development of technology based on the results of the previously implemented project (Pathfinder lub ERC Proof of Concept);
3. Accelerator – for the stage of development and market introduction.

Additionally, the Digital Innovation Hubs was created including: a network of centers supporting the implementation of AI in companies and administration, with training and testing. (Ecosystem for AI innovation in Europe https://digital-strategy.ec.europa.eu/en/node/13487/printable/pdf access on 14.06.2025 r.).

2.4.3.1 European Innovation Council (EIC) Work Programme 2025

The European Commission's exploration of the artificial intelligence ecosystem, where we support innovation and drive Europe's leadership in artificial intelligence through initiatives such as European digital innovation hubs, artificial intelligence factories, or the AI Skills Academy. The European Commission's commitment to supporting skills and knowledge is reflected in the upcoming AI Skills Academy, which will prepare workers for a future based on artificial intelligence, ensuring that Europe remains a leader in the field of AI expertise. Upskilling in artificial intelligence is a common mission of our initiatives, and the European digital innovation hubs and artificial intelligence factories also provide training for employees. These initiatives together create a dynamic and interlinked ecosystem, fulfilling the mission of the European Commission to create an inclusive and competitive landscape for artificial intelligence. The initiatives undertaken by the European Commission so far in the field of artificial intelligence development focus on the following areas:

1. European Digital Innovation Centers (EDIH) – these are comprehensive service points that help businesses become more competitive in their business/production processes, products, or services through the use of digital technologies, including artificial intelligence.
2. Test and experimental facilities (TEF) – specialized large-scale reference centers that help innovative technology providers bring their products from the laboratory to the market. It includes support for full integration, testing, and experimenting with the latest mature artificial intelligence technologies.
3. Artificial intelligence factories – specialized facilities designed to provide supercomputing capabilities for the development and training of advanced artificial intelligence models. The factories will also support talent development through advanced educational, training, acquisition, and reskilling activities for relevant stakeholders involved in artificial intelligence.
4. Regulatory sandboxes in the field of artificial intelligence – offer innovators a controlled environment to test artificial intelligence systems under the supervision of the appropriate national authorities, providing regulatory guidelines and learning while supporting innovation and competition.

5. On-demand artificial intelligence platform – offers access to a wide range of algorithms, tools, and expertise, as well as opportunities for knowledge sharing and collaboration.
6. Academy of Artificial Intelligence Skills (in preparation) – will be a comprehensive service point for a range of activities supporting or developing educational and training programs in two main areas:
   a. Skills in the absorption and implementation of artificial intelligence, especially 'GenAI', in key sectors of the economy.
   b. Skills related to the objects of „artificial intelligence factories”.

(https://eic.ec.europa.eu/document/download/5e1eb75f-e437-477f-9ee9 ef54ff6387fd_en?filename=EIC%20Work%20Programme%202025.pdf access on 12.06.2025 r.)

2.4.4. Policies supporting the implementation of artificial intelligence in selected European countries

Italy

a) National Strategy for Artificial Intelligence (Italy's AI Strategy)

Italy adopted its first National Strategy for Artificial Intelligence in 2019 as part of the European Union's initiative for a coordinated approach to AI. This document highlighted the need for investment in research, technology development, and the growth of human capital. The updated AI Strategy 2022-2024 was developed by the Ministry of Economic Development (now part of the Ministry of Entrepreneurship and Made in Italy – MiMIT) in collaboration with the Ministry of Universities and Scientific Research and the Ministry of Digital Transformation. This strategy includes specific goals grouped into three areas:

– Development of the AI ecosystem: supporting research and innovation, developing competence centers, supporting start-ups.
– Increasing AI adoption in the public and private sectors: digitization of public administration, supporting SMEs in implementing AI.
– Framework ethical and regulatory principles: promoting social trust, compliance with European values.

b) Public investments and funds

- National Recovery and Resilience Plan (NRRP)

Italy has allocated significant resources from the EU NRRP (almost €200 billion) for digital transformation, part of which is dedicated to the development of AI. This includes:

- Development of computing infrastructure (clouds, supercomputers),
- Digitalization of public administration,
- Training in digital skills,
- Support for innovative enterprises and AI start-ups.
- Research funding: Through programs like Horizon Europe, Italy supports research institutes and academic-industrial consortia engaged in AI. There are also national funds for R&D projects involving artificial intelligence

c) Centers of Excellence and Scientific Initiatives

- AI Competence Centers – Italy has established several AI competence centers (Centri di Competenza), which connect universities, businesses, and government institutions. Examples:
- CINI – National Laboratory of Artificial Intelligence and Intelligent Systems – a nationwide research network involving universities and research centers.
- ELIS AI Academy – an educational and research center promoting practical applications of AI. As for international cooperation, Italy is a member of European initiatives such as:
- European AI Alliance
- AI-on-Demand Platform
- Partnership on Artificial Intelligence, Data and Robotics

d) Regulations and ethics

Italy actively supports EU regulatory initiatives, including the AI Act, which aims to create common legal frameworks for the implementation of AI in EU countries. National regulations are being adjusted to EU requirements regarding transparency, accountability, privacy, and security. As for ethical standards, the AI Strategy promotes the use of AI in accordance with the following principles:

- respect for fundamental rights,
- absence of discrimination,
- transparency of algorithm operations,
- accountability of designers and users of systems.

e) Development of competencies and education

Italy is investing in educational programs at the high school, university, and postgraduate levels in the field of AI. The following are being created:

- specialized courses for engineers, programmers, data analysts,
- training for public administration and teachers,– information campaigns for the general public (digital education).

Initiatives like „brain gain" are supported, aimed at retaining Italian talents in the country and attracting foreign specialists in the field of AI.

f) Industry 4.0 and AI applications

The implementation of AI is part of a broader Industry 4.0 strategy, which includes:

- automation and robotization,
- collecting and analyzing production data,
- intelligent supply chain management.

Italy supports the use of AI in sectors such as:

- machine industry,
- precision agriculture (AgriTech),
- healthcare (MedTech, AI-based diagnostics),
- mobility and logistics (smart cities, autonomous vehicles).

(Strategia AI per gli anni 2024-2026 (https://www.ofmconv.net/pl/ai-assisi-act-carta-etica-sullintelligenza-artificiale-presentata-allassociazione-stampa-estera/ access on 14.06.2025 r.)

The Italian AI Strategy for 2024-2026 is to fit into the European context of artificial intelligence development and to promote anthropocentric, reliable, and sustainable solutions. The development vision indicated in the document assumes the simultaneous consideration of the necessity for: innovation, understanding and analyzing new conditions, as well as the strategic importance of adjusting the capabilities to implement and promote AI solutions in industry, business, education, and society at large, as well as public administration.

The strategy identifies four strategic macro-areas of action: Research, Public Administration, Enterprises, and Education/Training. Each of them has its own time horizon for execution tailored to its specific characteristics, while the sets of strategic actions undertaken, although specific to each area, will be coordinated with respect to the final goal of implementing the Strategy. This is intended to ensure that the good practices being implemented will be uniform, and that the exchange of information and knowledge among all entities, as well as the subsequent actions taken in the field of AI, will be efficient and aligned with each other.

The sets of activities have been divided into two types: those related to infrastructure and implementation, coordination, and monitoring activities. The first includes, among others, national knowledge resources (data sets and models) and network infrastructure for AI. The indicated Entity is to be responsible for the latter (Foundation for Artificial Intelligence), subject to executive authority and responsible for managing the registry of AI solutions and its maintenance. It will also serve as a central hub of entities promoting the development and implementation of AI systems, including across macro areas, and will monitor the implementation process and the fulfilment of strategic assumptions and goals. The Strategy lists strategic actions for each of the macro areas, along with their descriptions and a confrontation with the current state of affairs, as well as the determination of tasks and goals to be achieved in the future. Additionally, the document also defines the Monitoring System, which is based on the analysis of so-called flagship projects (representative of the given sector) and the analysis of KPIs related to the strategic area by the Entity, and in some cases, expert panels. For selected macro areas, specific numerical values have been directly indicated, which are to serve as metrics in the KPI analysis, e.g., the number of doctoral students in AI-related programs, CATI/CAWI survey research on the population measuring competencies and awareness related to AI, or the number of start-up enterprises or enterprises in general developing AI technologies.

The draft law introducing the principles of research, testing, development, introduction, and application of AI systems and models. On May 20, 2024, the Italian Council of Ministers presented to Parliament a draft law introducing the principles of research, testing, development, introduction, and application of AI systems and models. On November 27, 2024, the draft was submitted to the Italian Senate, and on March 24, 2025, it was referred for further work in the Italian Parliament. The presented draft law defines the principles of research, development, implementation, and use of artificial intelligence systems and models. It emphasizes responsible, transparent, and human-centered use of artificial intelligence, while ensuring oversight of economic and social risk factors and protecting fundamental rights. The draft allows for the financing of AI projects in public services and also supports startups and SMEs in this regard. The document introduces key definitions such as:

- System AI: Automated systems with varying degrees of autonomy, capable of generating output data such as predictions and decisions.
- Data: Digital representations of acts, facts, or information.
- AI Models: Systems identifying patterns based on data to perform various tasks.

According to the proposed regulations, AI activities must be in accordance with fundamental rights, principles of transparency, security, data protection, non-discrimination, and sustainable development. AI systems should support decision-making and human autonomy, counteract harm, and guarantee cybersecurity. In the case of the broadly defined sector of scientific research and education, the act has:

- promote the enhancement of skills and training in the use of AI, particularly in the STEM (science, technology, engineering, mathematics) fields,
- support research and technology transfer in AI,
- encourage collaboration between universities, research institutions, and industry.

The draft bill includes provisions concerning selected sectors:

- the use of AI models in the media sector must primarily occur with respect for freedom of speech and media pluralism. Other restrictions, such as those related to age, are also specified in the project – access to AI for minors will require parental consent.
- the project also includes the use of AI in the healthcare sector. In this regard, they aim to improve diagnostics, the treatment process, and accessibility for disabled individuals. AI systems must be reliable, periodically verified, and used under the supervision of medical professionals.

– regarding the labor market, artificial intelligence should improve working conditions, protect employee rights, and increase productivity, while its use should also occur with respect for the rights and dignity of employees.
– the use of AI by public administration aims to increase the efficiency, effectiveness, and quality of their services for citizens and entrepreneurs. In the case of the public sector, the government is tasked with promoting AI to increase productivity, innovation, and competitiveness.
– AI in the justice system is to be used solely for organizing and simplifying its work, as well as for research in the field of legal sciences. Regulations in this area are to be created by the Ministry of Justice.

Public sector tenders should prioritize AI solutions that ensure data localization and high standards of operational transparency. The government's task is to align national regulations with EU regulations on artificial intelligence, ensure its ethical use, and combat illegal activities related to AI. Furthermore, the central government is responsible for developing and updating the national AI strategy, promoting public-private collaboration and research. Agency for Digital Italy (Agenzia per l’Italia Digitale , AgID) and the National Cybersecurity Agency (Agenzia per la Cybersicurezza Nazionale, ACN) have been designated as national bodies for artificial intelligence.

Poland

1. Polish Artificial Intelligence Strategy (PAIS)

   The document "Poland's Artificial Intelligence Strategy for 2020-2027" was published by the Ministry of Digital Affairs (currently the activities have been taken over by, among others, the Chancellery of the Prime Minister) and serves as the main guiding document for the development of AI in Poland. The main objectives of the strategy:

– development of scientific and research potential.
– supporting entrepreneurship in the field of AI.
– development of the labor market and digital skills.
– improving the functioning of public administration with the help of AI.
– creating a friendly and ethical ecosystem for AI.
– active participation of Poland in European AI initiatives

Priority areas:

- Education and skills – development of educational programs, raising the qualifications of employees.
- Science and research – support for research units and science-industry collaboration.
- Data and infrastructure – building national data repositories, access to computing power.
- Business and industry – supporting startups, SMEs, and large companies in adopting AI.
- Public administration – implementing AI in public services (e.g., data analysis, chatbots, predictive systems).
- Operational programs and EU funds – Poland takes advantage of numerous EU funds that support the development of AI within the cohesion policy and the „Digital Europe" program. Programs:
- European Funds for Digital Development 2021–2027 (EFDD) – funding for projects in the field of AI, big data, cloud computing.
- Horizon Europe – the EU's research and innovation program supporting Polish scientific teams and consortia working on AI.
- Digital Europe Programme – an EU programme focused on the implementation of digital technologies, including AI, in administration and business.
- Digital Innovation Competence Centers and Hubs (DICC)

Examples of actions:

- polish EDIHs (European Digital Innovation Hubs) support SMEs and public administration in adopting AI through training, consulting, and technology testing.
- they offer access to testing infrastructure, technical skills, and a network of international cooperation.

Examples of centers:

- IDEAS NCBR (research center for AI),
- Hub4Industry (for Industry 4.0),
- Mazovia EDIH, HPC4Poland, or DIH4Future.

– Data and computation infrastructure

Support for AI includes:

– development of cloud computing (e.g. National Cloud).
– creation of public and industrial data repositories – e.g. geographic, health, transportation data. – access to supercomputers (e.g. PRACE-LAB, National Supercomputing Center in Poznań, CI TASK in Gdańsk).

When it comes to Regulations and ethics of AI application, Poland is implementing EU recommendations regarding:

– Compliance with the AI Act (EU regulation on AI),
– Ethical standards – e.g., principles of transparency, accountability, avoiding algorithmic biases,
– Risk assessment of AI systems – classification according to risk in accordance with the AI Act.

Guidelines are also being created for critical sectors (health, judiciary, transport) regarding the use of safe AI systems. With respect to international cooperation and participation in EU projects, it should be noted that Poland participates in initiatives such as:

– GAIA-X – a European initiative regarding data infrastructure.
– Partnership on AI, Robotics and Data – a EU consortium for coordinating research on AI.
– EuroHPC – a community of European computing powers.
– As part of education and the development of digital skills, programs are being implemented:
– Development of IT and AI personnel (e.g., postgraduate study programs, AI bootcamps),
– School and university programs with elements of AI and machine learning,
– Digital skills certifications (e.g., DIGCOMP).

Poland is investing in the digitization of public services using AI:

– Chatbots for citizen service (e.g., in Social Insurance Institution),
– Automation of data analysis and prediction of abuses (e.g., in the tax office),

– Systems supporting traffic management, public safety, and health.

(Polityka dla rozwoju sztucznej inteligencji w Polsce od roku 2020 Załącznik do uchwały nr 196 Rady Ministrów z dnia 28 grudnia 2020 r. (poz. 23) https:// Polityka_dla_rozwoju_sztucznej_inteligencji_w_Polsce_od_roku_2020.pdf, access on 15.06.2025 r.).

"The 'Policy for the Development of Artificial Intelligence in Poland since 2020" describes the actions that Poland should implement and the goals it should achieve in the short term (by 2023), medium term (by 2027), and long term (post-2027), aimed at serving the development of Polish society, the Polish economy, and Polish science in the field of artificial intelligence (AI). All goals and tools are divided into six areas:

1. AI and society – actions aimed at making Poland one of the larger beneficiaries of the data-driven economy, and Poles – a society aware of the necessity of continuously improving their knowledge and skills, including digital competencies.
2. AI and innovative companies – actions aimed at supporting Polish AI enterprises, creating mechanisms for financing their development, increasing the volume of orders, fostering cooperation between start-ups and the government, and implementing new pro-development regulations (digital sandboxes).
3. AI and science – actions supporting the Polish scientific and research environment in designing interdisciplinary challenges or solutions in the field of AI, taking into account the humanities and social sciences, as well as the creation of AI departments, training of PhD students, granting scholarships to researchers, and other activities aimed at preparing a cadre of experts capable of developing AI solutions with consideration for the framework of ethical and safe use of this technology, to the benefit of the economy and the well-being of citizens.
4. AI and education – actions taken from primary education up to the university level – course programs for individuals at risk of losing their jobs due to advancing automation and implementation of new technologies, educational grants aimed at helping prepare the best workforce for the Polish economy related to AI.
5. AI and international cooperation – actions on the international stage that will support the promotion of Polish business in the field of AI and the

development of AI technology with respect for human dignity and fundamental rights, in accordance with EU and OECD standards, as well as activities of digital diplomacy in the area of policies or regulations related to artificial intelligence.

6. AI and the public sector – actions aimed at supporting the public sector in fulfilling AI-related orders, better coordination of activities, and further development of programs such as GovTech Poland, as well as ensuring civil protection commensurate with the threat.

The next tools will be so-called virtual data repositories or data trusts (i.e., initiatives in the form of trusted data spaces), the Government Cloud, and opening and making as much public data as possible available for citizens and businesses. The aim of the AI Policy is to support society, businesses, representatives of science, and public administration in seizing the opportunities related to the development of AI, while simultaneously ensuring the protection of human dignity and conditions for fair competition in global competition. This AI Policy takes into account international, legal, ethical dimensions, and the standards of technical-organizational aspects that shape the requirements and conditions to reap benefits related to AI applications throughout its life cycle, covering design, research, development, implementation, application, use, withdrawal from circulation, and disposal.

The document „AI Development Policy in Poland 2025-2030” prepared by the AI Working Group (AIWG) presents a vision of making Poland a global center of trustworthy AI, where innovations drive economic growth, competitiveness, and social welfare. We sincerely thank the experts for their commitment to preparing this key document. The AI Policy outlined below is based on four pillars:

1. Human capital – the development of highly qualified specialists and increasing the availability of AI talents.
2. Innovations – support for scientific research and applications of AI in various industries.
3. Investments – strategic financial support for AI from public and private sectors.
4. Implementations – development of infrastructure and legal frameworks supporting AI in Poland.

The expertise was developed based on reports, analyses from national and international sources, scientific publications, and consultations with experts from various fields.

The document presents strategic objectives such as:

- development of the digital economy and social well-being,
- financing R&D and AI implementation,
- ensuring computing infrastructure,
- educating society and developing skills in AI,
- implementing AI in the healthcare system.
- coordination of policy and international cooperation.

The expertise also takes into account key areas of development, such as the competitiveness of the economy, social well-being, the digital industry, national security, and the construction of the Polish AI ecosystem, including platforms for cooperation between science, business, and the public sector.

(Polityka rozwoju sztucznej inteligencji w Polsce 2025-2030 https:/Ekspertyza_ws_aktualizacji_Polityki_AI_w_Polsce.pdf , access on 15.06.2025 r.)

Slovakia

1. National Artificial Intelligence Strategy (AI Strategy)

   In 2019, Slovakia developed a document titled „AI Strategy for the Slovak Republic" , which responds to the European Commission's initiative regarding the coordination of actions among member states.

   Main goals of the strategy:

   - increasing the competitiveness of the Slovak economy through the integration of AI in key sectors (e.g., industry, health, transport).
   - supporting research and innovation in the field of AI, with particular emphasis on collaboration between science and business.
   - increasing the digital competencies of society, including the development of education in the field of AI.
   - establishing ethical and regulatory frameworks for the responsible use of AI.
   - creating an ecosystem for innovation by supporting start-ups and pilot projects.

2. Slovakia has established special structures to support the development of AI:

a) Ministry of Investments, Regional Development and Informatization (MIRDI)

   – coordinates the digitalization and AI policy.

   – leads the implementation of EU programs (e.g. Digital Europe, Horizon Europe).

b) Center for Innovation and Artificial Intelligence (CIAI)

   – acts as a think-tank and a center for collaboration between public administration, science, and industry.

   – supports the development of innovation, analyzes risks, and conducts research.

c) Slovak University of Technology in Bratislava (STU)

   – a leading academic center engaged in research on AI and machine learning.

   – collaborates with public institutions and businesses.

3. Slovakia benefits from both national funds and EU resources.

Sources of financing:

– EU structural funds (ERDF, ESF+)

– Horizon Europe – research and development projects

– „The Digital Europe” programme – building European digital infrastructure, digital innovation hubs

– National Recovery and Resilience Plan (NRRP) – funding for digitization and development of AI

Sample programs:

– Digital Innovation Hubs (DIH) – digital innovation centers supporting SMEs in the implementation of AI

– AI for Slovakia – an initiative supporting pilot implementations of AI in the public sector.

Regarding education and the development of digital skills, it should be noted that Slovakia recognizes the lack of digital skills as one of the main barriers to implementing AI. Initiatives undertaken by Slovakia focus on the following issues:

- inclusion of AI in the curricula at the higher and secondary school levels.
- training programs for public administration employees on the use of AI.
- support for bootcamps and courses for IT specialists (e.g. Data Science, Machine Learning).

4. In AI policy, Slovakia refers to the ethical principles promoted by the European Commission.

   Ethical priorities:

   - transparency of algorithms.
   - human oversight over AI decisions.
   - protection of privacy and personal data (GDPR).
   - prevention of algorithmic discrimination.

5. In the area of international cooperation, Slovakia actively participates in EU and regional activities:

- membership in the European AI Alliance.
- collaboration within the V4 (Visegrad Group) regarding digitalization.
- participation in cross-border projects with Austria, the Czech Republic, and Hungary in the field of AI infrastructure. (Stratégia umelej inteligencie pre Slovensko https:/ Stratégia umelej inteligencie pre Slovensko.pdf , access on 16.06.2025 r.)

Spain

Estrategia Nacional de Inteligencia Artificial (ENIA) – 2020 – ENIA this is the main strategic document, announced in December 2020, which is part of the Spanish digital agenda „España Digital 2025". His goal is to promote the development and implementation of AI in various sectors of the economy and social life.

Main areas of activity:

- strengthening technological and research potential in the field of AI.
- promoting the integration of AI in the private and public sectors.

- supporting education and training in the field of AI.
- developing ethical and regulatory frameworks.
- increasing the use of AI in public administration.
- promoting AI projects that are inclusive and serve the entire society.

€ 600 million euros have been allocated for the implementation of the strategy in 2021–2023, mainly from EU funds under the instrument „Next Generation EU”.

1. Renewal, Transformation and Resilience Plan (RTR)
   Spain, as one of the largest beneficiaries of EU funds under the instrument „Next Generation EU”, adopted the PRTR, which includes huge investments in digital transformation, including in AI.

   Meaning for AI:

   - investments in digital infrastructure (cloud computing, supercomputers).
   - support for startups and innovative AI ecosystems.
   - development of DIH (Digital Innovation Hubs) networks, including those specialized in AI.
   - promoting „AI made in Europe” – in accordance with EU ethical standards.
2. Spanish Agency for the Supervision of Artificial Intelligence. In 2023, the establishment of the first national agency in the EU to oversee AI was announced – „Agencia Española de Supervisión de la Inteligencia Artificial” (AESIA), which was located in La Coruña (Galicia).
   AESIA tasks:

   - monitoring and enforcing compliance with EU regulations, including the AI Act
   - promoting ethical and responsible use of AI.
   - supporting collaboration between the public, private, and academic sectors.
   - protecting citizens' rights against algorithmic decisions.

3. As for support for research and development (R&D) in AI, Spain is undertaking the following public programs and actions, namely:
   - CDTI (Centro para el Desarrollo Tecnológico Industrial) offers grants and loans for companies developing AI.
   - Plan Nacional de Investigación Científica y Técnica y de Innovación includes components related to AI and big data.
   - collaboration with Spanish supercomputers, such as MareNostrum (Barcelona Supercomputing Center).
   - Digital Innovation Hubs (DIH) and European AI Testing and Experimentation Facilities (TEFs)
4. Spain actively participates in the construction of a network of digital innovation centers that: – support SMEs in the adaptation of AI.
   - connect research, industry, and administration.
   - provide access to computing resources and data.
5. Spanish centers have also been reported for TEF projects aimed at testing AI in sectors such as health, industry, or smart cities. Spain advocates for:
   - citizen participation in AI policy-making (public consultations).
   - the creation of regulations based on human rights.
   - adherence to the principles of the EU AI Act – the act on artificial intelligence, which is currently being implemented.
6. The educational and developmental initiatives undertaken by Spain revolve around the following tasks:
   - creating new undergraduate and postgraduate study programs in AI.
   - courses in AI available for public officials.
   - the „AI for All” initiative promoting digital inclusion.
7. As part of international cooperation, including within the EU, Spain collaborates with:
   - EU (coordination of the AI Act, participation in joint Horizon Europe projects).
   - UNESCO (ethical frameworks).
   - IPCEI initiative (Important Projects of Common European Interest) in the field of AI and data.

(Estrategia Nacional de Inteligencia Artificial (ENIA) https://www.incode2030.gov.pt/aip-2030/, access on 16.06.2025 r.).

2.4.5. Conclusions

The policy supporting the implementation of artificial intelligence (AI) in Europe focuses on creating a safe, ethical, and innovative ecosystem for the development of this technology. The goal of European policy is to create a trusted environment for AI development that combines innovation with social and legal responsibility. A key element is the EU's AI strategy, which aims to support research and innovation, develop digital infrastructure, and invest in the digital skills of citizens and professionals. In 2024, the European Union adopted the Artificial Intelligence Act (AI Act) – the world's first comprehensive law regulating the application of AI. This document introduces a risk-based approach and ensures that the development of AI will be in accordance with European values such as privacy, security, and human rights. The EU also supports the implementation of AI through funding programs such as „Horizon Europe” and „Digital Europe”, which enable the development of research and development projects and the application of AI in public and private sectors. Furthermore, cooperation among member states, research centers, and industry is promoted.

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2.5. AI applications in world-leading countries

2.5.1. The importance and scope of artificial intelligence applications in the modern economy

Without a doubt, artificial intelligence (AI) is a broad and rapidly developing topic in the scientific, journalistic, and political spheres. The role of AI is growing in the transformation of the global economy. It is used across many sectors, including industry, transport, energy, trade, and healthcare. Its growing importance is due, among other things, to technological advances stimulated by globalisation, which have created conditions in which knowledge and innovation have become key factors in generating new development opportunities. Artificial intelligence is considered to play a central role in information management amid technological progress and innovation, which, in evolutionary terms, is increasingly emerging as an essential determinant of innovation processes (Trocin et al., 2021; Truong and Papagiannidis, 2022). AI technology is increasingly supporting public administration entities, including the development of e-government systems and services (Izdebski, 2019). Experts predict that by 2030 we may see even more rapid, non-linear transformations in the civilisational environment (Gołąb et al., 2022; Gołaszewska-Kaczan, Kuzionko-Ochrymiuk, 2023).

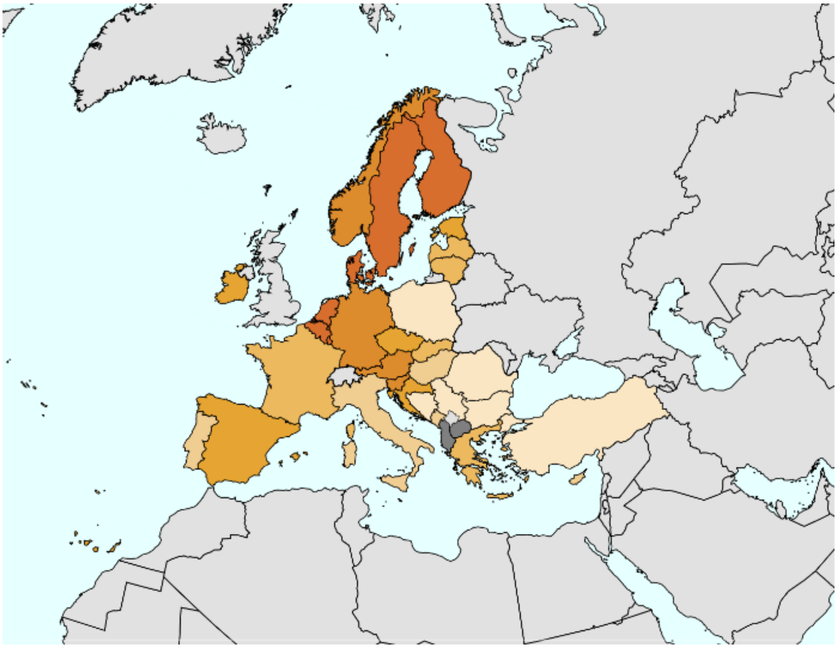
2.5.2. Scale and diversity of AI adoption in Europe

International organisations recognise the potential of AI and are taking steps to develop strategies, policies, and ethical regulations to support innovation. In official documents issued by European Union institutions and bodies, artificial intelligence is seen as a central element of the digital transformation of the socio-economic system. In July 2020, the European Commission published a report summarising the public consultation on the White Paper on Artificial Intelligence. On 20 October 2020, the European Parliament adopted three resolutions on ethics, civil liability, and intellectual property in relation to AI. In December 2020, the Council of Ministers of the Polish government adopted a document on establishing a policy for the development of artificial intelligence in Poland (Serwis..., 2025; European Commission, 2021). Data published by the Pollster Research Institute in June 2023 shows that 74% of Poles have encountered the concept of artificial intelligence. Interestingly, 28% of respondents recognise the Polish abbreviation “SI”, while the English equivalent "AI" (*Artificial Intelligence*) is already known to 49%

of respondents. The primary sources of knowledge about artificial intelligence are television programmes and services (51% each), as well as online publications, which were indicated by 48% of respondents (Konopka 2023). Artificial intelligence uses data analytics tools, primarily machine learning techniques such as deep learning. Thanks to these technologies, computers can be trained to perform specific tasks by analysing large data sets and identifying hidden structures within them (European Parliament, 2022). In today’s world, artificial intelligence plays an important role, and its potential across various fields is constantly evolving through research. however, these types of technologies have also permeated people’s everyday lives through ubiquitous smart devices and internet connectivity, often without them even being aware of it (Sáez-Velasco et al., 2024; Abdullahi et al., 2022; Katare et al., 2018). Education is one of the most critical drivers of technological innovation and long-term economic growth. For this reason, AI-supported education can significantly impact knowledge transfer, promoting innovation and stimulating economic development. Creating such an environment is a key condition for the effective functioning and long-term growth of a knowledge-based economy (Kirikkaleli D., Kirikkaleli N. O., 2025). When considering the application of AI from the perspective of EU countries, the literature on the subject reveals a diverse range of activity in this area. For example, the Scandinavian countries (Denmark and Sweden) have a dominant share and significance in the implementation of chatbots in public services (European Commission 2023). Service providers located in Germany, on the other hand, focus primarily on AI applications in logistics and transport. Financial service companies from the FinTech sector distinguish Estonia from other EU countries in terms of activity in the field of AI (Decyk k., Rzeszutek A. 2024). According to Eurostat data, over 13% of companies in the European Union with at least 10 employees use AI-based solutions, up 5.5 percentage points from 2023. A significantly higher level of adoption is observed among large economic entities, defined as companies employing at least 250 employees — in their case, the average percentage is around 42% (Eurostat, 2024). Denmark remains the leader in the implementation of artificial intelligence technologies in enterprises, with a rate of 27.6%. Sweden (25.1%) and Belgium (24.7%) follow. The lowest adoption rate was recorded in Romania (3.1%), followed by Poland (5.9%) and Bulgaria (6.5%). In Finland, over 70% of extensive enterprises report using artificial intelligence-based solutions, while in France and Italy, this percentage is around one-third, placing these countries below the EU average for large companies (Euronews 2025). There are also significant differences in the types of artificial intelligence technologies that companies most commonly use. The most widespread are solutions based on text mining, deep learning techniques, and operational process automation. The most widely used AI technology in European companies remains tools for working with text and content analysis, which are used by 7% of entities. In second place are systems that enable automatic text generation (5.4%). The third most popular category is speech recognition and conversion into a format that can be processed by computer systems, used by 4.8% of companies. The key impact of artificial intelligence will most likely be on the employment structure across numerous professions and sectors of the economy (Euronews 2025).

In 2023, around 8% of enterprises in the European Union with at least 10 employees reported using at least one artificial intelligence technology. In 2024, this percentage rose to 13.5%, representing a year-on-year increase of 5.5 percentage points. Large enterprises remain clear leaders in the implementation of AI-based solutions, achieving almost four times higher levels of use of these technologies than small enterprises in 2024. In 2023, large companies in Ireland used artificial intelligence to a much greater extent (approx. 37%) than medium-sized (approx. 18%) or small (approx. 5%) enterprises. The dynamic growth in the percentage of companies using AI between 2023 and 2024 highlights the rapid pace of adoption of these technologies in the European business sector (Eurostat 2022). The clear differentiation between company size classes suggests that access to resources, technical capabilities, and, possibly, economies of scale are key; larger enterprises are better equipped to invest in, implement, and maintain AI solutions. The delays observed in small and many medium-sized enterprises point to barriers such as costs, a lack of internal expertise or data infrastructure, and uncertainty about the return on investment.

Map 1. Artificial intelligence by the size class of enterprise



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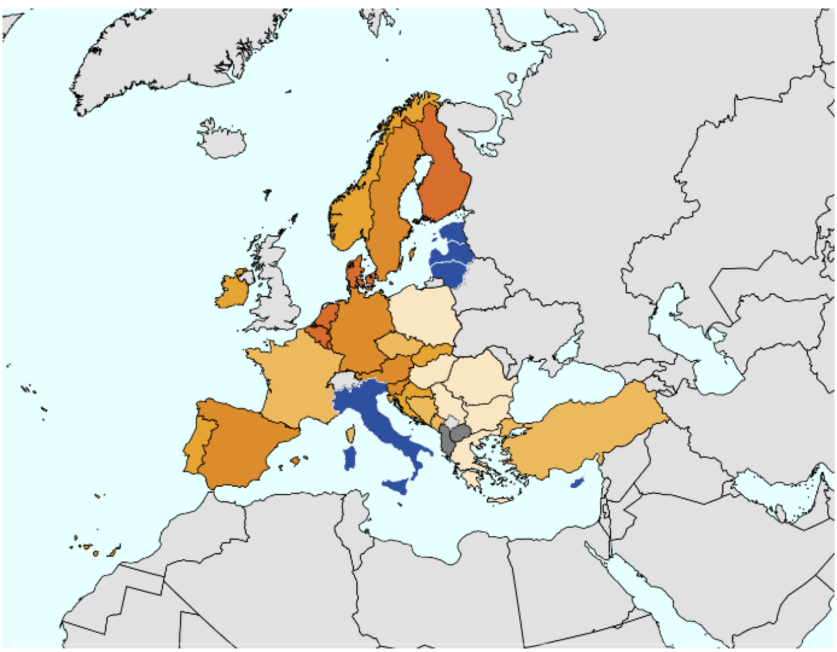

2024

Source: own study based on Eurostat data (accessed on 29 November 2025)

According to the European Union's policy assumptions, digital transformation and the development of modern technologies are key to strengthening entrepreneurship and increasing the competitiveness of the economy, while ensuring the safe and sustainable digital development of Member States. The dynamic growth of artificial intelligence requires accelerating the process of creating adequate legal regulations, both at the European Union level and in individual Member States. In designing the legal framework of the AI Act, the EU legislator focused primarily on limiting the risks arising from the use of artificial intelligence and on imposing obligations on AI system providers to ensure the safe and responsible operation of AI systems. As indicated on the European Parliament's website, the overarching objective of the AI Act is to provide a basic level of protection for users of artificial intelligence-based technologies and to counter potential abuses arising from their use.

2.5.3. Leading countries in AI development: potential, rankings, and implications

Due to its economic potential, artificial intelligence will play an essential role in international politics, and its development and applications may be crucial for the future functioning of the global economy, shaping global economic transformations.

The factors that are most likely to drive the impact of AI on the global economy will be increases in:

a) productivity resulting from the automation of processes in the private sector (including the implementation of robots and autonomous vehicles);
b) productivity associated with equipping the private sector workforce with AI technologies;
c) consumer demand driven by the availability of personalised and/or higher quality products and services supported by artificial intelligence (Morisson A. et al. 2017).

Countries with extensive data resources gain a strategic advantage in the development and implementation of AI technologies. In this context, the United States and China occupy a special position, with China having greater access to data of operational and economic importance. At the same time, many areas of economic activity are undergoing automation, with AI-based systems taking over tasks previously performed by humans. Much of the manufacturing sector is already at an advanced stage of this transformation, even without accounting for potential future AI technological breakthroughs.

Highly developed countries play a key role in shaping the future of industry and social structures on an international scale. At the forefront of global technological progress, they set the direction for development and establish standards that other countries aspire to. Countries that gain a competitive advantage in the development and implementation of AI technologies will hold a strategic position in shaping the global technological and economic order of the future.

The United States and China are widely recognised as global leaders in artificial intelligence. The United Kingdom, Canada, and India also occupy significant positions in this field. Other countries that contribute significantly to AI research and development include Israel, France, Germany, Japan, and Singapore. The development of artificial intelligence affects many areas of the economy. To capture the complexity and dynamics of the global artificial intelligence ecosystem, the Stanford Institute for Human-Centered Artificial Intelligence (HAI) compiles an annual *AI Index Report*. An integral part of this report is the **Global AI Vibrancy Ranking**, which classifies countries by their capacity for innovation, adoption, and integration, as well as for governance and ethics in AI systems. The ranking takes into account, among other things, the level of research funding, the quality of scientific publications, the development of AI personnel, the pace of technology commercialisation, and the consistency of regulatory policies. It is estimated that by 2030, the revenue from the application of artificial intelligence for the US will amount to approximately $3.7 trillion (14.5% of GDP), and $7 trillion (26.1% of GDP) for China (Verwei and Rao, 2017). The Global Vibrancy Tool, developed by Stanford University, aggregates 42 indicators to identify global leaders in artificial intelligence and analyses the reasons for the clear advantage of the United States over other countries. Stanford University’s Global Vibrancy Tool considers areas such as scientific publications, private investment, patents, and the development of responsible practices, showing that AI is a key element of today’s reality. With the ongoing and dynamic development of artificial intelligence technology, companies operating in global markets are intensifying their efforts to recruit highly qualified specialists in the field and to systematically improve the digital skills of their human resources in this area. This issue is a key priority for management, as confirmed by a 2024 report from Microsoft and LinkedIn, based on a survey of 31,000 respondents from 31 countries. According to the data presented, 66% of organisational leaders stated that they were not prepared to hire an employee without artificial intelligence skills. In comparison, 71% of respondents preferred hiring a candidate with less professional experience but equipped with such skills, rather than more experienced individuals without them. In response to the growing importance of these skills, LinkedIn has developed an AI Talent Concentration Index based on its members' profile data. This index is used to monitor the global supply of AI specialists and enables comparisons between countries. LinkedIn recognises both engineering skills, such as machine learning and natural language processing (NLP), and practical skills related to using AI-based tools, such as ChatGPT and GitHub Copilot, as AI talent. The Global Vibrancy Tool 2024 not only identifies leaders but also tracks the dynamics of national AI ecosystems over time and highlights areas where individual countries are gaining an advantage or encountering barriers to development.

The global artificial intelligence market was valued at $279.22 billion in 2024, and according to Grand View Research, it is projected to grow at an average annual rate of 35.9% from 2025 to 2030.

According to the Stanford report, the **United States dominates in many key areas** – it publishes the most groundbreaking machine learning models, attracts the most private investment capital in the AI sector, and leads in research on the responsible development of this technology. The United States has the strongest artificial intelligence ecosystem in the world, significantly outperforming other countries in key areas. According to data from the Global Vibrancy Tool, countries are assessed on three main pillars of AI importance: research and development (quality and quantity of AI research), economy (economic activity related to AI), and infrastructure (availability and development of the technological basis for AI). The United States clearly dominates in each of these areas. In 2023, the United States conducted the highest-quality research on artificial intelligence, developed the most advanced machine learning models, invested the most in private funds in AI development, and recorded the highest number of mergers and acquisitions in this sector. In addition, the United States had the highest number of AI-related job openings and the most AI-related start-ups (https://hai.stanford.edu).

Between 2013 and 2024, the highest level of total private investment in artificial intelligence development was recorded in the United States, where its value reached approximately USD 500 billion. This scale exceeds the total private expenditure on AI incurred by the rest of the world combined, confirming the dominant position of the US in the global ecosystem of AI-based innovation. China ranked second with investments of USD 119.3 billion, indicating its strategic commitment to the development of this technology. Next in line were the United Kingdom (USD 28.2 billion), Canada, and Israel (USD 15.0 billion each), which stand out for their strong research and development centres and favourable conditions for innovative technology companies. Significant, albeit relatively more minor, investments were also recorded in Singapore and Sweden (USD 7.3 billion each), Japan (USD 5.9 billion), Australia (USD 4.0 billion), and Switzerland (USD 3.9 billion).

In addition, significant private investment in artificial intelligence was observed in the United Arab Emirates, with total expenditure of USD 3.7 billion. These data confirm the growing importance of artificial intelligence as a key area of economic competitiveness and long-term technological development on the international stage.

The People’s Republic of China is consistently strengthening its position in the global artificial intelligence ecosystem by allocating significant financial resources to developing data infrastructure. The implementation of strategic projects’ considerable advantage in this development model is its access to extensive datasets, which enable effective and rapid training of machine learning algorithms at scale. At the same time, this approach is controversial in international debate, particularly regarding privacy protection and the use of artificial intelligence in social surveillance systems. Although China is ahead of many countries in the scale of AI-based technology implementation, it remains an open question whether this quantitative advantage will translate into a lasting qualitative and innovative advantage in the long term. India is focusing on the concept of “AI for All” and is leveraging its human capital, which is its most valuable resource. Competition between the US, the EU, and East Asia – especially China – will depend on technology development forecasts. In the region, only China, Japan, South Korea, and Taiwan have global innovation potential; the other countries lack the necessary educational and research facilities. These four economies stand out for their ability to innovate across a wide range of products and services. The higher education systems in these countries operate at a global level, enabling the training of a significant number of highly qualified graduates in science and engineering, which are key resources for further technological development (Financial Observer 2025).

The United Kingdom has a clear focus on ethical and regulatory issues in artificial intelligence, formulating its strategy for the development of this technology around responsibility and normative governance, and aspiring to become a global hub in this area. Its research potential is underpinned by strong academic institutions and the presence of specialised technology companies such as DeepMind and Graphcore, which strengthen the national innovation ecosystem. At the same time, the scale of investment in AI remains relatively lower compared to its main competitors, in particular the United States and China. The British model is sometimes viewed positively for its systematic consideration of ethical and regulatory dimensions. Still, the literature also contains critical voices pointing to the limited dynamics of the commercialisation of research results and the potential risk of an outflow of highly qualified personnel to larger, more capital-intensive markets.

Table 17. Countries dominating the implementation of SI

Country	National strategy (for example)	Academic centres	Companies /leaders	Strengths	Chellenges	Priority map
China	New Generation AI Dev. Plan (2017)	Beijing, Tsinghua; Shenzhen	Baidu, Alibaba, Tencent, Huawei	data scale, rapid commercialisation	privacy, governance, technological dependencies	medicine, finance, cybersecurity, transport, administration, Industry 4.0, smart cities
India	National Strategy for AI (NITI Aayog, 2018)	IIT, IISc Bangalore	Infosys, TCS, Wipro, HCL	human capital, IT services sector	infrastructure, sector data	medicine, agriculture, finance, education, smart cities
USA	American AI Initiative (2019)	MIT, Stanford, CMU	Google, Microsoft, Amazon, IBM, OpenAI	VC + science + Big Tech	Global competition, cohesion regulations	medicine, finance, cybersecurity, transport, Industry 4.0, education

Country	**National strategy (for example)**	**Academic centres**	**Companies /leaders**	**Strengths**	**Chellenges**	**Priority map**
United Kingdom	AI Sector Deal; National AI Strategy (2021)	Oxford, Cambridge, Imperial	DeepMind, Graphcore, Darktrace	World-class research, ethics/regulation	Scaling, growth financing	Medicine, finance, transport, cybersecurity, education
Canada	Pan-Canadian AI Strategy (2017)	Mila, Vector, Amii	Element AI* (ServiceNow), Layer 6 AI	Deep learning pioneers, science	Commercialisation, talent retention	Medicine, finance, transport, administration, Industry 4.0,
Israel	National AI Programme (2020)	TAU, HUJI, Technion	Mobileye, Zebra Medical, NICE	Cyber, dual-use, start-ups	Market scale, transfer to industry	Medicine, agriculture, transport, cybersecurity, Industry 4.0

Source: own study

Canada is one of the countries that recognised the strategic importance of artificial intelligence relatively early on, and its scientific community – represented by researchers such as Geoffrey Hinton and Yoshua Bengio – played a key role in the development of deep learning. Thanks to the activities of specialised research institutes such as Mila, Vector Institute, and Amii, the country has maintained its position as one of the major centres for AI research. At the same time, academic debate raises concerns about limited capacity to commercialise research results: a significant proportion of Canadian start-ups are acquired by foreign entities, casting doubt on the long-term viability of an autonomous and competitive AI sector.

Israel has the highest number of artificial intelligence start-ups per capita in the world, and its competitive advantage stems from strong synergies between the military and civilian sectors. A significant proportion of AI solutions are developed in specialised military units and then transferred and commercialised in the civilian economy. Its key areas of specialisation include cybersecurity, medical technologies, and mobility systems, as exemplified by Mobileye. At the same time, the literature on the subject highlights the limited scale of the domestic market and the high dependence of the innovation ecosystem on foreign capital and investors. The global race for dominance in artificial intelligence is not only about technology, but also about the values on which it is built. As a result of systematic investment and dynamic development of technological innovation, artificial intelligence is playing an increasingly important role in the transformation of key sectors of the economy.

2.5.4. Summary

The advantages of using artificial intelligence have long been demonstrated in numerous published works. According to Zhao et al. (2022), artificial intelligence has helped alleviate the problem of information asymmetry associated with remote operations. Chen et al. (2021) also found that advances in artificial intelligence have improved service quality and work efficiency in the financial services sector. Furthermore, Khalil et al. (2025) explained that FinTech can expand the banking sector, a view confirmed by the current chairman of the US Securities and Exchange Commission, who stated the potential and opportunities to improve bank efficiency through the application of artificial intelligence. Furthermore, artificial intelligence has been shown to influence the operational and technical efficiency of financial institutions. Mor and Gupta (2021) found in their case study on India that the use of these technologies, together with machine learning mechanisms, reduced the inefficiency of commercial banks by 11%, reducing non-performing assets and increasing performing assets. Its applications contribute not only to increasing the efficiency of economic processes but also to improving the quality of life and user experience globally. Contemporary digital technologies offer vast opportunities for development in both business and education. However, it should be emphasised that the effective implementation of these technologies is not determined solely by the level of sophistication of technical tools, but depends equally on the social skills, adaptability, and critical thinking of users (Nosalska, K.).

Countries should seek a compromise between innovation, regulation, and respect for citizens' rights. Otherwise, competition for AI will become not only a technological game, but also a political and social game for the future of the global order.

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3. Research methodology

The subject of the study was to analyse the conditions for the readiness of micro, small and medium-sized enterprises (SMEs) to implement solutions based on artificial intelligence (AI) and analytical tools related to Big Data technology. Organisational, cultural and management factors of the surveyed enterprises were taken into account. A diagnosis of the barriers to benefits and expectations of respondents in the face of the AI implementation process in SMEs was also made. The survey was designed to measure both the level of technical and organisational preparedness and the attitudes of management towards innovation. The issues covered included the existence of implementation strategies, the availability of human and financial resources, organisational culture and barriers to the implementation of new technologies.

The survey was conducted among managers representing a sector covering a variety of industries and economic entities that differed in terms of scale of operation and technological advancement. The respondents were a group of people responsible for strategic and operational decision-making, including the selection and implementation of digital solutions in their organisations. The survey included both companies operating on the domestic market and those with experience in foreign expansion, which allowed us to capture the perspective of different operating models and varying degrees of openness to innovation. The sample selection included companies of varying sizes within the SME category. The structure of respondents included senior managers responsible for shaping development strategies and technology implementation policies, as well as middle managers who oversee day-to-day operational and implementation processes. The sample characteristics took into account geographical diversity, reflecting different regional conditions, including access to digital infrastructure, local labour markets and environments supporting technological development. The varying levels of digitisation of organisations were also taken into account, from entities just embarking on technological transformation to companies that already have experience in implementing tools based on data analysis or artificial intelligence. As a result, the research material obtained allows for the achievement of research objectives and also constitutes valuable diagnostic material on the conditions in which SMEs make decisions about the implementation of digital solutions.

The measurement was based on a five-point Likert scale, with the coding of values allowing for an unambiguous determination of the respondent's approval or disapproval of the statements forming the questionnaire: -2 meant "definitely no", -1 "rather no", 0 meant "neutral/difficult to assess", +1 meant "rather yes" and +2 meant "definitely yes". The use of this form of scale allowed for a direct interpretation of the average results and rankings, while also enabling analysis in terms of both the intensity of acceptance and rejection of a given statement. This method of coding makes it possible to capture the polarity of respondents' opinions more precisely, which is particularly important in research on organisational readiness and attitudes towards technology. The tables presented in the study included several types of summaries. Some of them contained descriptive results, including mean scores, standard deviations and measures of dispersion, which allowed for the characterisation of the diversity of opinions in the sample. The tables also present comparative summaries between selected groups of respondents, e.g. broken down by companies differing in structural characteristics or experience in implementing new technologies, by country or by currently used digital and communication technologies. These summaries also indicated the levels of statistical significance for individual variables. In addition, separate tables present variables for which significant differences were noted, allowing for a more detailed analysis of these areas. The measures used in the study included mean values, which in the context of the scale used reflect the general trend of responses, and measures of variation, such as standard deviation, which in this case should be treated as a measure of the consistency of opinions within a given group. In comparative analyses, p-values were a key element, forming the basis for the verification of statistical hypotheses. Their interpretation was based on standard significance thresholds (0.05), taking into account additional criteria confirming the reliability of the observed differences.

The hypothesis testing methodology included the use of both parametric and non-parametric tests. For data meeting the assumptions of normal distribution (or possibly a weakened assumption of symmetry of distribution) and homogeneity of variance, Student's t-test for independent samples was used to compare the means between two groups. The homogeneity of variance was verified using Levene's test, which allowed us to confirm whether the assumption of equal variance could be accepted in the analyses and rely on the results of the t-test. In each case, the non-parametric Mann–Whitney U test was used.

It allowed us to assess the differences in the distributions of ranks between the compared groups, which is particularly useful in the case of ordinal scales, results with strong asymmetry or those that do not meet the requirements of the t-test. The interpretation was based on the assumption that the significance of the difference in both tests (parametric and non-parametric), with confirmed homogeneity of variance, provides strong evidence for the existence of real differences in the population of the sample studied. In cases where only one of the tests confirmed significance, this was treated as a premise for further research, taking into account the specificity of the compared measures (absolute values vs. ranks). The overall methodology of the report assumed a combination of statistical description and hypothesis verification in a mixed model, which allowed both the identification of general trends in attitudes and the detection of specific differences between distinct groups of respondents. This made it possible to comprehensively address the issue of SMEs' readiness to implement new technologies, taking into account both the quantitative and qualitative dimensions of measuring attitudes and organisational conditions.

3.1. Research sample structure

3.1.1. Structure of enterprises

The study included a total of 1,013 enterprises operating in five European countries (Table 18). The sample was selected in such a way as to ensure a relatively even distribution of entities from each of the countries included. As a result of the study, a sample was obtained in which the largest percentage of surveyed enterprises came from Slovakia and Spain (20.3% each), followed by Germany (19.8%), Poland (19.7%) and Italy (also 19.7%). The differences between the planned even distribution across countries and the actual distribution should be considered negligible. This distribution, with approximately 200 companies from each country, allows for a comparison of the characteristics of entities operating in different economic and cultural systems and is statistically justified.

Table 18. Distribution of countries in the research sample

Country	Number	Percentage
Poland	200	19.7
Slovakia	206	20.3
Spain	206	20.3
Italy	200	19.7
Germany	201	19.8

Source: own research

The sample consisted of SMEs. The largest group was small companies with 10 to 49 employees, which accounted for as much as 63.8% of all respondents. Medium-sized companies (50–249 employees) accounted for another 35.7% of the sample. Micro-enterprises (1–9 employees) were marginally represented (0.4%), as were entities classified by respondents as large or "other" (0.1%). This distribution of the survey sample is based on companies of moderate size, but very numerous, which constitute a very important segment of the European economy, especially in the context of innovation and dynamic development (Table 19).

Table 19. Distribution of company size according to respondents' declarations

Company size	Number	Percentage
Micro-enterprise (1–9 employees)	4	0.39
Small enterprise (10–49 employees)	646	63.77
Medium-sized enterprise (50–249 employees)	362	35.74
Large/other	1	0.10

Source: own research

Respondents represented various levels of the organisational structure. The most numerous groups were executives (28.2%) and managers (28.1%). Company owners (16.7%) and directors (16.6%), as well as board members (10.1%), also had a significant share in the survey. A small group (0.3%) indicated a position in the company other than those listed. This distribution indicates that, as intended, the survey reached people with a direct influence on operational and strategic decisions, which increases the accuracy and reliability of the responses obtained (Table 20). In terms of the industry structure of the surveyed entities, service companies dominated, accounting for 55.3% of the sample. Manufacturing companies represented 23.9% of the total, while trade accounted for 20.6%. Two companies (0.2%) were classified as "other". These proportions reflect current trends in the structure of the European economy, where the service sector is playing an increasingly important role (Table 21).

Table 20. Distribution of people in specific positions in the company

Position in the company	Number	Percentage
Company owner	169	16.7
Member of the board	102	10.1
Director	168	16.6
Manager	285	28.1
Supervisor	286	28.2
Other	3	0.3

Source: own research

Table 21. Main industry of the company covered by the survey

Industry	Number	Percentage
Manufacturing	242	23.9
Trade	209	20.6
Services	560	55.3
Other	2	0.2

Source: own research

The length of operation of the companies covered by the survey varied, with entities with an established market position predominating (Table 22). More than half (58.9%) of the companies had been operating on the market for over 10 years. The next largest groups were companies with 2 to 5 years of experience (17.8%) and 6 to 10 years of experience (16.3%). The youngest entities, existing for less than 2 years, accounted for 7% of the sample.

Table 22. Length of company operation

Length of operation	Number	Percentage
Less than 2 years	71	7.0
2–5 years	180	17.8
6–10 years	165	16.3
Over 10 years	597	58.9

Source: own research

Respondents were also asked to subjectively assess the competitive position of the companies they represent. The vast majority describe their companies as more competitive than their competitive environment (Table 23). The largest group (36.4%) considered their companies to be "somewhat more" competitive than other entities operating in the same industry. Another group of respondents (25.3%) indicated that their company is definitely more competitive. Approximately 29.7% of respondents assessed their position as similar to that of their competitors or found it difficult to assess it unequivocally. A small percentage of respondents considered their companies to be rather less (6.6%) or definitely less (2.0%) competitive. The survey indicates a high sense of competitive and innovative advantage among companies. It should be emphasised that in this survey, the percentage of companies that can be considered "more" competitive is approximately 55%. Meanwhile, estimates from various sources put this percentage at between 45% and 55%. Therefore, the results of this survey can also be related to the level of competitiveness of SMEs in terms of AI use, taking into account the possibility of a slightly over-optimistic assessment by respondents in the context of their perception of their companies.

Table 23. Distribution of responses to the question: "How do you rate the competitiveness of your company compared to similar companies?"

Assessment	Number	Percentage
Significantly less competitive	20	2
Somewhat less competitive	67	6.6
Similar level/Difficult to assess	301	29.7
Rather more competitive	369	36.4
Definitely more competitive	256	25.3

Source: own research

Basic characteristics of respondents

In terms of gender, men dominated the sample, accounting for 61.6% of all participants in the study. Women represented 38.4% of respondents (Table 24). Although this distribution may indicate a masculinisation of the survey results, the presence of women at a level of nearly 40% confirms their significant participation in the management or functioning of the surveyed enterprises and the relative balance of opinions. The random selection of respondents for the survey within individual country strata allows us to conclude that this result reflects the employment and gender representation structures in the small and medium-sized enterprise sector in individual European countries.

In terms of the respondents' education, the vast majority had a university education – 68.7% of respondents indicated this level. Another significant group were respondents with post-secondary vocational education (22.7%) and general education (7.4%). Only 1% of respondents declared primary education, while 0.2% refused to answer this question (Table 25). The distribution obtained suggests a high level of formal competence among the respondents, which increases the credibility, awareness and substantive accuracy of the answers provided, especially in the context of issues requiring managerial, technological or strategic knowledge.

Table 24. Respondent's gender

Gender	Number	Percentage
Female	389	38.4
Male	624	61.6

Source: own research

Table1. Distribution of respondents' education

Education	Number	Percentage
Primary	10	1.0
Post-basic general	75	7.4
Post-basic vocational	230	22.7
University/higher education	696	68.7
Refusal	2	0.2

Source: own research

Table 26. Declared educational profile

Education profile	Number	Percentage
Technical	608	60.0
Non-technical (Humanities)	325	32.1
Mixed	80	7.9

Source: own research

People with technical education, in the context of analysing innovative and technological processes in enterprises, allow for a reliable assessment of the use of AI in companies in a technical and technological context. This is because they are often involved in engineering, operational and implementation aspects as part of their professional activities. In this study, the dominant group were representatives of technical fields, who accounted for 60% of the sample. 32.1% of participants declared a non-technical education profile, while 7.9% indicated a mixed nature of their educational path (Table 26). The study also took into account the age of the respondents (Table 27).

The average age was 38.6 years, while the median was 38.0 years, which indicates a relatively balanced distribution of the variable. The youngest respondent was 22 years old, and the oldest was 59 years old. The standard deviation of 7.4 indicates a moderate age diversity in the sample. Analysing this data, it can be seen that most respondents were in the mature and effective stage of their professional activity, which is conducive to making business decisions and participating in activities of a strategic or technical nature. These data allow us to characterise the sample of respondents as a qualified group with higher education, largely technical in profile, predominantly male and located in an age range conducive to professional activity. This sample composition is consistent with the assumptions of a study focused on management and innovation processes in enterprises and provides a solid basis for further quantitative and qualitative analyses.

Table 27. Descriptive statistics for the age of respondents.

Mean	Median	Minimum	Maximum	Standard deviation
38.6	38.0	22.0	59.0	7.4

Source: own research

4. Research results – analysis and interpretation

As part of the statistical research conducted among company representatives, the respondents' level of understanding and experience in the field of artificial intelligence (AI) was assessed. The measurement was carried out using a set of 29 statements relating to various aspects of knowledge, practice and experience related to AI. Respondents answered on a five-point Likert scale, with values from -2 to 2 corresponding to: "definitely not", "rather not", "I don't know/I have no opinion", "rather yes", "definitely yes". The main objective of the analysis was to assess the perception and readiness of business representatives to implement artificial intelligence (AI) solutions. The survey covered a wide range of issues: from the declarative (subjective) level of knowledge about AI, through individual and organisational experiences, to awareness of the benefits, barriers and threats resulting from the use of AI in the company. The analysis also covered institutional conditions and predictions regarding the future role of AI in business. The Likert scale used made it possible to capture both the intensity and direction of the assessments to a significant extent. This, in turn, will allow quantitative conclusions to be drawn later in the study. The scope of this study can be divided into several key areas. First, the level of knowledge and understanding of AI was analysed, both at the individual and organisational levels. Secondly, the study concerned the subjective assessment of the benefits of using AI, such as increased productivity, improved decision-making processes and competitive advantage. Most respondents recognised the specific advantages of implementing AI, and although their level of trust in the technology itself was generally moderate and balanced, it was clearly positive. Another aspect assessed here was the analysis of the attitudes and actions of management. Both the openness of decision-makers to new technologies and their willingness to implement AI in practice were evaluated. It can be cautiously stated that company management is generally positive about AI solutions, although this is not always clearly emphasised or enthusiastic. The fourth area concerned the assessment of risk awareness in the context of the potential effects of AI use. Although some respondents expressed concerns about the impact of AI on the labour market, these were noticeable but not dominant. As it turned out, respondents consider the ability to use AI to be an important asset for the future. The last area covered by the survey was the assessment of the institutional environment, including the role of the state, public institutions and organisations supporting the development of new technologies. Respondents were rather sceptical about the actual involvement of these entities in supporting the implementation of AI in the private sector.

The data presented show the mean value of the ratings, the median (the point dividing the sample into two equal parts of 50/50), the standard deviation, allowing the mean to be positioned relative to the neutral value of the scale (=0), and the skewness, indicating a "predominantly" positive opinion (left-skewed) or a negative opinion (right-skewed). In the case of dichotomous variables, the percentages of respondents answering YES are presented; NO answers are easy to deduce.

4.1. Perception of AI use in enterprises

4.1.1. Assessment of respondents' understanding of AI mechanisms

The results of the analysis suggest that company representatives generally declare a moderately positive attitude towards their own knowledge and understanding of the mechanisms of artificial intelligence (Table 28). This applies in particular to understanding how AI works and awareness of its capabilities and limitations. However, in the case of declared experience in the practical application of AI, the level is noticeably lower. Differences in the standard deviations of the analysed variables and skewness values further indicate a clear divergence in responses on practical issues *versus* declarative knowledge. These results may suggest that there is significant polarisation in the mechanisms for developing practical competencies in AI implementation in the surveyed companies, but convergence in the level of declared (subjective) understanding of this technology. In short, employees show a similar level of openness to AI, but the specific nature of the companies causes differences in implementation processes.

Analysing the survey results in detail, understanding how AI works (question q11[A1]) received an average rating of 0.98, which indicates a moderately positive belief among respondents about their own understanding of the mechanisms of artificial intelligence (a rating close to "rather yes"). The median was 1.00, confirming that at least half of the respondents are positive about their understanding of AI. The standard deviation of 0.82 suggests relatively little variation in responses. The skewness value of -0.89 (left-skewed) indicates an asymmetry in the distribution towards positive responses: more people rated their understanding of AI higher than the average value suggests. The second statement, "I know how to use AI in my business," achieved an average rating of 0.73, which can also be interpreted as a moderately positive assessment of one's own competence in this area. The median was again 1.00, confirming the predominance of "rather yes" responses. The standard deviation (0.97) was slightly higher than for the previous question, indicating greater diversity of opinion. The skewness of -0.58 indicates a slightly less pronounced but still noticeable shift in the distribution towards positive responses. A similar interpretation applies to the question: "I understand the capabilities and limitations of AI." Its synthetic rating is 0.89, with a median also at 1.00. The standard deviation of 0.87 suggests moderate diversity among respondents, while the skewness of -0.78 confirms the dominance of positive ratings ( ) on this issue. The lowest values were obtained for the fourth statement relating to experience in using AI in the company (these are practical and implementation issues). The average response was 0.33, which indicates a relatively low level of declared experience in the practical use of AI. Although the median was 1.00, the standard deviation was the highest of all four questions (1.21), indicating significant diversity and polarisation of managers' opinions. There is a noticeable proportion of respondents with no experience of AI (despite their previously confirmed positive attitude towards this technology). The skewness of -0.45 indicates a slight shift in the distribution towards positive responses, but to a much lesser extent than in the case of the other statements.

Table 28. Synthetic assessment of understanding the mechanisms of AI application in the enterprise.

Question number	Question content	Average	Median	Standard deviation	Skewness
q11[A1]	I understand how AI works	0.98	1.00	0.82	-0.89
q11[A2]	I know how to use AI in my business	0.73	1.00	0.97	-0.58
q11[A3]	I understand the capabilities and limitations of AI	0.89	1.00	0.87	-0.78

Question number	Question content	Average	Median	Standard deviation	Skewness
q11[A4]	I have experience in using AI in my company	0.33	1.00	1.21	-0.45
q11[A5]	The level of knowledge about AI in my company is high	0.28	0.00	1.15	-0.27

Source: own research

4.1.2. Assessment of the benefits of using AI in the company

In this part of the study, the opinions of company representatives on the benefits of using AI were analysed. The results are compared to the previous ones (Table 29), in particular to the level of knowledge about AI in the company (q11[A5]). At this stage, it cannot be considered high. This variable has the lowest average in this group of questions, with an average of 0.28 and a median of 0.00, which means that the most frequently given answer was "I don't know" or "I have no opinion". The standard deviation of 1.15 indicates a significant variation in responses on this issue. It can be cautiously assumed that this aspect should be considered ambiguous: roughly the same number of respondents assess the level of knowledge positively as negatively. The skewness of -0.27 indicates a slight shift in the distribution of responses towards positive assessments. These results suggest that respondents do not clearly perceive a high level of knowledge about AI in their organisations, which may indicate uneven development of competences in this area, limited access to technological knowledge resources, or possibly indicate the initial stage of AI technology implementation. The relatively low level of knowledge may create demand for the development of employee competences in this area and may give rise to barriers to development. In this context, the perception of the advantages of using AI (presented in this subsection) should be assessed with caution, as it may result from expectations and declarations rather than actual knowledge about it.

The perception of the advantages of using AI in the company's operations (q11[B1]) shows decidedly positive assessments by respondents: average=0.70 with a median of 1.00. Therefore, moderately positive opinions prevail. The standard deviation of 1.06 and skewness of -0.71 indicate a relatively large diversity of opinions, but with a predominance of positive assessments.

This result may indicate growing expectations of potential benefits from the implementation of AI in economic practice, even if the level of implementation is not yet widespread and the level of knowledge about these tools is relatively low. Similar positive assessments apply to the positive perception of productivity and speed of decision-making: the average ratings were 0.58 and 0.38, respectively, and in both cases the median reached 1.00. These results confirm that most respondents see real improvements in their daily work thanks to the use of AI, although the standard deviations (1.13 and 1.18) indicate significant variation in experiences. The skewness of both distributions (-0.61 and -0.47, respectively) suggests that opinions are skewed towards positive responses, but to a lesser extent than in the case of the assessment of overall benefits.

Table 29. Perception of the advantages of using AI in enterprises

Question number	Question content	Average	Median	Standard deviation	Skewness
q11[B1]	I see many advantages to using AI in the company's operations	0.70	1.0	1.06	-0.71
q11[B2]	Thanks to AI, I am increasing my productivity	0.58	1.00	1.13	-0.61
q11[B3]	Thanks to AI, I make decisions faster in my company	0.38	1.00	1.18	-0.47

Source: own research

4.1.3. Awareness of risks and threats associated with the use of AI

Table 30. Assessment of awareness of risks and threats associated with the use of AI

Question number	Question content	Average	Median	Standard deviation	Skewness
q11[C1]	I see many risks associated with the use of AI in the company	0.42	0.00	1.05	-0.23
q11[C2]	The use of artificial intelligence increases the risk of the company's operations	0.22	0.00	1.04	-0.03
q11[C4]	I am concerned about the negative effects of using AI in my decisions	0.23	0.00	1.13	-0.13

Source: own research

The results of the risk awareness analysis may suggest that although respondents recognise the benefits of using AI, particularly in the context of individual efficiency and decision-making improvements (see above), the risks associated with AI are also noted. However, it should be emphasised that the respondents' statements are not unambiguous and should be considered scattered, without a clear bias towards concerns. This is evidenced by the relatively high standard deviation parameter: in the range of 1.04–1.13, and the low skewness values (from -0.03 to -0.23) indicate almost symmetrical distributions, with no clear dominance of one opinion. It can be assumed that the assessment of risk awareness is 50/50 and probably results from the above-mentioned lack of knowledge about AI.

4.1.4. Trust in AI results

Table 31. Assessment of the level of trust in results generated by AI

Question number	Question content	Average	Median	Standard deviation	Skewness
q11[D1]	AI-based systems are trustworthy	0.40	0.00	0.96	-0.31
q11[D2]	AI is capable of generating valuable and reliable recommendations	0.58	1.00	0.94	-0.55
q11[D3]	I trust the results generated by AI	0.41	1.00	0.97	-0.39

Source: own research

It is worth comparing the results of the risk assessment with the assessment of trust in AI-based systems. Respondents are divided on the assessment of AI reliability. This is reflected in the structure of responses to the statement "AI-based systems are trustworthy". Although the mean is 0.40, the median is 0.00 (Table 31). Thus, the number of supporters and opponents is roughly equal. There is also a group of extremely enthusiastic respondents who slightly "pull" the average rating upwards. This is confirmed by the standard deviation of 0.96 and the moderately negative skewness (-0.31): they suggest a slight, albeit insignificant, bias in the distribution of responses towards positive ratings. Greater confidence was shown in AI's potential to generate recommendations – the mean of 0.58 and the median of 1.00 indicate that most respondents consider the generated suggestions to be valuable and reliable. In turn, the statement "I trust the results generated by AI" achieved an average of 0.41 and a median of 1.00, which also confirms the prevailing positive attitude. Overall, respondents show moderate confidence in AI systems – especially in the context of their usefulness in the decision-making process.

4.1.5 Attitudes of staff and management towards the use of AI

The attitude of management is key to the process of adapting AI-based solutions in enterprises. In this study, the management team environment is assessed from the perspective of a manager who participates in decision-making processes. Respondents evaluated six statements relating to knowledge of AI potential, openness to new technologies, active support for the implementation of AI solutions, and overall organisational readiness. In addition, one of the questions concerned a comparative assessment of the company's competitiveness relative to similar companies from European Union countries. The question about competitiveness reflects the sentiments described in the metadata. The average rating is positive: 0.49, the median was 1.00, while the standard deviation (1.00) confirms the previously diagnosed perception of market position. The negative skewness (-0.45) indicates a slightly higher proportion of positive ratings among the responses. In the case of the statement "The management in my company is aware of the potential and possibilities of AI technology" (q11[E1]), the average rating was 0.50, with a median of 1.00. This value indicates a moderately positive attitude among respondents and relative agreement that managers are aware of the potential of the technology. The standard deviation (1.07) indicates significant diversity of opinion, and the skewness of -0.53 indicates a clear shift in the distribution of responses towards the positive. Similar values were obtained in the assessment of the active search for AI-based solutions by management (mean 0.38, median 1.00, standard deviation 1.14, skewness -0.47), which suggests that positive responses predominate, but there is a certain level of scepticism, or possibly some respondents do not make clear statements. Greater consistency in positive opinions was observed in the statement "Management is open to AI technologies", where the average rating was 0.55, the median was 1.00, and the skewness was -0.56. Respondents clearly perceive the openness of decision-makers to innovation, although again there was considerable variation in ratings (standard deviation 1.07). A similar interpretation applies to the assessment of active support for the use of AI in company processes. This indicates that support from the management board is noticeable, although in some companies it is not fully active or unambiguous. Respondents seem to declare the readiness of management to implement AI: it achieved an average of 0.48 and a median of 1.00. As in the case of the previous questions, there is a moderately positive assessment of organisational readiness, but the high standard deviation (1.10) and skewness of -0.53 signal a positive advantage for those who support the thesis of readiness, although there are obviously also negative opinions. Respondents generally perceive the management's attitude towards AI technology as positive. There is a visible openness to innovation and awareness of the potential of artificial intelligence, although the level of activity and involvement of management boards in implementation processes at this stage is not yet clear. AI solutions are not yet standard practice in SMEs. The results obtained indicate significant potential for the development of an innovative culture in enterprises (in the context of AI implementation), with a simultaneous need to strengthen decision-making and strategic competences in the area of advanced technology implementation.

Table 32. Assessment of management attitudes in the context of AI implementation

Question number	Question content	Average	Median	Standard deviation	Skewness
q11[E1]	The management team at my company understands the potential and capabilities of AI technology.	0.50	1.0	1.07	-0.53
q11[E2]	The management team at my company is looking for AI-based solutions.	0.38	1.00	1.14	-0.47
q11[E3]	Management is open to AI technologies	0.55	1.00	1.07	-0.56
q11[E4]	My company's management actively supports the use of AI in company processes	0.46	1.00	1.12	-0.52
q11[E6]	Our company is very competitive compared to similar companies in EU countries.	0.49	1.00	1.00	-0.45
q11[E7]	My company's management team is ready to implement AI	0.48	1.00	1.10	-0.53

Source: own research

4.1.6. Impact of AI use on market position

The study participants, recruited from the management staff of enterprises, set the direction for development and establish standards for the functioning of enterprises. It is therefore crucial to identify their opinions on the potential change in the company's position as a result of the implementation of AI-based solutions. This broad context is the subject of the last block of analysis in this part of the study. Respondents referred to both subjective assessments and expectations for the future, the role of public institutions and the level of readiness of companies to adapt AI-based solutions. A total of nine statements were evaluated, reflecting respondents' beliefs about the impact of AI on employment, the development of the SME sector, the level of digitisation, and the investment and technological aspirations of enterprises.

Table 33. Assessment of the impact of AI on the competitive advantages of enterprises in the opinion of respondents

Question number	Question	Average	Median	Standard deviation	Skewness
q11[F1]	My colleagues are concerned about the impact of AI on their employment	0.21	0.00	1.14	-0.18
q11[F2]	The government, public institutions or organisations actively support the implementation of AI in companies	0.24	0.00	1.02	-0.22
q11[F3]	Artificial intelligence will soon be a key factor in the development of SMEs	0.58	1.00	0.95	-0.41
q11[F4]	In the future, AI will be as common in companies as telephones or computers.	0.86	1.0	0.98	-0.85
q11[F5]	The ability to use AI at work will be an important asset in the labour market	0.88	1.00	0.93	-0.82
q11[F6]	AI will increase my company's competitiveness	0.59	1.00	1.04	-0.55
q11[F7]	I am in favour of my company investing in AI	0.57	1.00	1.10	-0.54

q11[F8]	My company should implement the latest AI-based solutions	0.57	1.00	1.05	-0.60
q11[R5]	Our company has a high level of digitalisation	0.62	1.00	1.08	-0.60

Source: own research

The impact of AI implementation on employment and support from external institutions may raise potential concerns. In this regard, the rating is 0.21 and the median is 0.00. Although there is a slight predominance of positive responses, the data suggest that no single attitude clearly dominates: concern. Respondents are divided on whether their colleagues are genuinely concerned about their jobs, with slightly more in favour than against (skewness equal to -0.18). Of course, the relatively limited knowledge about AI, the low implementation of this technology and the previously emphasised declarative attitude at the expense of experience are subject to discussion. Apparently, at this stage of AI implementation, the SME sector expresses high uncertainty about its effects. The high standard deviation (1.14) further confirms the significant diversity of opinions. A similar response pattern was observed for the statement "The government, public institutions or organisations actively support the implementation of AI in companies". The average response was 0.24 and the median was 0.00. This indicates a lack of conviction about the active support of the public sector in promoting and implementing AI technology. There is no clear positive assessment of institutional activities here.

Respondents showed much more decisive and optimistic attitudes towards the future of AI and its importance for the economy. In the case of the statement "Artificial intelligence will soon be a key factor in the development of SMEs", the average response was 0.58 and the median was 1.00. This is, of course, a subjective statement. This means that most respondents recognise the future role of AI in the development of small and medium-sized enterprises. The standard deviation of 0.95 and skewness of -0.41 indicate a predominance of positive assessments with moderate diversity of opinion. An almost identical interpretation applies to the prediction of competitiveness growth assessments, respondents' expectations regarding investment in AI, and the assessment of the level of digitisation of companies: in these aspects, opinions are much more positive and those who assess these aspects of company functioning positively dominate. This result may indicate a growing awareness of the strategic importance of implementing AI at the operational and market levels. The data also confirm that the vast majority of respondents are pro-innovation. It seems that a higher level of digitisation and technological preparedness will favour the implementation of AI. However, it should be emphasised that this does not apply to the entire group of surveyed companies: the level of digitisation is not assessed equally across the entire sample. This reflects the natural variation in technological advancement between companies, which is a natural phenomenon in competitive markets.

An even stronger perception of the benefits of using AI concerns the belief that this process is irreversible. The statement "In time, AI will be as common in companies as telephones or computers" received an average of 0.86 and a median of 1.00, which means that the vast majority of respondents agree with this prediction. The standard deviation (0.98) and clearly negative skewness (-0.85) indicate a strong shift in the distribution of responses towards the positive and a small number of sceptical attitudes. The assessments of the advantages offered by AI skills are similar: respondents are convinced that AI competencies will soon be an important part of employees' skills and knowledge.

4.2. Diagnosis of the level of advancement, readiness and support in the process of implementing AI in companies

This part of the study assessed the level of advancement of enterprises in the implementation of artificial intelligence (AI) technologies, the sources of implementation initiatives and forms of support. The survey questions cover organisational aspects, the existence of AI strategies, technology teams and the creation of databases for AI. Managers' expectations, their preferred participation in training and bottom-up initiatives were also assessed. The study also takes into account cooperation with national and international partners and the use of external technology providers. A significant part of the questions discussed below focus on financing the process of adapting AI solutions in enterprises: grants, loans and consulting services, both those already obtained and those planned. The data collected allows us to determine the level of preparedness of companies for digital transformation, identify barriers and understand the scale and nature of institutional support in the field of artificial intelligence to date (see chapters 4.1 and 4.2). Respondents answered the questions presented in this section with "yes" or "no" (dichotomous variable). The results are presented in Table 32, which shows the percentage of positive responses to the questions asked in the order presented.

4.2.1. Practical use of AI in enterprises

The group of questions q12, q13, q14, q15, q18, q110, q124 refers to the implementation of AI tools in the operational activities of companies. This includes both technological and organisational aspects. About half of the surveyed companies (49%) declared that they use AI tools, but only one-third (32.9%) have a formal implementation strategy. This suggests that the adaptation of AI may be proceeding in a non-systematic, somewhat bottom-up and informal manner. Bottom-up initiatives by employees (35.7%) and the presence of specialised IT teams (41.3%) indicate partial staff involvement, but probably without strong strategic support. Approximately 35.6% of companies create databases with AI in mind, and 34.6% cooperate with external suppliers in this area. Finally, 38.8% of companies have paid for an AI-related service or product at least once, which may suggest an initial stage of experimentation with technologies, but with a view to their permanent implementation.

Table 34. Level of advancement, readiness and support in the implementation of AI in companies. N=1013

Question number	Question wording	Percentage of positive responses (YES)
q12[q11]	Are your products or services delivered to foreign customers?	57.7
q12[q12]	Does your company use artificial intelligence-based tools?	49.7
q12[q13]	Is the use of AI in your company a bottom-up initiative by employees?	35.7
q12[q14]	Does your company have a formal strategy for implementing AI?	32.9%
q12[q15]	Does your company have a specialist team/unit for implementing new technologies in the area of IT?	41.3
q12[q16]	Do your company's employees participate in AI training?	40.6

Question number	Question wording	Percentage of positive responses (YES)
q12[q17]	Would you like to participate in such training in the near future?	62.2
q12[q18]	Does your company create databases with a view to using AI in company management?	35.6
q12[q19]	Have you obtained a grant or funding for the implementation of AI in your company?	22.5
q12[q110]	Do you work with an external AI technology provider?	34.6
q12[q111]	Has your company previously conducted technology readiness assessments?	33.7
q12[q112]	Does your company cooperate with international partners in implementing new technologies?	36.3
q12[q113]	Has your company applied for financial support for the implementation of AI technologies?	23.5
q12[q114]	Has your company received financial support for the implementation of AI technology?	23.1
q12[q115]	Has your company applied for support for the implementation of AI technology in the form of: grants	24.3
q12[q116]	Has your company applied for support for the implementation of AI technology in the form of: low-interest loans?	21.3
q12[q117]	Has your company applied for support for the implementation of AI technology in the form of: public services (consulting)	25.7
q12[q118]	Has your company received support for the implementation of AI technology in the form of: grants?	22.6
q12[q119]	Has your company received support for the implementation of AI technology in the form of: low-interest loans?	21.0
q12[q120]	Has your company received support for the implementation of AI technology in the form of: public services (consulting)	21.7
q12[q121]	Does your company plan to receive support for the implementation of AI in the form of subsidies?	26.2
q12[q122]	Does your company plan to apply for support for AI implementation in the form of: a low-interest loan?	24.2
q12[q123]	Does your company plan to apply for support for AI implementation in the form of public services (consulting)?	26.3
q12[q124]	Has your company ever paid for/purchased an AI-related service/product?	38.8

Source: own research

4.2.2. Employee training and awareness

Two questions, q16 and q17, assessed employee involvement in educational processes related to artificial intelligence. 40.6% of companies declare that their employees have participated in AI training, while as many as 62.2% of respondents expressed a willingness to participate in such training in the near future. This shows growing awareness, grassroots initiatives to use AI in companies, and a clear need to develop employee skills in the area of AI. Despite the relatively low level of training to date, there is a visible openness to learning and development, which represents significant implementation potential for companies planning to invest in AI.

4.2.3. Funding and support for AI implementation

The set of questions q19 and q113–q123 (Table 34) focuses on financial support: both implemented and planned. To date, 22–25% of companies have already used or applied for financial assistance (grants, subsidies, loans or consulting). These figures do not differ significantly from the data provided in this context by the European Commission[1]. It is reported that approximately 25–33% of enterprises receive public funding for innovation (figures vary depending on the profile and country). Plans to obtain support are slightly more common, but still concern less than 27% of companies. This may correspond to the low assessment of support from various institutions mentioned earlier. Only slightly more than 20% of companies declare that they have ever received financial support for the implementation of AI technologies. The number of those who have applied for such support is similar – around 23% of respondents indicated that they had made efforts to obtain funding for AI development. This means that the vast majority of companies have not used any form of support, even though dedicated programmes and instruments supporting digital transformation are available in many countries (including Poland and at EU level). Companies bear the costs of AI transformation themselves, or the process is at such a stage that there is not yet an absolute need to implement AI. When analysing specific types of support, a recurring pattern of relatively low engagement can also be seen: subsidies were of interest to less than 25% of companies, low-interest loans to around 21%, and public advisory

[1] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Innovation_profiles_of_enterprises_-_resultse (2025)

services to 26%. However, subsidies were received by 22.6% of respondents, loans by 21%, and advisory services by 21.7%. Therefore, there is reason to believe that those interested are receiving support. The percentage of companies declaring plans to apply for such support in the future may be a positive sign: about a quarter of respondents are interested in obtaining financial or advisory support. This may mean that companies are only now maturing to make investment decisions or are only now recognising the potential of these solutions in the context of increasing their competitiveness and operational efficiency. This scenario is realistic in the context of further results (0).

Cooperation with external entities – both AI technology providers (34.6% of companies) and international partners in the implementation of new technologies (36.3%) – is an important element in the development of AI solutions. The data presented in indicate the current state of AI implementation in companies in the context of financing. This may be due to several possible reasons: the untapped potential of available AI implementation financing instruments, low awareness of available programmes, administrative barriers, or the lack of organisational and technological readiness of SMEs. This aspect requires a more detailed analysis of co-financing programmes or grants available in each of the countries analysed.

4.2.4. Digital maturity and international relations

Cooperation between companies has been discussed to some extent above, but three consecutive questions in the survey were dedicated to this issue: q11, q111, q112. This group of questions concerns the overall digital maturity of companies and their relations with the international environment. 57.7% of companies supply products or services to foreign customers (however, we are not talking about AI solutions), which demonstrates the competitiveness and scale of enterprises, as well as the high level of integration of the internal EU market. At the same time, 33.7% of companies declare that they have carried out a technology readiness analysis (a key step before implementing AI). Cooperation with international partners on new technologies (36.3%) indicates moderately optimistic prospects, which is consistent with the previously discussed results. There is therefore potential for development in the area of international technological cooperation. The survey results show a varied but relatively high level of advancement among companies in the implementation of artificial intelligence-based technologies. Nearly half of the respondents already declare that they use AI tools, which may indicate the growing importance of these solutions in business practice. However, a relatively low percentage of companies have formal implementation strategies. AI implementation therefore often takes place without a clearly defined framework. Actions are often taken from the bottom up, rather than as a result of well-thought-out strategic decisions. According to the survey, some companies have dedicated IT teams responsible for new technologies, but few companies create databases for use by AI algorithms. This pattern of responses indicates that the integration of AI-based technology into internal company processes is still in its early stages rather than being a planned and systematic process. However, there is strong interest in developing AI skills – although employee participation in training has been moderate so far, the declared willingness to improve qualifications in this area is very high. This could provide a solid foundation for future implementations if companies decide to invest in staff development. There appears to be a certain shortage in terms of obtaining and utilising financial support for digital transformation. Although there is a solid group of companies (about 1/5) applying for and obtaining grants, this group is no larger than in the case of other innovation activities when it comes to AI implementation. A significant proportion of companies plan to seek aid in the future. In terms of overall digital maturity, companies are active internationally, but few have conducted technology readiness analyses or established international cooperation in the implementation of new technologies. This shows that despite their presence in foreign markets, the level of internal preparedness for AI implementation needs to be improved.

4.3. Management culture in enterprises

The management culture in companies was examined using a set of 16 survey questions rated on a Likert scale, where 1 means never, 2 rarely, 3 sometimes, 4 often and 5 always. This scale descriptively corresponds to the frequency of certain events and can be treated as an ordinal scale. Therefore, basic positional statistics of distributions were used in the synthetic assessment. The questions are part of a questionnaire used to measure managerial attitudes, with particular emphasis on preferences regarding employee autonomy, participation in decisions, organisational discipline and focus on the development of subordinates (see Table 35). The data analysis includes statistics such as the mean, median, standard deviation and skewness of the distribution, which allows for the identification of both dominant trends and internal diversity of attitudes. It should be emphasised that the results should not be interpreted as in a quotient scale. The results describe a specific range: more often-less often, rather than numerical relationships on a quotient scale. The use of many questions on similar topics also allows for a subsequent synthetic analysis of the issue. Thanks to this, the tool is not only a descriptive measure, but can also be used as a basis for creating more complex models explaining organisational behaviour.

In the group of survey questions (Table 35), two stand out clearly: q20[6] and q20[7]. These are the statements with the highest level of acceptance, corresponding to the fact that such practices are often used in the company (a rating of 4 means "often"): "Good interpersonal relations are the most important thing in the workplace" (average 4.05) and "Employees need to be provided with conditions for their development" (average 3.98). The practices indicated are also high on the managers' agenda ( ). Both responses also achieved a high level of agreement, as confirmed by the low dispersion. The negative skewness suggests a predominance of ratings indicating a higher frequency of actions taken. These attitudes indicate a widely accepted focus on employee well-being and development among respondents. Managers, at least declaratively, largely equate organisational success with investing in interpersonal relationships and human capital. This approach is in line with a management style in which not only operational goals are important, but also the development of employees' potential, their commitment and job satisfaction. It can be assumed that respondents assume that strong team relationships translate directly into organisational effectiveness. It is important to note that both attitudes belong to the so-called organisational climate support area. The high ranking of these postulates may also result from social pressure – the expectation that leaders are "people for people" is now strongly rooted in the internal communication of many organisations.

Table 35. Assessment of management style in companies

Question number	Question content	Average	Median	Standard deviation	Skewness
q20[1]	He makes decisions himself and then informs his superiors about them	3.40	4	1.01	-0.44
q20[2]	I let people work independently, even if they might make mistakes.	3.45	4.0	0.97	-0.47
q20[3]	I believe that the workplace exists primarily to achieve production targets.	3.67	4.0	1.0	-0.64
q20[4]	Meetings are helpful in the development of subordinates	3.70	4.0	0.99	-0.57
q20[5]	Subordinates perform their work properly without being instructed by their manager	3.61	4.0	0.93	-0.53
q20[6]	Employees need to be provided with conditions conducive to their development	3.98	4.0	1.01	-0.86
q20[7]	The most important thing in the workplace is good interpersonal relations.	4.05	4.0	0.96	-0.88
q20[8]	Subordinates should participate in decision-making	3.61	4.0	0.91	-0.39
q20[9]	I set a strict work schedule	3.46	4.0	1.05	-0.36
q20[10]	The most difficult tasks should always be assigned to the most experienced employees.	3.61	4.0	0.95	-0.43
q20[11]	Never make concessions that compromise work efficiency	3.51	4.0	1.02	-0.39
q20[12]	If necessary, most subordinates could perform their duties without the manager's assistance.	3.47	4.0	0.94	-0.43
q20[13]	As many powers as possible should be delegated to subordinates	3.40	3.0	0.93	-0.3
q20[14]	Caring about increasing the general and professional knowledge of subordinates, even when it is not necessary in the current situation, is the manager's responsibility.	3.7	4	0.9	-0.44
q20[15]	Work discipline should be strengthened	3.59	4.0	0.93	-0.30
q20[16]	Changes to objectives and methods should be agreed with subordinates.	3.69	4.0	0.95	-0.5

Source: own research

Questions q20[1], q20[2], and q20[13] are somewhat in opposition to the above. This is a category of statements in which respondents gave the lowest frequency ratings. It can be described as a state between "sometimes" and "often." It is therefore less intense/frequent than in the previous statements. These are questions concerning: independent decision-making (average=3.40), delegating authority to subordinates (3.40) and accepting employee independence with tolerance for their possible mistakes (3.45). Although the differences in average ratings are not extremely large, they do stand out noticeably from those described earlier. An interesting correlation emerges here: on the one hand, respondents rated highly the need to care for employee development (q20[6]) and good relations (q20[7]), while on the other hand, they were much more cautious about actually delegating responsibility and decision-making autonomy to them. This can be interpreted as a manifestation of a management style that declaratively supports development and dialogue, but in practice consists of cautious control transfer, especially in situations of potential risk. Caution in delegating competences indicates a strong attachment to a hierarchical management model, in which decision-making and responsibility are strictly assigned to formal positions. Secondly, fear of employee mistakes may be related to low levels of trust or a lack of an adequate system to support autonomous work (e.g. mentoring, training, IT tools). This indirectly describes the previously assessed technological and organisational readiness to implement AI. Thirdly, it is also possible that respondents were guided by the realities of their own organisations, where structures do not support participatory management. Here, we have a clear reference to the previously described existence of a formal AI implementation strategy and clear bottom-up AI implementation initiatives. A centralised management system can potentially be an obstacle, as the individual use of artificial intelligence can lead to wrong decisions.

A very wide range of questions fits into the moderately frequent use of a given aspect of management. This group includes the following statements: q20[3], q20[4], q20[5], q20[8], q20[9], q20[10], q20[11], q20[12], q20[14], q20[15], q20[16]. In general, they are characterised by similar distribution parameters, thus describing a certain current state, apparently well established in the management practice of the surveyed companies. The average values obtained range from 3.46 to 3.70. This range indicates moderate frequency. This group of questions can be described as relatively "balanced" – it includes attitudes related to discipline, operational pragmatism and moderate participation. This group includes statements such as: "Meetings are helpful in the development of subordinates" (3.70), "It is the manager's responsibility to care about increasing the general and professional knowledge of subordinates [...]" (3.70) and "Changes should be agreed with subordinates" (3.69). At the same time, we see the importance of pragmatic statements: "The workplace functions primarily to achieve production goals" (3.67), "Work discipline should be strengthened" (3.59), "The most difficult tasks should be assigned to the most experienced employees" (3.61). These responses indicate that respondents are trying to combine elements of a modern approach to management with the needs of the organisation's day-to-day operations. Participation and development are appreciated, but they are not unconditional – they coexist with the belief in the need to maintain order, responsibility and a focus on efficiency.

The results of the analysis of managerial attitudes describe a certain state of management styles in the surveyed companies. It balances people orientation with task and hierarchy orientation. The highest-rated managerial attitudes, such as caring for employee development and good interpersonal relations, indicate a strong humanistic orientation. Respondents seem to assume that people are eager to develop and value a work environment based on trust and cooperation, which indirectly paves the way for their independence. The high acceptance of such attitudes suggests that managers are aware of the need to create conditions for employee self-fulfilment. On the other hand, attitudes towards delegating responsibility, increasing employee independence and granting them the right to make mistakes are ranked lowest. This may indicate limited trust or a belief that too much autonomy undermines efficiency, discipline and the achievement of goals. Respondents seem to support transformational elements in their declarations, but in practice they still rely heavily on control mechanisms. It should be noted that in the flow of information about work performance in a company, AI can be a very useful tool for diagnosing the commitment and performance of subordinates. The results therefore indicate the existence of a management model that contains both elements of the traditional model ( ) and the modern model (people-oriented, development, participation). To some extent, this demonstrates the adaptation of the management style to the level of maturity of the employees and the specific nature of the situation. Attitudes classified as average ratings can be interpreted as an expression of a pragmatic compromise, common in the surveyed population. Respondents accept the legitimacy of participation, training and communication, but do not give up their belief in the need for control and operational effectiveness. It should be noted that there are certain discrepancies between declarations and practice in the ratings. It can be assumed that respondents are familiar with and understand modern standards of people management, but everyday organisational practice (time pressure, hierarchical structures, organisational culture) forces them to behave in a more controlling and cautious manner. The hybrid nature of the management style may reveal a process of transformation: values open to employee comfort dominate, but elements of traditional leadership are still strong. As further analyses within the study show, management style can influence the process of AI implementation in an enterprise.

4.4. Management styles and mental and organisational barriers to

Table 36 shows the relationships between specific components of management styles and mental and organisational barriers that influence the process of implementing artificial intelligence in the SME sector. The results show only statistically significant differences that allow for a better understanding of the mechanisms determining managers' readiness to implement innovative technologies. The terms referred to by SME managers describe specific types/profiles of management styles. For example, autocratic, supportive, excellence-driven, etc. Each type/style is associated with the perception of certain barriers. Thus, some types (such as q20[6] or q20[7]) are much more likely to depend on the perception of obstacles than others (e.g. q20[11], q20[12]). This relationship is based on an assessment of the differences in the levels of ratings (identification with a specific attitude/style) given by respondents in two groups: those indicating a barrier and the rest. Table 36 p. 32 therefore contains three categories of information: grey fields indicate that the management style is the same regardless of whether someone perceives an obstacle or not. Blue fields mean that managers who perceive a given obstacle identify more with a specific aspect of management style. Pink fields, on the other hand, indicate the opposite relationship: those who perceive a given barrier identify less with a specific attitude than those who do not see such an obstacle. This reveals an interesting picture of the relationship between management culture and the identified barriers to AI implementation in SMEs. A very interesting finding is that both the autocratic style, characterised by unilateral decision-making (q20[1]), and the style based on entrusting autonomy to employees (q20[2]) are associated with increased concerns about data and process security. Managers who adopt one or the other model are cautious and recognise the potential risks associated with digitalisation. In the first case, this may be due to a feeling of loss of control over technological processes when decisions are not made "personally". Those who delegate decisions to their subordinates may be concerned about maintaining discipline and procedures related to data use. An interesting correlation also exists in the case of an approach focused on achieving production targets (q20[3]). Managers who attach importance mainly to manufacturing efficiency are more likely to perceive difficulties in obtaining external funding as a serious barrier. This may mean that their focus on operational goals (and attachment to internal procedures) may limit their ability to respond flexibly to the requirements of institutions financing innovation. It should be emphasised that concerns about data security are one of the most important barriers associated with many, often different, management styles. The participatory style, expressed in the appreciation of deliberation as a tool for development (q20[4]) and in emphasising the importance of interpersonal conditions (q20[7]), appears to be associated with organisational barriers such as a lack of specialists or problems with change management.

A particularly strong link between barriers and management style can be observed in the case of q20[6] and the related q20[7]. Managers who are more inclined to create conditions for employee development (q20[6]) and who care about interpersonal relationships are much more likely to perceive a number of barriers, especially in terms of company operating mechanisms, customer resistance, staff shortages or mentality. Of course, security is also an important factor. On the other hand, managers who emphasise the need for a strict work schedule (q20[9]) are less concerned about security issues, and strengthening discipline (q20[15]) is usually associated with management's fear of losing their position in the company. However, formalisation and rigour can help to streamline processes and improve safety, but at the same time they can arouse distrust of flexible digital solutions.

Table 36. Management style and indications of mental and organisational barriers to AI implementation. P-value in the U-Mann-Whitney test

ID	Survey question on management style	A	B	C	D	E	F	G	H	I	J	K	L
q20[1]	I make the decision myself and then inform my superiors	0.168	0.034	0.37	0.268	0.720	0.585	0.754	0.659	0.045	0.574	0.929	0.608
q20[2]	I allow people to work independently, even if they may make mistakes	0.712	0.001	0.293	0.723	0.980	0.878	0.113	0.309	0.000	0.373	0.345	0.899
q20[3]	I believe that the workplace exists primarily to achieve production targets.	0.003	0.504	0.173	0.093	0.650	0.070	0.547	0.083	0.105	0.819	0.374	0.276
q20[4]	Discussions are helpful in the development of subordinates	0.109	0	0.122	0.234	0.701	0.630	0.918	0.017	0.020	0.797	0.010	0.783
q20[5]	Subordinates perform their work properly without being instructed by their manager	0.387	0.000	0.265	0.281	0.003	0.036	0.640	0.298	0.003	0.692	0.025	0.967
q20[6]	Employees need to be provided with conditions conducive to their development.	0.003	0.000	0.023	0.001	0.121	0.199	0.981	0.017	0.000	0.529	0.028	0.001
q20[7]	The most important thing in the workplace is good interpersonal relations.	0.329	0.000	0.177	0.000	0.725	0.055	0.935	0.012	0.001	0.498	0.048	0.185
q20[8]	Subordinates should participate in decision-making	0.343	0.178	0.414	0.983	0.717	0.729	0.120	0.837	0.640	0.530	0.012	0.378
q20[9]	I set a strict work schedule	0.318	0.048	0.074	0.174	0.808	0.094	0.212	0.455	0.128	0.053	0.280	0.644
q20[10]	The most difficult tasks should always be assigned to the most experienced employees.	0.072	0.055	0.812	0.569	0.274	0.540	0.791	0.090	0.002	0.346	0.438	0.315
q20[11]	Never make concessions that compromise the effectiveness of your work	0.110	0.742	0.952	0.996	0.043	0.559	0.344	0.537	0.411	0.902	0.933	0.843

ID	Survey question on management style	A	B	C	D	E	F	G	H	I	J	K	L
q20[12]	If necessary, most subordinates could perform their duties without the manager's assistance.	0.869	0.566	0.091	0.766	0.033	0.065	0.061	0.410	0.069	0.322	0.103	0.658
q20[13]	As many powers as possible should be delegated to subordinates	0.625	0.647	0.193	0.597	0.837	0.513	0.039	0.097	0.529	0.200	0.373	0.889
q20[14]	It is the manager's responsibility to ensure that subordinates increase their general and professional knowledge, even if it is not necessary in the current situation.	0.476	0.030	0.255	0.057	0.276	0.102	0.417	0.100	0.029	0.101	0.204	0.267
q20[15]	Work discipline should be strengthened	0.338	0.249	0.959	0.354	0.149	0.102	0.013	0.674	0.828	0.011	0.926	0.876
q20[16]	Changes to objectives and methods should be agreed with subordinates	0.566	0.154	0.042	0.004	0.337	0.073	0.127	0.140	0.014	0.706	0.259	0.930

Legend:

A – Difficult procedures for obtaining external funding
B – Security considerations
C – Customer reluctance to these solutions
D – Lack of knowledge in this area
E – Employee resistance to change
F – Problems with change management
G – Fear of management and executives losing their positions
H – Lack of specialists in my company
I – Concerns about data security
J – Fears of senior and middle management about losing their independence
K – Regulations concerning intellectual property in the company
L – Managerial mentality

People who indicate a higher barrier rate a given aspect of management style more highly

People who indicate a given barrier rate the aspect of management style lower

There are no differences in management style ratings regardless of the barrier indicated

The analysis also confirms that assigning tasks according to experience (q20[10]) is associated with heightened concerns about data security, which can be interpreted as a belief that only the most qualified employees should have access to key technologies. Finally, a stronger belief in the need to agree on the objectives and methods of change with subordinates (q20[16]) is associated with a greater perception of organisational barriers, including those related to intellectual property regulations.

Several key relationships can be identified between management styles and the perception of mental and organisational barriers in the process of implementing artificial intelligence in the SME sector. Analysis of the results also shows that it is possible to classify styles in terms of their potential to reduce existing barriers. In the case of a trust-based style, it is possible to reduce employee resistance to change and change management issues. In companies where trust in employee autonomy prevails, the implementation of AI and other technologies encounters less resistance. Order-oriented style: strict schedules and clear work organisation potentially reduce the perception of security risks. Well-structured processes facilitate the implementation of technology by reducing uncertainty. In contrast, an autocratic style reinforces concerns about security and data protection. This usually leads to decision-making being concentrated in the hands of a single individual, but it also inhibits openness to innovation and often causes decision-making bottlenecks. A delegating style, in conditions of a shortage of competence or trust, can lead to increased concerns about a lack of specialists and data security. A participatory approach certainly increases awareness and recognition of a wide range of barriers. It is likely that this type of manager has the broadest understanding of the team's resources and capabilities and procedures. To summarise the results of the study, it should be emphasised that the above analysis determines the "sensitivity" of managers with a specific management style to the perception of mental and organisational obstacles. More traditional styles focus on more formal barriers, while newer management concepts often focus on the human factor, without neglecting security issues. These obstacles should be classified as "soft" in nature, internal and probably temporary (except for security considerations). They do not directly determine the implementation or abandonment of AI to the same extent as the lack of IT infrastructure, funds for implementation or knowledge of how to formally, effectively and safely implement AI in a company. To a large extent, the barriers described above will disappear as AI becomes more widely adopted and the belief that this technology brings many benefits takes hold.

4.5. Technologies used and implementation plans

Based on the data contained in the table above (Table 37), which includes responses from 893 companies, it can be concluded that the degree of saturation with modern technologies in the surveyed companies is varied and indicates a selective approach to the implementation of solutions supporting management, communication and data analysis. The most commonly used category of technological solutions are instant messengers (e.g. Microsoft Teams, WhatsApp, Zoom), which were declared by as many as 70% of respondents. The high level of use of these tools can be explained by their key role in everyday teamwork, especially in the era of remote and hybrid work. In second place is artificial intelligence (AI), used by 54% of respondents. This is a relatively high result, reflecting the growing awareness of the potential of AI-based tools such as ChatGPT, Gemini, Copilot and DeepSeek.

Table 37. Technologies used in enterprises. n=893

question code	Technological solution	Percentage
q3[q31]	ERP systems	30
q3[q32]	CRM	30
q3[q33]	Analytical tools (e.g. Big Data)	39%
q3[q34]	Artificial intelligence (AI) (chat GPT, Gemini, Copilot, Deepseek, etc.)	54
q3[q34b]	Messaging apps (Teams, WhatsApp, Zoom, etc.)	70
q3[q35]	Other	6

Source: own research

It also confirms the bottom-up nature of the AI initiative. This also indicates the rapid pace of adaptation of generative and analytical technologies in various areas of business operations. It can be assumed that the popularisation of accessible and intuitive AI tools has contributed to the dynamic growth of interest in this technology, also in the SME sector. Business analytics tools are declared by 39% of respondents. The presence of Big Data solutions and analytical platforms suggests that almost two in five companies recognise the importance of data in the decision-making process. However, a significant percentage of companies still do not use these capabilities, which may indicate competence or financial limitations or a lack of input data (as already discussed in relation to the technological preparedness of companies) in the area of advanced data analysis. On the other hand, ERP and CRM systems are used by 30% of companies. Although systems of this type are considered basic tools for supporting resource management and customer relations, their relatively low popularity is not surprising. Possible reasons include the high cost of implementation, the complexity of integration with other business processes, or the lack of adaptation to the needs of smaller SMEs. 6% of companies indicated the use of other technological solutions, which may suggest that they are outside the mainstream of tools used or that they are turning to more specialised or niche technologies. The results indicate that the surveyed companies are strongly focused on practical, easily accessible and communicationally useful technological solutions. The high popularity of AI and instant messaging contrasts with the moderate level of implementation of complex ERP and CRM systems.

Table 38. Technology implementation plans

Question number	System being implemented	We are not planning	Up to 6 months	Up to approximately one year	Up to 2 years	Over 2 years	I do not know	Number of responses n
q3[q31]	ERP systems	17.9	21.6	12.1	14.7	11.7	22.0	273
q3[q32]	CRM	20.1	21.2	13.4	12.6	12.3	20.4	269
q3[q33]	Analytical tools (e.g. Big Data)	12.4	21.3	16.4	18.2	15.0	16.7	347
q3[q34]	Artificial intelligence (AI) (chat GPT, Gemini, Copilot, Deepseek, etc.)	9.8	31.0	19.5	12.9	10.6%	16.2%	481
q3[q34b]	Messengers (Teams, WhatsApp, Zoom, etc.)	17.2	32.4	8.3	8.8	12.4	20.9	627
q3[q35]	Other	23.0	11.5	9.8	4.9	8.2	42.6	952

Source: own research

The table 38 presents plans for the implementation of technological solutions in enterprises. It outlines a diverse picture of the digitisation and technological development process in the surveyed entities. The most dynamic implementation plans concern artificial intelligence (AI). As many as 31% of enterprises declare their intention to implement AI solutions within the next 6 months, and another 19.5% within a year. This means that more than half of the companies (51%) plan to adapt AI tools within the next year. This reveals the picture of the digital transformation process and the great interest in the potential of generative and assistive AI in business operations. A relatively low percentage of companies declare that they have no implementation plans in this area (9.8%). However, it is impossible to assess whether these are companies that are least capable of implementing AI or, on the contrary, already have developed AI-based decision support systems and do not need further implementation. We observe similar dynamics in the case of instant messaging applications (e.g. Teams, Zoom, WhatsApp). 32.4% of companies plan to implement them within six months. Interestingly, as many as 20.9% of respondents selected the "I don't know" option , which may indicate an undefined strategy or decentralisation of decisions regarding communication technologies. This corresponds perfectly with the previously described bottom-up nature of AI use, with companies not taking a very common strategic approach to this process. Approximately 17% of companies do not plan to implement instant messaging. In the case of analytical tools such as Big Data, we observe a more even distribution of declarations: 21.3% plan to implement them within 6 months, but 49.6% in the longer term (up to 2 years). Data analytics is therefore becoming an increasingly recognised element of strategy. On the other hand, ERP and CRM systems, despite being the core of the management infrastructure in many organisations, are being implemented with less intensity. In the case of ERP, 21.6% of companies plan to implement it within six months, and 12.1% within a year. The situation is similar for CRM. At the same time, a large percentage of companies declare that they have no plans (ERP – 17.9%, CRM – 20.1%) or no knowledge of the implementation date (ERP – 22%, CRM – 20.4%). This may suggest that these systems are perceived as complex, costly or requiring long-term infrastructure investments. It is likely that non-mainstream technologies are implemented sporadically and often depend on the specific nature of the industry or the individual needs of the organisation. Responses regarding "other technologies" show that as many as 42.6% of companies are unable to specify the implementation date, and 23% do not plan to implement them at all. In practice, this means that "no others" are planned. The surveyed companies most often plan to implement solutions that are easily accessible, adaptable and quick to implement (AI, instant messaging). The implementation of more complex systems (ERP, CRM) is slower and requires greater organisational involvement.

Based on both sets of data, a cautious forecast can be made regarding the development and adaptation of digital solutions in the surveyed companies. The data indicate a strong variation in the pace of implementation of individual technologies, which to some extent describes the levels of digital maturity and the diversity of companies' technological strategies. The most commonly used technologies at the time of the study are instant messaging (70%) and artificial intelligence tools (54%). Their popularity is certainly due to their easy availability, low entry threshold and wide range of applications. In the era of widespread remote working, they seem to be an indispensable tool for achieving business goals. The vast majority of companies that have not yet implemented them declare their intention to do so within 6 to 12 months, which means that within the next year, these technologies may become almost universal standard in the business environment. Analytical tools (e.g. Big Data), despite their relatively low current implementation level (39%), have strong growth potential. A significant number of companies plan to implement them within 1-2 years, which may indicate a growing awareness of the value of data in management and the ongoing professionalisation of decision-making processes. At the same time, the high percentage of undecided companies suggests that for many organisations, the implementation of such solutions involves technical, competence or organisational challenges. ERP and CRM systems, currently used by about 30% of companies, are developing more slowly but relatively steadily. Their implementation is often more complex, costly and requires deeper changes in the organisational structure. Despite this, nearly 50% of respondents indicate plans to implement them in the next two years. It can be expected that in the medium term, these systems will become an important part of the digital infrastructure of companies, especially those seeking to integrate internal processes and increase operational efficiency. In the coming year, further expansion of communication and AI solutions is to be expected. This shows how dynamic the process of AI adaptation in companies is. In the longer term, analytical, ERP and CRM systems are likely to become more widespread. Observed trends indicate that digital transformation will continue in both the operational (communication, AI) and strategic (knowledge management, data integration) areas.

4.6. The impact of AI on selected areas of business activity

The table 39 presents a subjective assessment by company representatives of the areas of activity that they believe could benefit most from the use of artificial intelligence. Respondents answered "yes" or "no", and the table shows the percentage of positive responses in which respondents see a significant impact of the technology. Respondents assessed which departments and processes in their organisations have the greatest potential to benefit from the implementation of AI tools. Their responses not only identify key areas for technological innovation, but also capture the mechanism driving digital transformation and its strategic implications. The most frequently indicated area that, according to respondents, can benefit most from the implementation of AI is data analysis (45% of positive responses). This reflects the growing awareness of companies of the need to use data as a strategic resource. Artificial intelligence enables the processing of large volumes of information, the identification of patterns, the forecasting of trends and the support of operational and strategic decisions. The high ranking of in this area indicates that companies are beginning to treat data analytics not as a support function but as an integral part of the management process. However, it should be remembered that at the current stage of transformation, only some companies collect the relevant data that can feed AI. Also, plans to implement Big Data systems take slightly longer to implement than more intuitive and accessible generative systems. The second important element is customer service (43%). These include chatbot and voicebot solutions, recommendation systems, intelligent ticketing systems, transaction processing, invoicing, etc. They enable the automation of customer contact, personalisation of communication and faster response to needs. The high number of responses in this area may be due to the fact that improvements in customer service are relatively easy to implement and do not require large infrastructure investments, while at the same time bringing noticeable results quickly. These are usually ready-made tools that require integration with the existing customer communication system. The third group in terms of frequency of responses are marketing (40%) and process automation (36%) departments. In the case of marketing, consumer behaviour analysis systems, predictive tools, advertising campaign automation and personalised content creation are likely to play a key role. This aspect requires further research and has not been analysed in detail in this study. An important element from the point of view of manufacturing companies is the area of logistics (32% positive responses). AI allows for potential supply chain efficiency, for example through demand forecasting, route optimisation, warehousing automation and real-time management of large inventory volumes. The survey respondents certainly recognise that AI not only reduces costs, but also increases the flexibility and resilience of logistics processes. Manufacturing and finance gain 25% and 24% of supporters, respectively. In the case of production, we can talk about applications such as quality monitoring, predictive equipment maintenance, control of technological process parameters and optimisation of resource utilisation. In the finance department, AI can support, among other things, risk analysis, fraud detection, automation of accounting processes and cash flow forecasting. The relatively lower level of responses in these areas may be due to the specific nature of the companies surveyed, rather than actual interest in AI in these areas. In financial companies, the implementation of AI in the financial sphere will certainly be key. Manufacturing companies will respond accordingly.

Table 39. "Which areas of your company's operations could benefit most from the use of AI?" N=1013

Question code	Area of activity	Percentage of responses
p1[11]	Customer service	43
p1[12]	Production	25
p1[13]	Marketing	40
p1[14]	Logistics	32
p1[15]	Finance	24
p1[16]	Process automation	36
p1[17]	Data analysis	45
p1[18]	Human resource management	15
p1[19]	Sales	15

Source: own research

The least significant benefits are those related to human resource management and sales (15%). The low ranking of these areas may be due to a lower awareness of the potential applications of AI in these fields or concerns about its impact on interpersonal relationships (note that relationships were the most important element in managers' statements). In the area of HR, however, AI can play an important role in recruitment, employee engagement analysis, career path planning and HR process automation, which respondents may not be aware of at this stage of the transformation. In sales, on the other hand, it is possible to use demand prediction systems, intelligent recommendations, segmentation analysis and dynamic pricing. Low scores may therefore indicate untapped potential in these two areas.

4.7. Identification of barriers to AI implementation in enterprises

This part of the study assessed the significance of barriers to AI implementation. Respondents could select the barriers that they considered to be key. The results are presented in 40. It describes the percentage of "yes" responses in a 1013-element research sample. The results of the analysis allow us to identify three main categories of barriers. The most significant ones are those with over 30% of responses. These are therefore variables describing financial costs and competence deficits. The most frequently indicated barrier is the cost of training (p4[42], 61%), followed closely by the cost of purchasing AI licences (p4[41], 54%). A slightly less significant barrier is the cost of purchasing equipment (p4[43], 32%). This shows that despite the general availability of many AI tools, their effective use requires investment in appropriate systems, infrastructure and staff training, which can be a significant barrier, especially for micro and small businesses. This result can be compared with the interest of companies in financial support systems.

Table 40. Assessment of the significance of barriers to AI implementation in enterprises. N=1013

Question code	Barrier category	Percentage of responses
p2[21]	Lack of advisory support from specialists	21
p2[22]	Lack of specialist advisory and implementation services	23
p2[23]	Lack of specialist training	29
p2[24]	Excessive costs of employing specialists	27
p2[25]	Excessive costs of services	25
p2[26]	Lack of specialists on the local labour market	15%
p2[27]	Lack of IT infrastructure	19
p2[28]	Difficulties with data access	10

Question code	Barrier category	Percentage of responses
p2[29]	Insufficient financial resources	18
p2[210]	Difficult procedures for obtaining external funding (EU, national, local subsidies)	10
p2[211]	GDPR regulations	11
p2[212]	Security considerations	18
p2[213]	Customer reluctance to accept these solutions	12
p3[31]	Lack of knowledge in this area	31
p3[32]	Reluctance to change	25
p3[33]	Employee resistance to change	22
p3[34]	Problems with change management	17
p3[35]	Employees' concerns about their jobs	24
p3[36]	Fear among managerial and executive staff of losing their position and authority	16
p3[37]	Lack of specialists in my company	22
p3[38]	Concerns about data security	25
p3[39]	Concerns of senior and middle management about loss of autonomy	12
p3[310]	Regulations concerning intellectual property in the company	12
p3[311]	Financial issues	10
p3[312]	Managerial mentality	7
p4[41]	Licence purchase costs	54
p4[42]	Training costs	61
p4[43]	Equipment purchase costs	32

Source: own research

Many companies point to a general lack of funds for AI systems, but this barrier may be underestimated. In practice, some companies may not realise that their decision not to use AI is due to insufficient budgets rather than, for example, technological scepticism. It was also mentioned that a small percentage of companies indicated difficulties in obtaining grants, which, when compared to the number of companies applying for funding, may indicate that, in general, few companies even attempt to apply for external funding. Therefore, the combination of financial barriers and activity in obtaining external funding may indicate a specific gap: despite their needs, companies are not seeking funding for the AI transformation process. This may be related to certain competence-related or even psychological barriers, as the second significant problem area is a lack of knowledge (p3[31], 31%). Respondents may not be able to independently identify the potential needs and benefits of implementing AI, nor plan an effective process for integrating these technologies into existing business practices. The high significance of these barriers reflects not only budgetary constraints, but also a possible structural lack of competence. This may lead to the temporary abandonment of transformation initiatives or to their implementation in a fragmented manner.

Another group of barriers can be described as moderately significant. These are barriers for which the percentage of responses ranged from 18% to 29%. This is potentially the most dynamic category, which may undergo significant changes as the AI technology market matures. In this group, we can distinguish between barriers with growth potential (i.e. those that may become more significant in the future) and those with decline potential, which are likely to lose their significance. It is worth noting that moderately significant barriers may also be susceptible to changes resulting from education, public policy, falling technology costs and increased experience of companies. Their development (or decline) will depend not only on internal organisational decisions, but also on macroeconomic, legal and technological trends that were not diagnosed in this study. Tracking their dynamics may be crucial for designing effective strategies to support digital transformation in the enterprise sector. Moderately significant barriers are very diverse in terms of subject matter – they include costs, concerns and organisational constraints. For example, 29% of respondents pointed to a lack of specialist training (p2[23]), and 27% to the excessive costs of hiring specialists (p2[24]). This indicates current difficulties in accessing human capital, knowledge resources and funds. It is worth noting that this is not only a financial problem, but also an organisational one – companies may not know what specialists they need, and the market is probably not keeping up with the supply of suitably qualified staff. In the same vein are employees' concerns about their jobs (p3[35], 24%), employee resistance (p3[33], 22%) and reluctance to change (p3[32], 25%) (compare chapter 3.1.6, which reveals significant difficulties in managing technological transformation and indicates relative resistance from human capital. At the beginning of digital transformation, organisations often show enthusiasm without being fully aware of the consequences of the changes. It is likely that when AI begins to actually interfere with existing processes, structures and work models, changing them significantly and affecting, for example, employment or salary levels, psychological resistance may increase. This is especially true when the social sense of justice, agency or transparency is disrupted. This phenomenon, known as ' ', is well documented in management literature and may manifest itself in this barrier. This will particularly affect organisations that fail to ensure adequate communication and employee participation. The survey also reveals concerns about data security (p3[38], 25%). These are typical for technologies that require the processing of large amounts of information, often in the cloud. With the growing scale of AI implementations based on large data sets and cloud solutions, the issue of security will certainly become more important. Companies that are just starting their adventure with AI may not yet be aware of threats such as data leaks, unauthorised access or the vulnerability of algorithms to unauthorised changes. In the event of repeated data leaks and observation of the effects of this phenomenon, these concerns may become one of the key barriers, especially in sectors that collect sensitive data (e.g. medicine, finance). The high cost of hiring specialists (p2[24]; 27%). The demand for AI specialists is growing faster than their supply. In the long term, this means an inevitable increase in the cost of hiring them. If universities and education systems fail to keep up with the training of new staff, this barrier may move up to the category of the most significant ones, effectively constituting a bottleneck for AI transformation.

The category of barriers of medium importance also includes those that may lose their significance over time. This group includes the (currently) high costs of services (p2[25]; 25%). It can be expected that as the AI market develops, the prices of implementation services will fall. Growing competition among consulting firms, the popularisation of open-source models and ready-made components are likely to lower the entry threshold for many companies. This mechanism is clearly evident, for example, in relation to generative models. A similar mechanism applies to the current shortage of specialist training (p2[23] ; 29%) and the lack of consulting and support – (p2[22], p2[21]; 23%, 21%). Currently, this problem stems mainly from the immaturity of educational and training offerings. However, the growing interest in AI in business will certainly lead to a rapid development of training, online courses, postgraduate studies and certification. Employee resistance to change is natural when new solutions and technologies are introduced (p3[33] ; 22%). Employees may always be distrustful at the initial stage of transformation. However, as this technology becomes more widespread and familiar in everyday work, the level of resistance is likely to decrease.

A very large group consists of the least significant barriers (indicated by less than one in five respondents). These mainly concern organisational and mental factors, as well as legal and institutional conditions. However, according to entrepreneurs, these do not constitute serious obstacles to the implementation of artificial intelligence. First and foremost, they cover issues related to legal regulations, such as the GDPR or intellectual property regulations – areas that could potentially be at risk. The attitude of management and executives was rated equally low (compare with the ratings of understanding and perceived benefits, chapter 3.1). Managers' reluctance to change and their fears of losing their independence or position in the organisation are of limited significance. Similarly, low importance was assigned to customer resistance to new solutions and general financial problems, suggesting that entrepreneurs do not equate the difficult economic situation of their companies with specific barriers to the development of artificial intelligence. The least significant barriers also included difficulties in accessing data or obtaining external funding (discussed in more detail in chapter 4.2.3), which may indicate that companies either do not consider these processes to be problematic or do not yet have experience with limitations in AI implementation.

4.8. Identification of the benefits of AI implementation in enterprises

The most important benefit perceived by respondents is increased organisational efficiency through the use of AI. Half of the respondents indicate this option (Table 40). AI is usually perceived as a tool that automates processes, reduces task completion times and improves operational precision. However, it is worth noting that this should be understood more in terms of speed of operation. Efficiency, on the other hand, is a broad category that can also refer to better resource management, error elimination, improved information flow within the organisation, and improved quality of operation. These types of benefits are strongly linked to automation and predictive use of data, which is in line with the current direction of AI development in business. Cost reduction is also a key benefit of using AI. Respondents recognise that the implementation of AI can lead to savings. This is achieved both through the potential reduction in the number of errors and through the reduction in the need to involve employees in simple, repetitive processes. Cost reduction will be more related to efficiency than to job cuts, as discussed below. Companies often see AI as an investment which, although costly at the outset (as indicated by the analysis of barriers, see chapter 4.7), can significantly reduce the operating budget in the long term. Increasing efficiency and reducing costs are fundamental economic goals for companies operating in a competitive environment. In general, it can be assumed that companies strive to maximise profits and therefore naturally seek ways to optimise production, reduce unit costs and make better use of resources. These trends are clearly reflected in the survey results (Table 41).

Table 41. Assessment of the benefits of AI implementation in enterprises

Question code	Benefit category	Percentage of responses
p6[61]	Increased efficiency	50
p6[62]	Cost reduction	42
p6[63]	Reduction in employment	20
p6[64]	Improving the quality of services/products	38
p6[65]	Better understanding of customers	26
p6[66]	Expansion	19
p6[67]	Increasing competitiveness	27
p6[68]	Increasing innovation	22

Source: own research

Improving the quality of services and products was also given relatively high priority. This means that companies expect AI not only to optimise internal processes, but also to bring direct benefits to the end customer (and possibly to set them apart from the competition). It can be assumed that this refers to AI functions such as automatic quality control, personalised recommendations and optimisation of production processes. Today, quality, alongside efficiency, is one of the key criteria for competitive advantage. A better understanding of customers and an increase in the quality of customer service also fit in with modern management concepts, where adaptation to customer needs and continuous innovation are key success factors. This rule is also reflected in the survey results: respondents consider better understanding of customers, increased competitiveness and increased innovation to be important, though not priority, benefits (Table 41). These are important aspects, but less direct and therefore less frequently mentioned. Companies understand that analysing customer expectations can help them personalise services or design products that better meet market needs, but implementing such functionalities requires an integrated analytical infrastructure and often significant investment. A large group points to other benefits, although these should not be seen as key from the point of view of companies: reducing employment and expansion (probably understood as entering new markets or scaling up operations). Despite this, that one in five respondents sees job cuts as a benefit, entrepreneurs are unlikely to treat AI as a tool for mass layoffs (especially in the context of the declared importance of interpersonal relationships and employee-oriented management styles). Expansion, on the other hand, although theoretically possible thanks to AI, requires not only technology but also appropriate marketing, legal and operational strategies, which makes it a less immediate benefit. Therefore, this indication is not common in the sample surveyed. Companies see AI primarily as a tool for streamlining operations, improving quality and reducing costs. More abstract benefits, such as innovation or expansion, although important in the declarative sphere, are currently in the background as a distant prospect, probably due to the requirement to commit significantly more resources than just AI technology. On the other hand, the aspect of job cuts, often discussed in the media, turns out to be relatively insignificant in the eyes of managers themselves. The implementation of AI will be more of a process of supporting employees than automation at the expense of employment. In theory, automation could lead to a reduction in a company's human resources, but even in this context, changes in positions and transfers are more likely to be expected. Reductions will only be possible in a situation of labour oversupply, but in the current reality, there is a very significant shortage of workers in industry and services in the EU. Those affected by the AI transformation should have no problem finding work.

4.9. Expected support in the process of implementing AI technology

The final topic of the study was to identify expectations for support in the implementation of AI in companies. The summary data is presented at Table 42. Based on this data, a very interesting conclusion can be drawn: companies expect know-how rather than financing for digital transformation. Respondents' indications focus primarily on the need to develop competences, followed by financial support, with clear differences in preferences regarding the forms of such support. The most frequently declared expectation is training, which was indicated by more than half of the respondents (p7[73]; 54%). Managers are most likely aware of the lack of sufficient knowledge and skills in the implementation and use of AI solutions. This is also identified as a major obstacle (see chapter 4.7). The need for training may cover both technical and managerial aspects, as well as the ability to interpret the results of AI-based tools. This indicates that companies are currently focused on the long-term development of soft skills in the context of technology, rather than the development of technical infrastructure and software. Competence barriers are seen by respondents as a real limitation. The second most frequently mentioned expectation is co-financing (p7[72]; 44%). The costs of transformation can be particularly severe for small and medium-sized enterprises. Funding is probably understood here as non-repayable support, e.g. in the form of grants or subsidies, rather than as a credit mechanism as discussed in previous chapters. In third place was technological consulting (p7[71]; 39%). This result shows that enterprises need not only general knowledge, but above all specialist support tailored to their industry, scale of operation and level of technological advancement.

Table 42. Entrepreneurs' expectations

Question code	Support category	Percentage of responses
p7[71]	Technological consulting	39
p7[72]	Subsidies	44
p7[73]	Training	54
p7[74]	Financing – low-interest loan	19
p7[75]	Financing – grants	21
p7[76]	Financing public services (training, consulting, etc.)	12

Source: own research

Significantly lower values were achieved by various forms of financing. Low-interest loans were indicated by slightly less than one-fifth of respondents (p7[74]; 19%). Direct subsidies also enjoyed moderate interest (p7[75]; 21%). It can be assumed that the lower level of responses results from limited knowledge about the availability of such instruments or from the belief that they are insufficiently flexible in practice. The least interest was shown in public support services, such as training or consulting financed from public funds (p7[76]; 12%). Moreover, the relatively low assessment of the participation of external institutions in the process of AI implementation in companies was indicated earlier. This may indicate a low assessment of the effectiveness of administrative support. Entrepreneurs probably feel that public support mechanisms are inflexible, bureaucratic or unsuited to the real needs of the market. Entrepreneurs' expectations focus primarily on increasing the availability of knowledge and technological competences, which is reflected in the dominant indication of the need for training and consulting ( ). Financial aspects, although important, are secondary and vary depending on the preferred form of support. Therefore, the key is to provide know-how, followed by financial support. These results indicate a very rational approach by respondents to the issue of AI implementation, in which substantive preparation takes precedence, followed by obtaining funds for the implementation of projects.

4.10. Achievement of research objectives

4.10.1. Identification of the level of readiness for technological adaptation of SMEs to implement artificial intelligence in selected European countries

This study analysed the level of readiness of companies to implement artificial intelligence (AI) solutions, with particular emphasis on the attitudes of management and the overall level of digitalisation of organisations. The measurement was carried out in five European countries: Poland, Slovakia, Spain, Italy and Germany. Respondents assessed their agreement with seven statements relating to the technological readiness of their companies to implement AI. These questions were expertly recognised as indicators of readiness for implementation. Certain elements of the analysis have already been included in previous chapters, but here a distinction was made between the measurements for the countries analysed. As already mentioned, a five-point Likert scale was used, with values ranging from -2 (definitely not) to +2 (definitely yes), with 0 representing a neutral attitude. For each statement, arithmetic means were calculated for individual countries and for the sample as a whole, and a series of statistical tests were performed to identify significant differences between national groups. The data analysis methodology included the following steps: first, the mean values for each variable were calculated within countries and for the sample as a whole. Next, the Shapiro-Wilk test was used to assess the normality of the data distribution (Normality Test). It showed that the variables were not normally distributed, but exhibited relatively high symmetry of distribution. Therefore, parametric ANOVA was conditionally applied to assess potential differences between countries. This method required the Levene's test to be performed to assess the homogeneity of variance. The analysis of variance was supported by the non-parametric Kruskal–Wallis test to identify differences in ranks between country groups. For variables where the test results suggested statistical significance, post hoc tests were performed (parametric or non-parametric depending on whether the assumptions of the analysis were met).

The results of the study presented in the previous chapters showed that the overall readiness of company management boards to implement AI is moderately positive. This indicates the existence of a relatively favourable climate for technological innovation, although the level of active support from management boards for AI implementation and the declarative readiness of management to implement AI are significantly lower. The results of statistical tests allow us to conclude that for all variables analysed here (Table 43) there are no statistically significant differences between countries (ANOVA $p > 0.05$; Kruskal–Wallis $p > 0.05$). One exception is variable q11[F8], concerning the belief in the need to implement the latest AI solutions. In this case, the p-value for the ANOVA test is 0.06 (at the threshold of significance), while the Kruskal–Wallis test indicates significance ($p = 0.04$), confirming potential differences between countries in terms of this variable. The p-value for the post hoc test (0.10) suggests that despite the overall significance of the non-parametric test, the differences between country pairs do not reach statistical significance after adjusting for multiple comparisons. In summary, companies in the countries surveyed show a moderately positive readiness to implement AI, with differences between countries being small and statistically negligible. The lack of significant differences in most cases may suggest common challenges and a similar level of digital maturity at the management level across Europe.

The analysis of companies' readiness to implement artificial intelligence (AI) solutions also included a number of binary indicators – affirmative answers (yes/no) relating to the use of digital technologies and strategic practices in five countries: Poland, Slovakia, Spain, Italy and Germany. The data is presented as a percentage of affirmative responses [%], while the chi-square test

(χ^2) was used to assess the differences between country groups. It should be noted that this test takes into account the distribution of yes/no responses in individual countries, revealing potential differences in the ratio of positive and negative responses. The country factor should be treated as an independent variable in this part of the study. As above, the p-values indicate the statistical significance of any differences. The analysis covered both aspects directly related to the implementation of AI (e.g. formal strategy, technology teams, training, cooperation with suppliers, financial support) and the use of various digital tools, including ERP, CRM, analytical tools and instant messaging.

Table 43. Comparison of average values for assessments of individual areas of AI implementation readiness by country

Question code		Territorial unit						p-value				
		Poland	Slovakia	Spain	Italy	Germany	Overall	Normality Test	Leaven's Test	ANOVA	Kruskal-Wallis Test	Post Hoc Test
q11[E1]	The management team at my company understands the potential and capabilities of AI technology.	0.44	0.52	0.56	0.49	0.48	0.50	0.00	0.34	0.81	0.69	-
q11[E2]	The management team at my company is looking for AI-based solutions.	0.44	0.30	0.43	0.46	0.31	0.38	0.00	0.85	0.45	0.36	-
q11[E3]	Management is open to AI technologies	0.59	0.50	0.52	0.57	0.60	0.55	0.00	0.21	0.83	0.83	-
q11[E4]	My company's management actively supports the use of AI in company processes	0.44	0.42	0.44	0.53	0.46	0.46	0.00	0.54	0.89	0.75	-
q11[R5]	Our company has a high level of digitalisation	0.70	0.57	0.51	0.66	0.68	0.62	0.00	0.16	0.36	0.39	-

Question code		Territorial unit						p-value				
		Poland	**Slovakia**	**Spain**	**Italy**	**Germany**	**Overall**	**Normality Test**	**Leaven's Test**	**ANOVA**	**Kruskal-Wallis Test**	**Post Hoc Test**
q11[E7]	My company's management team is ready to implement AI	0.49	0.36	0.48	0.59	0.50	0.48	0.00	0.38	0.39	0.33	-
q11[F8]	My company should implement the latest AI-based solutions	0.51	0.41	0.67	0.66	0.59	0.57	0.00	0.65	0.06	0.04	0.10

Source: own research

Table 44. Comparison of average values for assessments of individual areas of AI implementation readiness by country

Question code	[%] affirmative responses	Poland	Slovakia	Spain	Italy	Germany	n=	p-value chi-square test
q12[q12]	Does your company use artificial intelligence-based tools?	11.8	12.3	13.3	12.4	12.0	815	0.30
q12[q14]	Does your company have a formal strategy for implementing AI?	8.0	8.4	9.2	10.6	9.6	728	0.17
q12[q15]	Does your company have a specialist team/unit for implementing new technologies in the area of IT?	11.1	10.6	9.9	11.1	9.9	794	0.26
q12[q16]	Do your company's employees participate in AI training?	10.2	9.9	11.0	10.7	9.8	798	0.29
q12[q19]	Have you obtained a grant or funding for implementing AI in your company?	5.8	5.4	7.4	5.9	6.2	746	0.02
q12[q110]	Do you work with an external AI technology provider?	7.8	8.2	9.9	10.0	9.6	768	0.13
q12[q111]	Has the company previously conducted technology readiness assessments?	9.8	8.2	9.6	11.2	10.2	696	0.14

Question code	[%] affirmative responses	Poland	Slovakia	Spain	Italy	Germany	n=	p-value chi-square test
q12[q112]	Does your company cooperate with international partners in implementing new technologies?	8.5	10.2	9.7	11.4	10.7	729	0.40
q12[q113]	Has your company applied for financial support for the implementation of AI technology?	5.8	6.7	7.0	8.9	6.3	684	0.25
q12[q114]	Has your company received financial support for the implementation of AI technology?	6.8	5.8	5.7%	8.4%	6.5	706	0.15
q3[q31]	ERP systems	7.3	6.0	4.7	5.3	6.9	893	0.03
q3[q32]	CRM	6.2	5.3	5.7	5.4	7.3	893	0.09
q3[q33]	Analytical tools (e.g. Big Data)	7.6	6.2	8.1	8.7	8.1	893	0.06
q3[q34]	Artificial intelligence (AI) (chat GPT, Gemini, Copilot, Deepseek, etc.)	9.3	9.9	12.1	11.9	10.5	893	0.14
q3[q34b]	Messaging apps (Teams, WhatsApp, Zoom, etc.)	12.7	13.7	15.7	14.2	13.8	893	0.57

Source: own research

Methodologically, each variable was treated as a dichotomous variable, with individuals responding affirmatively or negatively to the question of the existence of a specific piece of digital infrastructure or organisational practice. For each country, the percentage of affirmative responses was calculated, and then a chi-square test was performed for each variable separately to check whether the differences between countries were statistically significant ($p < 0.05$).

The results indicate a relatively low (at present) but fairly consistent level of AI implementation and related practices across all countries surveyed. For example, the percentage of companies declaring current use of AI tools (q12[q12]) ranged from 11.8% (Poland) to 13.3% (Spain), with a value of $p = 0.30$, which, despite differences in observable values, indicates a statistical lack of significant differences between countries at the population level. Similarly low was the declared presence of a formal AI strategy (below 11% on average) and specialist teams for the implementation of new technologies (around 10-11%), also without significant national differences ($p > 0.10$). The variable for which statistically significant differences between countries were found was q12[q19] – concerning the acquisition of grants or funding for AI implementation. The p-value was 0.02, which confirms the existence of differences in access to funding, although the scale of the phenomenon itself is relatively low (from 5.4% in Slovakia to 7.4% in Spain). However, it points to different public support systems or differences in the effectiveness of applying for funding in individual countries. It should be emphasised that Spain is the leader in this case. For other variables related to funding (q12[q113] – applying for support and q12[q114] – receiving support), the p-values were insignificant (0.25 and 0.15, respectively), suggesting a uniform, moderate level of involvement in activities related to financing AI technology implementations.

When analysing the use of digital tools, significant differences between countries were found for ERP systems (q3[q31], $p = 0.03$). In this case, Poland is the leader in the implementation of this system. Other technologies – CRM ($p = 0.09$) and AI ($p = 0.14$) – had p-values clearly above the significance threshold. Only Big Data analytical tools could potentially show significant differences ($p = 0.06$). This suggests that the implementation of systems may result from different levels of development of resource management systems in enterprises, but in most cases all countries should be considered similar. Interestingly, the highest level of digital tool usage was recorded for instant messaging (q3[q34b]), which was widely used in all countries (13–16%), with no significant differences between them ($p = 0.57$).

The results confirm the moderately low level of formalisation and institutionalisation of AI implementation processes in European companies. The only area where statistically significant differences between countries were found was in obtaining funding for AI implementation and the use of ERP systems. The other areas remain relatively uniform. This may indicate both common barriers to the development of AI competences and similar opportunities. This certainly requires further research in the context of technological innovation implementation in the enterprise sector.

4.11. Identifying key technological, organisational and financial barriers limiting the implementation of artificial intelligence in SMEs.

The results of the study indicate that the implementation of artificial intelligence in the SME sector faces a number of serious barriers, which can be divided into three main categories: technological, organisational and financial. Each of these categories represents important areas of business operations that affect the pace and scope of AI-based solutions implementation. The previous chapters discussed the obstacles and expectations in detail. This section will summarise the information obtained.

4.11.1. Technological barriers

The most significant technological barriers identified in the study include:

Lack of specialist training (p2[23]; 29%) – the demand for this type of service, expressed by management staff, clearly reveals the insufficient preparation of managerial staff to use AI in management practice. According to the respondents, training is the foundation for the effective adaptation of new solutions. It should be noted that company representatives are undertaking grassroots initiatives outside of formalised company development plans and strategies.

The lack of specialised consulting and implementation services (p2[22]; 23%) and the lack of expert consulting support (p2[21]; 21%). This is a barrier of the same category. Limited access to specialised entities that could act as guides for technological transformation leads to a significant unmet demand for such services. The low involvement of external institutions suggests that there is a lack of institutional support that would facilitate the transition from needs to implementation for companies.

Lack of IT infrastructure (p2[27]; 19%) – this problem may likely stem from insufficient performance of own equipment, insufficient network or server resources, or insufficient funds to upgrade hardware for advanced digital technologies. This potentially limits the possibility of installing and operating advanced AI algorithms.

Difficulties in accessing data and a reluctance to collect data and create databases (p2[28]; 10%) and concerns about data security (p3[38]; 25%) – data is the primary source of information for AI models, and its limited availability or uncertainty about security directly affects its effectiveness and, consequently, the quality of the results offered. This, in turn, leads to growing mistrust and reservations about the implementation of AI.

Some of the technological barriers are currently rated as moderate, but in the future, as AI becomes more popular, both hardware requirements and requirements for the security and confidentiality of the data obtained will increase. Furthermore, IT barriers and data access may become more important as secondary barriers when organisational and competence barriers become less significant.

4.11.2. Organisational barriers

Organisational barriers mainly relate to issues arising from organisational culture, management style, companies' readiness to adapt to change, and the knowledge and skills of employees. Among these, the following are particularly significant in the light of the research:

Lack of knowledge about AI (p3[31]; 31%) – this is the most frequently cited organisational barrier, reflecting the early stage of technology awareness in the SME environment. Lack of knowledge about the capabilities, limitations and applications of AI naturally increases mistrust and blocks decisions about digital transformation.

Reluctance to change (p3[32]; 25%) and employee resistance to change (p3[33]; 22%) indicate relative organisational conservatism, which, however, is likely to become less significant as AI becomes more widespread. This will be the case provided that the process is legitimate, transparent and inclusive of those affected by its potential effects. Technological innovations are usually perceived as a threat to the established order and employee security until their beneficial effects are confirmed.

Fears of job losses (p3[35]; 24%) and concerns among management about losing their position and authority (p3[36]; 16%). These aspects are still relevant. AI can be perceived as a threat to the status quo, which translates into a passive attitude or even outright hostility towards its implementation. This barrier will also become less significant over time.

Change management issues (p3[34]; 17%) – managing digital transformation requires appropriate managerial skills. This aspect was not directly studied, but statements about the need for training and knowledge expansion confirm that management currently feels the need to build competencies.

In the case of SMEs, where management is often intuitive, even awareness of the need for formalised change management is low in companies.

Managerial mindset (p3[312]; 7%) – this is the least frequently mentioned aspect in the survey, but it should be remembered that managers were assessing themselves here. This barrier is symbolic of a deeper phenomenon, namely a practical lack of openness to innovation among management, and a relatively centralised, traditional and partly authoritarian management style. At least at the current stage of transformation, this circumstance may inhibit grassroots initiatives to some extent.

4.11.3. Financial barriers

The cost of training (p4[42]; 61%) is the most frequently cited barrier in the entire list. This shows that even if entrepreneurs recognise the need to improve their skills, they are unable or unwilling to bear the associated costs.

The cost of purchasing licences (p4[41]; 54%) – shows that AI-based software is still perceived as too expensive in relation to the budgetary capabilities of the SME sector.

The cost of purchasing equipment (p4[43]; 32%) – as in the case of IT infrastructure, modern equipment may be a prerequisite for the effective operation of AI applications.

Excessive costs of services (p2[25]; 25%) and hiring specialists (p2[24]; 27%) – these indications highlight the problem of financial accessibility to external expertise. Insufficient financial resources (p2[29]; 18%) and difficult procedures for obtaining external funds (p2[210]; 10%) – show that although external funds may exist, obtaining them is not easy or commonly used.

A comparison of key barriers with the results concerning entrepreneurs' expectations (p7[72–76]) confirms that financial barriers are among the most serious constraints to AI implementation. Importantly, the entrepreneurs surveyed clearly expect training and advisory support that could alleviate these difficulties. The first and most obvious area of barriers is the competence of employees and management. Companies currently do not have the appropriate substantive preparation to plan and implement digital transformation processes. In light of the research, this problem concerns managers (research sample), but it can be expected to affect operational employees to an even greater extent. This is particularly true in the context of possible resistance to change and concerns about job stability. It can be concluded that at this stage, companies are able to carry out AI projects on their own, but may not have sufficient knowledge to optimise the process.

The second area of limitations is the relatively low technical capacity to implement technology. Respondents' statements indirectly indicate that technical resources are not adapted to the needs of AI. In addition, companies do not have sufficient expert support, which prevents them from effectively transforming business needs into technological solutions. At the management level, certain mental and systemic barriers emerge, as already mentioned in previous chapters. The indicated lack of ability (or awareness) to manage change and the clear conservatism of the management style hinder the implementation of innovative projects, which by definition require organisational flexibility and the ability to respond to a dynamic technological environment. The last area is financial issues: the high costs of training and licences effectively discourage companies from investing in AI, which is particularly evident with the limited budgets of SMEs. In addition, the cost of purchasing equipment and expert services (which are already considered to be inaccessible) creates a significant barrier. At the same time, companies express expectations for public and advisory support, suggesting that the current structure of available aid instruments is insufficient or ill-suited.

It should be emphasised here that the barriers identified rarely occur as isolated problems for companies. Much more often, they can enter into synergistic (accumulating difficulties) or neutralising (weakening negative effects) relationships. It is therefore possible to propose possible scenarios for AI implementation in conditions of development barriers. Below is a set of scenarios in which the existence of barriers accumulates negative effects:

The link between a lack of financial resources and a lack of competence. A lack of funds (p2[29]; p3[311]) limits the possibility of investing in training (p2[23]; p4[42]) and hiring experts (p2[24]; p3[37]), which in turn results in low awareness of AI applications and a possible belief in its inadequacy, unreliability or high risk. Schematically, this leads to the following scenario: low knowledge → lack of investment → lack of results → confirmation of reluctance to change → lack of positive experiences → technological exclusion.

The relationship between a lack of staff and resistance to change. The lack of internal specialists (p3[37]) makes the implementation of AI a process that is unclear and incomprehensible to most of the team. This causes growing resistance, a sense of the futility of the digital transformation initiative (p3[33]) and management's reluctance to lose influence (p3[36];

p3[39]). This leads to the consolidation of an organisational culture based on the status quo, with no readiness for transformation.

A combination of organisational and technological barriers. A shortage of IT infrastructure (p2[27]) and difficulties in accessing data (p2[28]) can undermine even well-planned implementation processes. If a company has neither the technology, access to reliable data, nor organisational capabilities, the AI implementation process will certainly not go smoothly, if at all. These deficiencies exacerbate organisational problems: the lack of visible results breeds frustration and discourages further attempts.

"Implementation barriers ramp". In this scenario, the following phenomena occur simultaneously: lack of funds prevents the purchase of licences, equipment and training services → lack of internal and external expertise leads to wrong strategic decisions or failure to make them → resistance from employees and management prevents the smooth implementation of the change process → technological deficiencies (infrastructure, data) make AI implementation technically unfeasible or ineffective → growing distrust of innovation → lack of results → perpetuation of stagnation. In this scenario, the barriers reinforce each other and create a temporary systemic blockage to digital transformation. This situation is particularly threatening to micro and small businesses operating in less developed regions, where local labour markets do not provide access to digital skills and IT infrastructure is inadequate.

Despite the existence of significant obstacles, it is possible to identify mechanisms that mitigate the effects of the above scenarios. These involve interrupting a certain course of events and the relationship between individual barriers. This is facilitated by the temporary nature of the obstacle or existing mitigation mechanisms. According to the expectations of the surveyed companies, such a remedy could be:

External training and consulting support (p7[71]; p7[73]). This allows companies to gain knowledge that overcomes resistance to change and increases acceptance of AI.

Grants and subsidies (p7[72]; p7[75]) – enable initial investments that reduce technological and financial constraints. This should also include information campaigns on the availability of specific funds. This increases the willingness of companies to apply for funding.

Development of open **tools** – makes AI implementation cheaper and possible even without extensive IT infrastructure based on existing solutions. This method helps build trust and a positive assessment of the initial benefits of using AI.

Examples of success stories from other companies in the corresponding sector act as a mechanism of positive pressure (imitation effect), which can influence a change in management attitudes and increase strategic readiness.

Local clusters, collaboration and innovation ecosystems – sharing competencies, services and infrastructure can significantly lower barriers to entry for SMEs. However, this element of is rarely a bottom-up initiative of companies. Institutional support is required: in such a model, even if not all resources are available internally, they can be significantly supplemented.

4.12. Analysis of the impact of management style and personality traits of managers on decisions regarding AI implementation

The aim of this part of the study is to verify whether there is a relationship between the introduction of specific CRM or ERP systems, the use of Big Data analytics or AI or instant messaging, and management culture and individual characteristics of managers. The analysis concerns the management culture described in detail in the chapter 3.3. It was assumed that if the use of specific digital tools is related to management practices, statistically significant differences will be observed in the levels of respondents' ratings in two groups: companies using the tool (marked "YES" in the results tables) and companies not using it (marked "NO"). This type of analysis makes it possible to assess whether companies belonging to specific categories differ in terms of preferred managerial behaviours, approach to cooperation with subordinates, attitude towards organisational discipline, communication style and commitment to employee development.

In the comparative analysis of managerial attitudes, the average values of the ratings for individual statements were calculated. In order to examine the significance of the differences between the groups, Student's t-test for independent samples was used, while verifying the assumption of equality of variance using Levene's test. It should be emphasised that the analysed variables do not have a normal distribution, but they do exhibit symmetry, which is why the t-test was used with some reservations. In the event of a violation of the assumption of homogeneity of variance, or in order to increase the reliability and credibility of the results based on the t-test, the analysis was supplemented with the results of the non-parametric Mann-Whitney U test. For this test, the sum of ranks in each group was given as an indicator of the distribution of responses. The analysis highlighted statements for which p-values < 0.05 in any of the tests indicate statistical significance of differences between groups. It was assumed that the differences are unquestionable if both tests show statistical significance and Leaven's test indicates homogeneity of variance. Otherwise, we assume that there are indications of differences, but they cannot be confirmed unequivocally.

4.12.1. Implementation of ERP systems and management styles and characteristics of managers

Table 44 presents the results of the analysis in the context of ERP system implementation. A comparative analysis of average ratings for questions concerning management style was conducted in two groups of respondents – those who had implemented an ERP system ("YES") and those who had not implemented such a system ("NO"). Of the sixteen statements analysed, one meets the condition of a significant difference, confirmed by two statistical tests. This is question q20[13]: "As many powers as possible should be delegated to subordinates". On this issue, the average in the "YES" group was 0.6, while in the "NO" group it was 0.4. This difference was confirmed by both the t-test (p = 0.01) (while maintaining the condition of homogeneity of variance) and the U-test (p = 0.01). This suggests that people working in organisations that have implemented an ERP system are more inclined to delegate authority, which may be due to greater transparency of processes and easier control over activities thanks to integrated IT tools. In the case of the next three statements, the results suggest the possibility of differences: q20[4]: "Meetings are helpful in the development of subordinates." The average in the "YES" group is 0.8, and in the "NO" group – 0.7. The t-test showed statistical significance (p = 0.04), as did the U-test (p = 0.05), but Levene's test indicated a lack of homogeneity of variance (p = 0.01). Therefore, only the U test can be formally relied upon. The differences can thus be considered potentially significant, but their analysis requires further research taking into account the heterogeneity of the data. Statement q20[14]: "It is the manager's responsibility to care about increasing the general and professional knowledge of subordinates, even if it is not necessary in the current situation." shows clear differences (mean "YES" = 0.8, "NO" = 0.7). The t-test (p = 0.04) and U-test (p = 0.05) indicate significance, while Levene's test suggests homogeneity of variance. It can therefore be clearly stated that there are strong indications that companies that have implemented ERP systems are more interested in developing the competences of their employees. In the case of q20[16]: "Changes in goals and methods should be agreed with subordinates," the difference in means (3.8 vs. 3.7) proved to be significant in both the t-test ($p = 0.01$) and U-test ($p = 0.01$), but Levene's test showed non-homogeneity of variance ($p = 0.01$). This does not allow for unequivocal confirmation of the differences. Certainly, the importance of employee inclusion in the decision-making process is higher in companies that have implemented ERP systems. Therefore, we can speak of a higher level of participation, but further analysis is needed, especially to control for the diversity of responses within the two populations studied. In the case of the other statements, no statistically significant differences between the groups were found. This applies, among other things, to aspects such as: authoritarian style ("I make the decision myself..."), approach to employee mistakes, the importance of interpersonal conditions, and schedule rigidity. Despite slight differences in the averages (most often in the range of 0.1–0.2), the lack of statistical significance indicates the independence of management style in companies that use ERP and others. ERP systems are associated with a management style based on greater autonomy and employee engagement. In particular, managers in companies that have implemented ERP are more likely to delegate authority and promote the development of employee competencies.

4.12.2. Implementation of CRM systems and management styles and characteristics of managers

Table 44 shows that the implementation of the system and management styles have no impact. The subpopulations studied do not differ in terms of management culture in the context of CRM.

4.12.3. Use of Big Data and management styles and characteristics of managers

Table 44 indicates two potential management factors that distinguish companies using Big Data analytics solutions from others. The first (q20[14]) refers to the belief that it is the manager's responsibility to ensure that subordinates increase their general and professional knowledge, even when it is not necessary in the current situation. Companies using these solutions usually give higher priority to this aspect than others. This is evidenced by the U test result. In the sample studied, the average scores were 0.8, and in the "NO" group – 0.7. These differences were confirmed by the t-test ($p = 0.02$) and the U test ($p = 0.05$). However, the homogeneity of variance showed that both analysed groups are not Levene's homogeneous ($p = 0.00$). Therefore, the t-test should not be considered a method of confirming differences in the ratings of this aspect. The U test, on the other hand, allows us to conclude that respondents from organisations implementing Big Data clearly place greater emphasis on the role of human resource development, regardless of the current usefulness of knowledge. This indicates a long-term orientation in human capital management. The results for q20[16] should be interpreted similarly: "Changes, goals and methods should be agreed with subordinates." The results of the t-test ($p = 0.02$) and U-test ($p = 0.02$), with homogeneity of variance (Levene: $p = 0.00$), suggest that companies using Big Data value transparency and dialogue more highly when implementing changes, which may be the result of the need to better embed technological changes in the organisational culture and a reflection of experience with implementing this type of technology. A clear distinction between subpopulations of respondents can be seen in the case of q20[15]: "Work discipline should be strengthened." The test results indicate statistically significant differences – t-test ($p = 0.02$), U-test ($p = 0.02$), with confirmed homogeneity of variance ($p = 0.35$). Respondents from the "YES" group (average 0.7) rated this statement higher than those from the "NO" group (average 0.6), which may indicate a greater need for formalisation and organisation of activities in environments requiring the processing of large volumes of data.

For the remaining statements – such as q20[1], q20[2], q20[3], q20[5], q20[6], q20[8], q20[10], q20[12], q20[13] – no statistically significant differences were observed in terms of either averages or ranks. This may prove that there are universal management principles in the EU economic system in the context of Big Data use, such as delegation of authority, autonomy in action, or treating organisations as places for achieving production goals. The differences between the analysed groups are most visible in areas related to the formalisation of work, employee involvement in change and investment in their development. These are situations where the implementation of Big Data solutions may require a profound change in organisational culture, operational precision and managerial flexibility. At the same time, no clear discrepancies were noted in many basic aspects of management styles, which may suggest the stability of certain managerial values regardless of the implementation of advanced technologies.

4.12.4. The use of AI and management styles and characteristics of managers

The table 45 presents the results of a study of management styles and manager personalities in the context of generative AI use. The results show that openness to the use of generative AI greatly differentiates managers' preferences in terms of management style. What is more, it also reveals an interesting picture of managerial attitudes in EU companies. Those who use AI tools are more likely to declare that they make decisions independently without prior consultation with their superiors (q20[1]; average "YES" = 0.5; "NO" = 0.3; $p < 0.01$ for all tests), which may suggest a greater willingness to be transparent and take responsibility within the organisational structure. At the same time, they rate significantly higher that they allow employees to act independently, even if there is a risk of error (q20[2]), which may indicate greater openness in delegating responsibility and involving subordinates in decision-making. On the other hand, the statement about the ability of employees to function independently without the help of a manager (q20[12]) was rated significantly lower by those who do not use AI, which may reflect a slightly more centralised and authoritarian approach in the "NO" group. These differences are also consistent in terms of delegating authority to subordinates (q20[13]), where significance was achieved in the U test ($p = 0.05$), although the t test showed only borderline values ($p = 0.05$). This shows a slightly higher ranking assigned by AI users to the idea of decentralising responsibility. It can therefore be concluded from the research that the most prominent characteristic of the managers surveyed who use artificial intelligence is a pragmatic, open and results-oriented approach. This group more often (than their counterparts who refrain from using AI) declares a higher willingness to share responsibility, both in strategic decisions and in everyday activities (a greater willingness to leave room for employee autonomy). AI managers show less need for control, which may be due to the fact that AI tools facilitate real-time progress tracking, data analysis and error identification. This, in turn, can lead to increased trust as a basis for delegation, despite the potential reduction in collaboration and communication resulting from the use of AI. The management style of managers who refrain from using AI seems to be more focused on formalising the task execution process, even at the expense of delegation or autonomy. This is more of an attitude focused on adherence to traditional, hierarchical structures of knowledge and task flow. It should be noted that AI performs many tasks that previously had to be delegated or required joint analysis and decisions. This required a certain amount of confrontation, analysis of possible errors and, above all, time. AI effectively eliminates many of these challenges. This certainly reduces tension within the organisation, which can be important in interpersonal relationships. The psychological aspect is a very interesting prospect for further research.

Questions q20[4], q20[6], q20[14] and q20[16] cover the area of employee development and knowledge orientation. Respondents who declare that they use AI tools are significantly more likely to give high ratings to statements emphasising the need for subordinate development. This applies both to the importance of meetings in the development process (q20[4]) and the need to create conditions for employee development (q20[6]). There is also a difference with regard to the manager's obligation to increase the general and professional knowledge of the team, even if it is not relevant at the moment (q20[14]). Similarly, opinions differ on the need to agree on changes with subordinates (q20[16]). These results suggest that AI users are significantly more oriented towards relational and educational development within organisational structures, which may result from a focus on efficiency through the use of technology. Perhaps they are aware of the importance of training, knowledge and the benefits of their experience with AI, which leads them to adopt a promotional attitude conducive to the diffusion of this technology. It should be noted that this is fully consistent with the results of the benefit assessments described in the chapters 3.1.2, 3.1.4 and 3.1.6. Managers who have not yet implemented AI in their work present a slightly less employee-oriented pattern in light of the data. They rate the importance of interpersonal relationships, joint decision-making and employee development slightly lower, even if it does not bring immediate production results. They appear to be more rooted in traditional participatory and educational patterns. It can even be assumed that formal relationships are more important in this group than the need for cooperation and shared organisational values. However, it should be emphasised that, in light of the research, this does not mean that such managers are opposed to the aspects of management discussed here. They also positively assess the importance of these values and management styles, but AI users are even more open and positive about the statements discussed. The "AI manager" type seems more inclined to support and inspire employees than to manage through numbers, control and reports. They are also distinguished by a higher attachment to developmental values, which may indicate a long-term orientation towards building the organisation's human capital. The statement regarding employee involvement in decision-making (q20[8]) also shows a significant difference in favour of AI users (average "YES" = 0.5; "NO" = 0.8; $p < 0.01$). This may indicate either a less centralised and more flexible management model adopted by this group. Alternatively, it may indicate a lack of need to consult and control the decision-making process when using AI recommendations. Another interesting area of analysis is the perception of autonomy – both one's own and that of employees. AI users are more likely to admit that they consult decisions, while at the same time being willing to leave decision-making space to their teams. This type of situation may be the result of operating in an environment where the availability of data and analytical reports reinforces the need for consistency and compliance with the results set by central (higher in the hierarchy) management systems. The statement about the importance of good interpersonal relationships in the workplace (q20[7]) also received significantly higher ratings among AI users. This may suggest that users of analytical tools are more likely to recognise the soft aspects of an organisation's functioning or assign them a higher priority while focusing on the technological side of their work. In two cases concerning discipline and work efficiency, AI users display attitudes that indicate a more demanding and restrictive approach to discipline in the workplace. This may be due to the need for consistency of results and behaviour in processes when using sophisticated digital decision support tools. This can be seen, for example, in the statements (q20[11]) and (q20[15]). In both cases, AI users rate the value of discipline higher, which may indicate their greater attachment to the principles of hierarchy and formal order in the organisation in which they work. With regard to the statement about the main goal of the workplace being the achievement of production targets (q20[3]), this indicates that AI users identify somewhat more strongly with a hard, production-oriented approach to the functioning of the organisation.

Based on the distribution of the presented results, it is possible to formulate types of managers' attitudes, depending on the use of AI. According to the research, a manager who uses AI is a person who more intensively develops, supports, co-decides and cares for relationships within the team. They show a greater tendency towards empathy and building employee engagement in organisational processes. On the other hand, a manager who has not yet used AI is a person who focuses on coordinating processes, results, efficiency, analysis and optimisation. They are willing to involve others in decision-making processes, but to a lesser extent than an AI manager. Despite their positive attitude, they attach slightly less importance to aspects such as discipline, formalisation, co-decision-making and cooperation. Their actions are subordinated to the logic of the company's operations and have a slightly weaker relational component. These differences allow us to formulate the hypothesis that there is a specific process of change in management style in connection with the use of AI. Analytical tools can act as a "virtual executor", but this requires intensive relationships and the building of knowledge and competence within the team. As a result, managers adapt their practices towards slightly less formal centralisation of the information processing process.

4.12.5. The use of instant messaging and management styles and characteristics of managers

The table 47 presents the results of a comparison of two groups of managers: those who declare that they use instant messaging in their daily company management processes. It should be emphasised that in the era of dynamic development of remote work and several years of functioning in pandemic conditions, as many as one third of respondents declare that they do not use such tools (Teams, WhatsApp, Zoom, etc.) in their company. What is more, it turns out that, similar to the use of AI, the use of modern means of communication also clearly differentiates managers. AI causes a relative loosening of centralised decision-making structures, while instant messaging additionally stimulates the process of humanisation and strengthens the decentralisation of management processes in companies. Messaging apps are an important factor influencing areas related to employee autonomy and inclusion, participation in decision-making, professional development and the formation of interpersonal relationships within the team.

The aspects of autonomy and independence of managers are addressed in questions q20[1] ("I make the decision myself and then inform (...)") and q20[2] ("I allow people to work independently (...)") and q20[3] ("I believe that the workplace functions (...) to achieve production goals"). The differences are clear – both statistical tests confirm significance, and the variances are homogeneous. The average responses in the "YES-I use" group are higher

(0.5 vs 0.2; 0.6 vs 0.3; 0.8 vs 0.5), which indicates that managers who use instant messaging more often combine independent decision-making with greater flexibility in delegating tasks and allowing mistakes as part of development. High statistical significance and clear differences in averages were also noted in questions q20[4] ("Meetings are helpful in the development of subordinates"), q20[6] ("Employees need to be provided with conditions for their development"), q20[7] ("The most important thing (...) is good interpersonal relations") and q20[16] ("It is necessary to consult with subordinates (...)"). In each of these categories of statements, instant messenger users obtained higher average ratings (from 0.8 to 1.2 in the "YES" group compared to 0.5-0.8 in the "NO" group), which suggests that such tools promote intensified dialogue, ongoing coordination of activities and a better understanding of the team's needs and goals. This definitely promotes the process of involving team members in decision-making processes and fosters the development of a specific culture of communication in companies.

Questions q20[10] and q20[11] (Table) also showed significant differences in terms of the impact of experience and work efficiency on task distribution. Managers who use instant messaging tend to favour an approach in which task selection and maintaining efficiency standards are more strongly emphasised; their average ratings of the importance and rank assigned to these aspects are significantly higher than in the "non-users" group. In question q20[13], however, the t-test results were not conclusive, which essentially confirms the diagnosed situation, although given the higher rank of instant messaging users, it may attest to a "team-oriented" approach to work and decision-making. The last area in which significant differences in managers' assessments were found in the context of the use of communication tools is employee development and education. This is addressed in question q20[14]. It shows clear differences in both analysed groups. Users more often perceive competence development as a manager's responsibility. It is worth noting that this approach may be supported by the ease of organising remote training and sharing materials via instant messaging, daily briefings and ongoing problem solving.

4.12.6. Conclusions

The analysis shows some very interesting specifics regarding the use of the systems analysed. It can be said that ERP, CRM and Big Data analytical systems have a much smaller impact on managers' attitudes than widely available, intuitive and user-friendly generative AI and communication tools. Certainly, the latter two technologies are distinguished by their characteristics: they are more common and "democratic". The former require costs, preparation, expenditure and, above all, a company strategy. A strategy, i.e. "top-down" and coordinated, formal and highly centralised actions. The second group of tools are "bottom-up" systems. They do not require special technological and hardware preparations, training or expenditure. They are often "brought in" spontaneously by employees into the company's operating space. As practice shows, this is often done without the explicit consent of the management or a formal strategy. The results of the study are particularly interesting in relation to the comparison of AI and instant messaging. In both cases, users of digital technologies (whether AI or instant messaging) are more open to cooperation and flexible in their management compared to those who do not use such tools. A kind of bottom-up mechanism for promoting employee independence can be observed: both AI and instant messaging users are more likely to allow their subordinates to act autonomously. The use of both characterises managers with a greater tendency to create opportunities for employee development and to care about their knowledge and competences. There is also a greater tendency to agree on changes with subordinates and a higher importance attached to meetings and direct communication with the team (consultations, briefings, working meetings). It can also be said that the use of these solutions characterises managers who are focused on the quality of relationships. Both AI and messenger users support the perception of good interpersonal conditions as a key factor. AI and messengers activate similar psychological and organisational mechanisms: they stimulate independent decision-making to the same extent (see average values in question q20[1]). Despite many similarities, there are potential, albeit minor, differences in the way technology users shape their management style. They differ slightly in their slightly stronger (if we analyse the average values) emphasis on production goals. In AI, respondents more often agree that the workplace exists primarily to achieve production goals (q20[3]), which is less emphasised in communicators.

Table 45. Management style in companies and the use of ERP systems. Synthetic assessments and statistical tests

Questionnaire		Does the company use ERP systems?		Statistical tests				
Question number	**Statement**	**Average (YES)**	**Average (NO)**	**p-value (t-test)**	**p-value (Levene's)**	**Sum of ranks (YES)**	**Sum of ranks (NO)**	**p-value U test**
q20[1]	He makes the decision himself and then informs his superiors about it	0.5	0.4	0.18	0.7	126375	272,796	0.09
q20[2]	I allow people to work independently, even if they may make mistakes	0.5	0.4	0.18	0.11	125,490	273,681	0.15
q20[3]	I believe that the workplace exists primarily to achieve production targets.	0.7	0.7	0.77	0.2	122245	276,927	0.64
q20[4]	Meetings are helpful in the development of subordinates	0.8	0.7	0.04	0.01	127251	271,921	0.05
q20[5]	Subordinates perform their work properly without being instructed by their manager	0.7	0.6	0.13	0.0	124981	274,190	0.20
q20[6]	Employees need to be provided with conditions conducive to their development.	1.1	1.0	0.29	0.65	124,250	274,922	0.29
q20[7]	The most important thing in the workplace is good interpersonal relations	1.1	1.0	0.45	0.41	122677	276,495	0.55
q20[8]	Subordinates should participate in decision-making	0.7	0.6	0.25	0.0	124896	274,275	0.21
q20[9]	I set a strict work schedule	0.5	0.5	0.33	0.72	124424	274747	0.27

Questionnaire		Does the company use ERP systems?		Statistical tests				
Question number	Statement	Average (YES)	Average (NO)	p-value (t-test)	p-value (Levene's)	Sum of ranks (YES)	Sum of ranks (NO)	p-value U test
q20[10]	The most difficult tasks should always be assigned to the most experienced employees.	0.6	0.6	0.85	0.93	120150	279021	0.87
q20[11]	Never make concessions that compromise the effectiveness of your work.	0.6	0.5	0.11	0.64	126171	273,000	0.10
q20[12]	If necessary, most subordinates could perform their duties without the manager's assistance.	0.6	0.5	0.13	0.85	125608	273563	0.14
q20[13]	As many powers as possible should be delegated to subordinates.	0.6	0.4	0.01	0.45	129732	269,439	0.01
q20[14]	It is the manager's responsibility to ensure that subordinates increase their general and professional knowledge, even if it is not necessary in the current situation.	0.8	0.7	0.04	0.15	127299	271,873	0.05
q20[15]	Work discipline should be strengthened	0.7	0.6	0.08	0.21	126143	273,029	0.10
q20[16]	Changes to objectives and methods should be agreed with subordinates.	0.8	0.7	0.01	0.01	129609	269,563	0.01

Source: own research

Table 46. Management style in companies and the use of CRM systems. Synthetic assessments and statistical tests

Survey form		Does the company use CRM systems?		Statistical tests				
Question number	Statement	Average (YES)	Average (NO)	p-value (t-test)	p-value (Levene's)	Sum of ranks (YES)	Sum of ranks (NO)	p-value U test
q20[1]	He makes the decision himself and then informs his superiors about it	0.5	0.4	0.14	0.07	123312	275860	0.19
q20[2]	I allow people to work independently, even if they may make mistakes	0.5	0.4	0.24	0.13	122853	276,318	0.23
q20[3]	I believe that the workplace exists primarily to achieve production targets.	0.7	0.7	0.7	0.1	119914	279,257	0.76
q20[4]	Meetings are helpful in the development of subordinates	0.8	0.7	0.29	0.74	122362	276,809	0.30
q20[5]	Subordinates perform their work properly without being instructed by their manager	0.7	0.6	0.66	0.03	120656	278,516	0.59
q20[6]	Employees need to be provided with conditions conducive to their development	1.1	1.0	0.36	0.9	121647	277,525	0.41
q20[7]	The most important thing in the workplace is good interpersonal relations	1.1	1.1	1.0	0.81	119650	279,522	0.82
q20[8]	Subordinates should participate in decision-making	0.7	0.6	0.29	0.05	122596	276,575	0.26
q20[9]	I set a strict work schedule	0.4	0.5	0.10	0.77	113141	286,030	0.09

Survey form		Does the company use CRM systems?		Statistical tests				
Question number	**Statement**	**Average (YES)**	**Average (NO)**	**p-value (t-test)**	**p-value (Levene's)**	**Sum of ranks (YES)**	**Sum of ranks (NO)**	**p-value U test**
q20[10]	The most difficult tasks should always be assigned to the most experienced employees.	0.6	0.6	0.31	0.30	115928	283,243	0.37
q20[11]	Never make concessions that compromise the effectiveness of your work.	0.6	0.5	0.54	0.94	120779	278,392	0.58
q20[12]	If necessary, most subordinates could perform their duties without the manager's assistance.	0.5	0.5	0.57	0.29	121012	278159	0.53
q20[13]	As many powers as possible should be delegated to subordinates.	0.5	0.4	0.2	0.77	122431	276,741	0.29
q20[14]	It is the manager's responsibility to ensure that subordinates increase their general and professional knowledge, even if it is not necessary in the current situation.	0.7	0.7	0.97	0.77	119,360	279,811	0.89
q20[15]	Work discipline should be strengthened	0.5	0.6	0.15	0.08	114294	284,878	0.17
q20[16]	Changes to objectives and methods should be agreed with subordinates.	0.8	0.7	0.25	0.33	123044	276,128	0.21

Source: own research

Table 47. Management style in companies and the use of Big Data tools. Synthetic assessments and statistical tests

Survey form		Does the company use Big Data?		Statistical tests				
Question number	Statement	Average (YES)	Average (NO)	p-value (t-test)	p-value (Levene's)	Sum of ranks (YES)	Sum of ranks (NO)	p-value U test
q20[1]	He makes the decision himself and then informs his superiors about it	0.4	0.4	0.90	0.14	155115	244056	0.80
q20[2]	I allow people to work independently, even if they may make mistakes	0.5	0.5	0.43	0.32	156,805	242,366	0.46
q20[3]	I believe that the workplace exists primarily to achieve production targets.	0.7	0.7	0.55	0.3	156849	242,322	0.46
q20[4]	Meetings are helpful in the development of subordinates	0.8	0.7	0.06	0.07	159989	239,183	0.11
q20[5]	Subordinates perform their work properly without being instructed by their manager	0.7	0.6	0.64	0.12	155348	243,824	0.75
q20[6]	Employees need to be provided with conditions conducive to their development	1.0	1.0	0.89	0.25	155334	243,838	0.75
q20[7]	The most important thing in the workplace is good interpersonal relations.	1.0	1.1	0.19	0.92	149313	249,859	0.17
q20[8]	Subordinates should participate in decision-making	0.7	0.6	0.52	0.04	156211	242,961	0.57
q20[9]	I set a strict work schedule	0.6	0.4	0.1	0.25	159854	239,317	0.12

Survey form		Does the company use Big Data?		Statistical tests				
Question number	**Statement**	**Average (YES)**	**Average (NO)**	**p-value (t-test)**	**p-value (Levene's)**	**Sum of ranks (YES)**	**Sum of ranks (NO)**	**p-value U test**
q20[10]	The most difficult tasks should always be assigned to the most experienced employees.	0.6	0.6	0.72	0.83	155273	243,899	0.77
q20[11]	Never make concessions that compromise the effectiveness of your work	0.6	0.5	0.16	0.94	158948	240,223	0.19
q20[12]	If necessary, most subordinates could perform their duties without the manager's assistance.	0.5	0.5	0.31	0.13	157093	242,078	0.42
q20[13]	As many powers as possible should be delegated to subordinates	0.4	0.4	0.6	0.39	155315	243,857	0.76
q20[14]	It is the manager's responsibility to ensure that their subordinates increase their general and professional knowledge, even if it is not necessary in the current situation.	0.8	0.7	0.02	0.0	161152	238019	0.05
q20[15]	Work discipline should be strengthened	0.7	0.6	0.02	0.35	162575	236,597	0.02
q20[16]	Changes to objectives and methods should be agreed with subordinates.	0.8	0.6	0.02	0.0	162174	236,998	0.02

Source: own research

Table248. Management style in companies and the use of AI. Synthetic assessments and statistical tests

Survey form		Does your company use AI?		Statistical tests				
Question number	Statement	Average (YES)	Average (NO)	p-value (t-test)	p-value (Levene's)	Sum of ranks (YES)	Sum of ranks (NO)	p-value U test
q20[1]	He makes the decision himself and then informs his superiors about it	0.3	0.5	0.0	0.0	174745	224,426	0.00
q20[2]	I allow people to work independently, even if they may make mistakes.	0.3	0.6	0	0.05	171611	227560	0.00
q20[3]	I believe that the workplace exists primarily to achieve production targets.	0.6	0.8	0.03	0.01	177617	221554	0.04
q20[4]	Meetings are helpful in the development of subordinates	0.6	0.8	0.0	0.03	173077	226,095	0.00
q20[5]	Subordinates perform their work properly without being instructed by their manager	0.6	0.6	0.87	0.55	185813	213359	0.83
q20[6]	Employees need to be provided with conditions conducive to their development	0.9	1.1	0.0	0.01	170,480	228,691	0.00
q20[7]	The most important thing in the workplace is good interpersonal relations	0.9	1.2	0.0	0.01	173531	225,640	0.00
q20[8]	Subordinates should participate in decision-making	0.5	0.8	0.0	0.02	171758	227,414	0.00
q20[9]	I set a strict work schedule	0.4	0.5	0.10	0.99	179331	219,840	0.12

Survey form		Does your company use AI?		Statistical tests				
Question number	Statement	Average (YES)	Average (NO)	p-value (t-test)	p-value (Levene's)	Sum of ranks (YES)	Sum of ranks (NO)	p-value U test
q20[10]	The most difficult tasks should always be assigned to the most experienced employees.	0.6	0.6	0.55	0.55	182845	216,326	0.54
q20[11]	Never make concessions that compromise the effectiveness of your work	0.4	0.6	0.01	0.5	175308	223,863	0.01
q20[12]	If necessary, most subordinates could perform their duties without the manager's assistance.	0.4	0.6	0.0	0.11	173266	225,905	0.00
q20[13]	As many powers as possible should be delegated to subordinates.	0.4	0.5	0.05	0.34	178074	221,097	0.05
q20[14]	It is the manager's responsibility to ensure that subordinates increase their general and professional knowledge, even if it is not necessary in the current situation.	0.6	0.8	0	0.43	174319	224,853	0.00
q20[15]	Work discipline should be strengthened	0.5	0.7	0.01	0.83	175494	223,678	0.01
q20[16]	Changes to objectives and methods should be agreed with subordinates.	0.6	0.8	0.01	0.38	175126	224,046	0.01

Source: own research

Table 49. Management style in companies and the use of instant messaging. Synthetic assessments and statistical tests

Questionnaire		Does the company use instant messaging?		Statistical tests				
Question number	Statement	Average (YES)	Average (NO)	p-value (t-test)	p-value (Levene's)	Sum of ranks (YES)	Sum of ranks (NO)	p-value U test
q20[1]	He makes the decision himself and then informs his superiors about it	0.5	0.2	0.0	0.89	294755	104,416	0.00
q20[2]	I allow people to work independently, even if they may make mistakes	0.6	0.3	0.0	0.52	292631	106,540	0.00
q20[3]	I believe that the workplace exists primarily to achieve production targets.	0.8	0.5	0.0	0.27	293472	105,699	0.00
q20[4]	Meetings are helpful in the development of subordinates	0.9	0.5	0.0	0.01	297001	102170	0.00
q20[5]	Subordinates perform their work properly without being instructed by their manager	0.7	0.6	0.15	0.0	285353	113,819	0.07
q20[6]	Employees need to be provided with conditions conducive to their development.	1.2	0.6	0.0	0.0	307,433	91,738	0.00
q20[7]	The most important thing in the workplace is good interpersonal relations.	1.2	0.8	0.0	0.0	297750	101,421	0.00
q20[8]	Subordinates should participate in decision-making	0.7	0.6	0.05	0.0	285401	113,771	0.07
q20[9]	I set a strict work schedule	0.5	0.5	0.54	0.05	278390	120,782	0.77

Questionnaire		Does the company use instant messaging?		Statistical tests				
Question number	Statement	Average (YES)	Average (NO)	p-value (t-test)	p-value (Levene's)	Sum of ranks (YES)	Sum of ranks (NO)	p-value U test
q20[10]	The most difficult tasks should always be assigned to the most experienced employees.	0.7	0.5	0.0	0.0	288051	111120	0.01
q20[11]	Never make concessions that compromise the effectiveness of your work.	0.6	0.4	0.01	0.9	287538	111,633	0.02
q20[12]	If necessary, most subordinates could perform their duties without the manager's assistance.	0.5	0.4	0.2	0.	283178	115,994	0.25
q20[13]	As many powers as possible should be delegated to subordinates.	0.4	0.5	0.01	0.35	271689	127,483	0.02
q20[14]	It is the manager's responsibility to ensure that subordinates increase their general and professional knowledge, even if it is not necessary in the current situation.	0.8	0.6	0	0.2	289002	110169	0.00
q20[15]	Work discipline should be strengthened	0.6	0.6	0.75	0.25	277620	121552	0.6
q20[16]	Changes to objectives and methods should be agreed with subordinates.	0.8	0.5	0.0	0.01	292727	106,444	0.00

Source: own research

The differences are also evident in the way tasks are assigned to competencies. With AI, the attitude of assigning the most difficult tasks to the most experienced is more emphasised (q20[10]), as is the tendency to avoid concessions that threaten work efficiency (q20[11]). Messenger users are distinguished primarily by a stronger emphasis on interaction in the decision-making process. Although this is present in both technologies, the role of deliberation (q20[4]) and agreeing on changes (q20[16]) is more pronounced in messengers. Messengers are synonymous with interaction among colleagues and potentially stimulate greater sensitivity to the team atmosphere. However, the differences in the averages for question q20[7] show that messengers only slightly support the importance of relationships as a value in themselves. As mentioned above, AI users greatly value relationships within the team. These slight, insignificant differences can also be seen in the support for development in everyday practice and the pursuit of increasing general knowledge (q20[6], q20[14]).

AI supports managers in decentralising decision-making while maintaining high discipline and assigning tasks to competencies. The AI-based style is more firmly rooted in analysis, effectiveness and measurable results. Messengers promote intensive dialogue and a culture of feedback, increase the sense of closeness within the team and facilitate the implementation of changes through consultation. The messenger-based style is softer, more relational and based on ongoing support.

The question should be asked whether the data presented suggests that the use of AI can lead to the alienation and atomisation of employees using AI technologies in companies. Will interaction with this tool reduce the tendency to communicate with colleagues and, in a pessimistic scenario, lead to communication paralysis and the breakdown of relationships? Several areas of risk associated with AI adaptation can be identified. Managers using AI tools may increasingly rely on automated recommendations and reports. This trend is likely to continue, which could potentially reduce the propensity to exchange information within the team. AI can provide personalised data, dedicated only to selected individuals, which can lead to the fragmentation and atomisation of messages and information. This, in turn, limits the common (team-level) understanding, interpretation and use of data. In extreme cases, "information islands" may arise, each with a different source of knowledge and different recommendations. There is also a real risk of "relational deficiency", as communication in a company is not only about conveying facts, but also about interaction, building trust, showing intentions, etc. Reducing human relations to the flow of operational information can lead to the relational alienation of employees. In organisations, at least in light of the survey results, there is a strong tendency for structures (i.e. their representatives: managers) to adopt attitudes focused on interpersonal relationships. It should be noted that organisations are relatively quick to adapt their communication models to new tools. Companies implementing AI place even greater emphasis on interpersonal relations, employee well-being and development than companies that do not implement these tools. The awareness of the management staff is certainly important, which in this study manifests itself in a particularly high focus on interpersonal relations. If the organisational culture clearly defines when to use AI and when direct contact is necessary, these tools can relieve communication channels of an excess of uncomplicated, repetitive matters, leaving more space for building interpersonal relationships within the company and more in-depth strategic discussion. In light of research, a humanistic approach favours a situation where AI becomes more of a "participant" in the decision-making process rather than a substitute for human relationships. Communication impairment as a result of AI implementation is possible, but more likely in companies that already face significant deficiencies in this area. A lack of strategy and control over the flow of information, and a lack of a consistent management and communication culture, can make the implementation of AI risky. It can introduce an uncontrolled decision-making factor, in which AI recommendations are based on fragmentary, inconsistent input data. In well-managed organisations, AI has the potential to support communication, eliminating unnecessary stages of decision-making by organising information. This can foster the development of interpersonal relationships.

4.13. Management styles and plans for implementing AI, Big Data, and management and communication systems

The sample of respondents was divided into two groups: those who declared that they had no plans to implement the tools, and those who declared that their company planned to introduce the IT systems or tools indicated in the survey within the next two years. The dichotomous variables constructed in this way allow us to examine whether managers declaring plans are characterised by a specific management style. The results of the study are presented in Table 50. The plan to implement ERP systems generally differentiates managers in terms of two management style characteristics (q20[2], q20[6]). Managers of companies that plan to implement these systems declare a lower level of identification with allowing independent work, potentially fraught with error, and a lower level of striving to create conditions for people to develop. The latter aspect characterises companies planning to implement CRM, Big Data and instant messaging systems in equal measure. The result confirms the reality: the implementation of such systems requires discipline, a reduction in employee freedom and more task-oriented, specific, formalised procedures for employees. There is no room for freedom here, especially when potential errors must be taken into account.

The complexity of an ERP system requires a high degree of integration of various areas of the company's operations, including finance, production, logistics and HR. Errors in one module can have serious consequences for the entire company. Therefore, managers may prefer greater control over employee activities to minimise risk. Managers implementing these systems (ERP, CRM and Big Data) may be more aware of operational risk and therefore limit autonomy to maintain predictability of results. The issue of development may be debatable, but this general category can be viewed in such a way that the implementation of all the above-mentioned tools often becomes a necessity rather than a "condition" for development or improvement of employee well-being. The inevitability of this process may lead to technology being perceived as a substitute for the development of individual competences in favour of organisational development. Companies planning to implement advanced tools often assume that the systems will improve the efficiency and accuracy of processes, reducing the need for individual employee competence development in certain areas, but building it in relation to the ability to function within formalised systems. It can also be expected that automation and streamlining of processes will enable centralised monitoring of activities, including employee activities. Managers may therefore be less inclined to invest in employee development, as they assume that technology will replace some of the initiative, competence and individual knowledge of employees.

Table 50. Management styles and plans to implement systems and tools. P-value for the Mann-Whitney U test

Question number	Survey question	A	B	C	D	E
q20[1]	He makes the decision himself and then informs his superiors about it	0.495	0.813	0.445	0.153	0.634
q20[2]	I allow people to work independently, even if they may make mistakes	0.048	0.673	0.576	0.392	0.218
q20[3]	I believe that the workplace exists primarily to achieve production targets	0.376	0.891	0.203	0.866	0.944
q20[4]	Meetings are helpful in the development of subordinates	0.108	0.709	0.642	0.538	0.995
q20[5]	Subordinates perform their work properly without being instructed by their manager	0.835	0.507	0.811	0.809	0.324
q20[6]	Employees need to be provided with conditions conducive to their development	0.006	0.023	0.011	0.152	0.008
q20[7]	The most important thing in the workplace is good interpersonal relations	0.092	0.381	0.589	0.088	0.628
q20[8]	Subordinates should participate in decision-making	0.375	0.297	0.559	0.038	0.350
q20[9]	I set a strict work schedule	0.909	0.629	0.189	0.179	0.169
q20[10]	The most difficult tasks should always be assigned to the most experienced employees	0.907	0.055	0.481	0.004	0.598
q20[11]	Never make concessions that compromise the effectiveness of your work	0.059	0.535	0.336	0.901	0.543
q20[12]	If necessary, most subordinates could perform their duties without the manager's assistance.	0.566	0.774	0.809	0.425	0.150
q20[13]	As many powers as possible should be delegated to subordinates	0.754	0.807	0.611	0.179	0.029

Question number	Survey question	A	B	C	D	E
q20[14]	It is the manager's responsibility to ensure that subordinates increase their general and professional knowledge, even if it is not necessary in the current situation.	0.470	0.947	0.687	0.279	0.514
q20[15]	Work discipline should be strengthened	0.084	0.887	0.599	0.062	0.158
q20[16]	Changes to objectives and methods should be agreed with subordinates	0.469	0.128	0.091	0.604	0.340

Legend:

A – ERP system implementation plan
B – CRM system implementation plan
C – Big Data tool implementation plan
D – AI tool implementation plan
E – Plan for implementing instant messaging tools

People who rate the tool higher evaluate a given aspect of management style more positively

People who rate the tool lower evaluate a given aspect of management style

There are no differences in management style ratings regardless of the barrier indicated

An interesting situation concerns plans to implement AI, which were asked about directly in the survey. Managers of companies planning to implement this tool have more visible participatory attitudes (p20[8]) and are more likely to express the belief that the most difficult tasks should be assigned to the most experienced employees (p20[10]). This phenomenon can be explained by the specific nature of AI projects, which are characterised by high complexity, unpredictability and the need to incorporate the knowledge and creativity of specialists from different areas of the organisation. A participatory management style enables managers to leverage the collective knowledge of the team during the implementation and testing of AI models. It is important to make joint decisions in processes with a high degree of uncertainty, in which AI is potentially to operate. At the same time, selectively assigning the most difficult tasks to the most experienced employees clearly responds to this need. It reduces the risk of errors and ensures the proper implementation of critical project elements. As a result, the combination of participation and selectivity in task allocation reflects an adaptive and strategic management style typical of companies implementing innovative solutions that require both expert knowledge and teamwork. The results of this part of the analysis indicate that the characteristics of the management style of managers in SMEs are in some respects related to technology implementation plans. The implementation of ERP, CRM, Big Data and instant messaging systems encourages a more controlling style, with limited employee autonomy and less emphasis on competence development. AI implementations, on the other hand, require a more participatory approach, with selective task allocation, reflecting the complexity and innovative nature of such projects. These mechanisms indicate that managers adapt their management style to the specific nature of the technology being implemented, taking into account both the requirements of process efficiency and the need to use expert competences in conditions of uncertainty.

4.14. To develop practical recommendations for public institutions and SME support organisations on how to support the implementation of AI

The recommendations are based on the data collected in the study. They refer to three key aspects: companies' expectations of surrounding institutions, barriers encountered, and benefits identified by entrepreneurs in connection with the implementation of artificial intelligence. Each recommendation corresponds to a specific area of company operations and the public support system. This study also presents the effects that can be expected if individual measures are implemented effectively.

4.14.1. Building competences and transferring know-how

Companies most often point to the need for support in the area of training (p7[73]; 54%) and technological consulting (p7[71]; 39%). At the same time, they signal a lack of knowledge (p3[31]; 31%) and difficulties in accessing training (p2[23]; 29%). These are therefore barriers hindering the development of AI technology in enterprises.

Recommendation

Public institutions should be involved in creating modular, short-term educational programmes and organising expert advice, including technological and business consultations.

Expected results:

Increased technological awareness in companies and a better understanding of the potential of AI. Reduction in the number of failed implementations resulting from a lack of competence or misidentification of needs. Increase in the percentage of companies ready to make investment decisions in AI.

The most frequently mentioned financial barriers are the high costs of training (p2[21]; 61%), licences (p2[22]; 54%), equipment (p2[25]; 32%) and expert services (p2[24]; 27%). At the same time, entrepreneurs expect co-financing (p7[72]; 44%) and subsidies (p7[75]; 21%), and express the need to develop knowledge and competence in the field of AI implementation.

Recommendation:

Introduction of financial instruments dedicated to SMEs that promote the development of the training sector and subsidise AI education, with particular emphasis on technical universities and those offering courses in science and IT. Due to the high dynamics of the AI adaptation process, simplified procedures and clear criteria are recommended. It is advisable to target the offer at universities that have.

Expected results:

Reducing the costs of training SME managers, stimulating the adoption of AI technologies by micro and small enterprises, increasing the number and quality of AI training programmes, accelerating the pace of AI adoption by SMEs.

Companies also point to difficulties in obtaining external funding (p2[210]; 10%) and low interest in public services (p7[76]; 12%). This is not a dominant group of companies, but they directly refer to the role of the public sector in digital development. The statements quoted from respondents may indicate insufficient transparency of the support system, excessive formal complexity of support programmes, or a lack of knowledge among managers about the types and programmes of support available.

Recommendation:

Review existing support programmes for digital transformation and AI adaptation. Create a unified service system for entrepreneurs interested in AI. For example, a portal offering information, advice, implementation guides and support in applying for funds.

Expected results:

Shortening the decision-making path on the part of entrepreneurs: from idea to implementation. Streamlining the subsidy system in the area of digital transformation, increasing the number of companies using public forms of support, reducing digital exclusion among SMEs unfamiliar with AI.

The study identified the problem of employee resistance to change (p3[33]; 25%), fear of losing authority (p3[34]; 16%) and lack of preparation for change management (p3[32]; 17%). These elements point to psychological and informational barriers. Organisational problems or a conservative approach to business management may also be possible.

Recommendation:

Public institutions should support initiatives that strengthen managerial competences in the areas of digital transformation, internal communication and team engagement. This should be complemented by information campaigns with examples of successful implementations in similar companies, creating a positive image and image of the benefits of using AI solutions, and campaigns raising awareness of the role and prevalence of AI solutions already in use. Also in the public sphere.

Expected results:

Increased organisational readiness for change and reduced concerns among employees and management, increased trust in technology through convincing examples from industry and everyday life, increased implementation effectiveness through increased openness and trust in AI among management, and alleviation of fears that the technology could potentially "get out of control".

The proposed measures have the potential to bring both short-term effects (e.g. an increase in the number of trained companies, the number of pilot projects, a reduction in entry costs) and long-term effects: building competence in the SME sector, lasting links with science, and increased innovation and competitiveness. These measures stem primarily from the expectations of business representatives, who reasonably expect knowledge and experience first, and financial support only at a later stage. The effectiveness of the proposed measures obviously depends on the coherence of the support system. It is therefore recommended that they be implemented in a coordinated manner, while maintaining regional sectoral specificity. It should be emphasised that innovators have already undergone or are in the process of undergoing digital transformation. They currently represent the innovation elite in the five countries surveyed, and can be expected to gain a competitive advantage as a result. However, the role of the public sector will be to counteract the technological stratification of the entire SME sector. It can, of course, be argued that the market will regulate itself, but the extremely dynamic, even turbulent nature of the current stage of digital transformation may lead to excessive digital exclusion of a large number of enterprises. Regardless of whether they are supporters or opponents of AI. These companies are not faced with their own aversion to the latest digital technologies, but are struggling with the pace of change: their staff cannot keep up with the technology in terms of skills, and its costs are currently prohibitive for a significant part of the sector. It is in this area that public intervention should come into play, and its effectiveness will have an impact on the competitiveness of the entire sector.

4.15. To compare the level of readiness for AI adaptation in SMEs between Central and Western Europe against the backdrop of Germany, and to draw conclusions about the development of technology in the context of the specific characteristics of each country

The study compared the level of companies' declared readiness to implement artificial intelligence (AI) solutions in three distinct territorial units: Western Europe, Central Europe and Germany (see chapter 4.1). As in the country-by-country analysis, seven variables were used to measure the perception of management competence, the level of digitalisation and the openness of organisations to technological innovation. The same methodology was also used here to measure interregional dependencies and assess differences. In the case of significant differences, post hoc tests were used to identify pairs of groups with statistically significant differences. The analysis focuses on comparing Germany – considered economically and culturally as a reference point – with Western Europe represented by Italy and Spain and Central Europe (Poland and Slovakia). The results of the study show relative homogeneity in the assessments of management knowledge, attitudes and strategies towards AI (Table 51). For six of the seven variables analysed, no statistically significant differences between regions were found ($p > 0.05$ in ANOVA and Kruskal–Wallis tests). For example, the level of knowledge of AI potential (q11[E1]) was rated at 3.5 in all three groups. The *p-values* for these variables remained well above the significance threshold, confirming the high consistency of management perceptions regardless of region.

As in Chapter 4, 4.1. variable q11[F8], referring to the belief that "the company should implement the latest AI-based solutions," proved to be an exception. In this case, ANOVA showed statistical significance ($p = 0.02$). This time, however, it was confirmed by the Kruskal–Wallis test ($p = 0.01$) and post hoc tests. They showed that there is a significant difference between the declarations in Western Europe (mean = 3.7) and Central Europe (mean = 3.5). In this context, Germany (mean = 3.6) ranks between these two groups, without any significant difference between them. This situation may indicate the existence of diverse innovation impulses between regions. Managers from Western Europe are clearly more convinced of the need to implement the latest technologies, which is probably due to more advanced markets and higher competitive pressure. Germany, as the largest economy in the EU, seems to play a role that may reflect the strong influence of this economy on the entire economic ecosystem of Europe. For methodological reasons, we should add that all the variables analysed showed significant deviations from the normal distribution ($p = 0.00$ in the Shapiro-Wilk test), which confirms the validity of the parallel use of non-parametric tests. Levene's test for variable q11[F8] did not indicate a violation of variance homogeneity ($p = 0.52$), which justified the use of ANOVA as the main comparative method.

The results of this part of the study confirm the overall consistency of management attitudes towards AI in the regions surveyed, with the exception of beliefs about the need to implement the latest solutions. Western Europe clearly stands out in this respect compared to Central Europe, while Germany represents an intermediate position.

In order to identify potential interregional differences in the level of preparedness of companies to implement artificial intelligence (AI) solutions, an analysis of binary responses ("yes"/"no") was conducted for thirteen variables describing the presence of various aspects of digital readiness. The methodology for analysing the differences is analogous to that in chapter 4.1.

The results indicate that in most cases the differences between regions are not statistically significant (Table 52. Significance of interregional differences based on yes/no response distributions in questions about readiness to implement AI). This suggests a relatively consistent and balanced process of AI preparation and adaptation. With regard to the key question about the actual use of AI tools (q12[q12]), no significant differences were found p = 0.27). Similarly, for the question about a formal AI strategy (q12[q14], p = 0.06), the p-value is just below the significance threshold, which may suggest a tendency towards differentiation, although not sufficient to draw clear statistical conclusions based on the sample analysed. The variable that achieved statistical significance is question q12[q110] concerning cooperation with an external AI technology provider. The p-value was 0.04, which indicates statistically significant differences between regions. Variables concerning applying for financial support for AI implementation (q12[q113], p = 0.08) and participation in AI training (q12[q16], p = 0.12) were also close to the significance threshold. Although they are not formally significant, they may indicate differences in the level of organisational activity and the availability of development programmes in individual regions.

Table 51. Comparison of mean values for assessments of individual areas of AI implementation readiness: regional analysis

Question number		Territorial unit				p-value				
		Western Europe	Central Europe	Germany	Overall	Normality test	Leaven's Test	ANOVA	Kruskal-Wallis Test	Post Hoc Test
q11[E1]	The management team at my company understands the potential and capabilities of AI technology.	0.5	0.5	0.5	0.5	0.00	0.15	0.82	0.55	-
q11[E2]	The management team at my company is looking for AI-based solutions.	0.4	0.4	0.3	0.4	0.00	0.73	0.35	0.25	-
q11[E3]	Management is open to AI technologies	0.5	0.5	0.6	0.6	0.00	0.17	0.77	0.84	-

Question number		Territorial unit				p-value				
		Western Europe	Central Europe	Germany	Overall	Normality test	Leaven's Test	ANOVA	Kruskal-Wallis Test	Post Hoc Test
q11[E4]	My company's management actively supports the use of AI in company processes	0.5	0.4	0.5	0.5	0.00	0.71	0.75	0.60	-
q11[R5]	Our company has a high level of digitalisation	0.6	0.6	0.7	0.6	0.00	0.08	0.54	0.67	-
q11[E7]	My company's management team is ready to implement AI	0.5	0.4	0.5	0.5	0.00	0.37	0.39	0.35	-
q11[F8]	My company should implement the latest AI-based solutions	0.7	0.5	0.6	0.6	0.00	0.52	0.02	0.01	0.01/0.04

Source: own research

With regard to IT systems, significant interregional differences were found in the use of ERP systems (q3[q31], p = 0.004) and generative AI (p = 0.04). However, the use of CRM systems (q3[q32]) and analytical tools (q3[q33]) did not show any significant differences (p = 0.06 and 0.22, respectively).

Table 52. Significance of interregional differences based on yes/no response distributions in questions about readiness to implement AI

Question number	Question	p-value chi-square test
q12[q12]	Does your company use artificial intelligence-based tools?	0.27
q12[q14]	Does your company have a formal strategy for implementing AI?	0.06
q12[q15]	Does your company have a specialist team/unit for implementing new technologies in the area of IT?	0.39
q12[q16]	Do your company's employees participate in AI training?	0.12

Question number	Question	p-value chi-square test
q12[q19]	Have you obtained a grant or funding for the implementation of AI in your company?	0.11
q12[q110]	Do you work with an external AI technology provider?	0.04
q12[q111]	Has your company previously conducted technology readiness assessments?	0.13
q12[q112]	Does your company cooperate with international partners in implementing new technologies?	0.19
q12[q113]	Has your company applied for financial support for the implementation of AI technologies?	0.08
q12[q114]	Has your company received financial support for implementing AI technology?	0.27
q3[q31]	ERP systems	0.004
q3[q32]	CRM	0.06
q3[q33]	Analytical tools (e.g. Big Data)	0.22
q3[q34]	Artificial intelligence (AI) (chat GPT, Gemini, Copilot, Deepseek, etc.)	0.04
q3[q34b]	Messengers (Teams, WhatsApp, Zoom, etc.)	0.27

Source: own research

As part of an in-depth analysis of interregional differences in companies' readiness to implement artificial intelligence (AI), two variables were identified for which statistically significant differences in the distribution of "yes"/"no" responses were noted. These are: q12[q110] – cooperation with an external AI technology provider and q3[q31] – use of ERP systems. In both cases, the p-values in the chi-square test were lower than the accepted significance level of $\alpha = 0.05$ (0.04 and 0.004, respectively), which confirms the diversity of responses between the analysed regions. Variables characterised by statistically significant differences require further comment. The variable (q12[q110]) refers to the question: "Do you collaborate with an external AI technology provider?" (see Table 53). The p-value of 0.04 indicates that there are significant differences between regions in terms of implementation strategies. Companies in different parts of Europe have different approaches to technology acquisition, with representatives from Western Europe showing the highest level of positive declarations of cooperation. This diversity may be due to many factors, primarily market maturity and cooperation culture. It may also result from the level of development of the national sector, the availability of local AI suppliers, the complexity of technological needs, or even differences in management culture. In regions with lower digital maturity and limited human resources (Central Europe is often cited as such a region), cooperation with external partners may be necessary due to a lack of internal expertise. In contrast, companies in Western Europe are more likely to have dedicated IT teams and strategically develop AI on their own. In Germany, as a country with a developed but balanced industrial model, both strategies can coexist, which explains their intermediate positioning in the analysis. The second important variable (q3[q31]) concerns the question: "Does your company use ERP systems?". The value of $p = 0.004$ indicates very significant differences between regions in the use of integrated management systems. ERP systems have been the foundation of digital infrastructure in enterprises for years – their implementation is a prerequisite for the efficient management of resources, finances, logistics and production processes. For this reason, they can be considered one of the key indicators of a company's technological maturity. Central Europe and Germany show a clear convergence of distributions, which may result from the high integration of production processes and local markets.

Table 53. Distribution of responses to questions by region for statistically significant differences.

Question number	Question	Region	No	Yes
q12[q110]	Do you collaborate with an external AI technology provider?	Western Europe	50	50
		Central Europe	60	40
		Germany	53	47
q3[q31]	ERP systems (implemented)	Western Europe	76%	24%
		Central Europe	66	34
		Germany	65	35
q3[q34]	Artificial intelligence (AI) (chat GPT, Gemini, Copilot, Deepseek, etc.)	Western Europe	42	58
		Central Europe	51	49
		Germany	47	53

Source: own research

The analysis of the results for question q3[q34] is also important for interpretation. This variable can serve as an indicator of the initial adaptation of AI tools. It is usually based on individual, bottom-up and often spontaneous implementations of artificial intelligence technology. The data indicate that the use of this type of AI tools in companies is still not widespread, but already half of the respondents indicate such use. We also note a significant level of interregional differences. This shows that representatives of Western Europe, including Germany, are slightly ahead of managers from Central Europe in their openness to new digital solutions. However, the differences are minor, and it is to be expected that all countries are in the same phase, although, as the results of this study indicate, the means and strategies for reaching this and subsequent stages may vary.

4.16. The influence of countries on management styles, approaches to AI implementation and readiness to implement AI

4.16.1. Assessment of managers' approaches to the AI implementation process in the countries surveyed

This analysis corresponds to the content described in the chapter 4.1. Here, an assessment was made as to whether the approach and openness to AI implementation depends on the country in which the company operates. The overall results indicate that knowledge and understanding of the capabilities of this tool are of the utmost importance in AI implementation (questions A1, A3, F5). Respondents most often declare that they understand how AI works, are aware of its limitations, and believe that the ability to use it will be an important asset in the labour market. The common denominator of this group is strategic and cognitive awareness – managers value AI primarily as a tool whose proper understanding and competence in its use are key to the development of their careers and companies. The group of moderately important variables includes issues related to the practical benefits of using AI (questions A2, B1, B2, D2, F6, F7, F8). Respondents indicate that AI enables them to increase productivity, generate valuable recommendations and improve the competitiveness of their companies. A focus on operational efficiency and the practical use of the tool provides real support in decision-making and improving business results. The least important aspects relate to experience in using AI and trust in its results (questions A4, A5, B3, D1, D3). Managers declare a lower level of practical knowledge and less confidence in the reliability of AI-based systems. This reveals a certain uncertainty and limited experience on the part of managers. AI is still in the exploration phase, and managers perceive barriers to practical application and doubts about the reliability of the generated results.

Table 54. Average values of managers' attitudes towards AI implementation by country. ANOVA and Kruskal-Wallis test results

Question code	Survey question	Poland	Slovakia	Spain	Italy	Germany	Total	P-value of the Kruskal-Wallis test	ANOVA**
q11[A1]	I understand how AI works	0.96	0.89	0.93	1.03	1.09	0.98	0.12	0.10
q11[A2]	I know how to use AI in my business	0.70	0.59	0.77	0.82	0.79	0.73	0.13	0.12
q11[A3]	I understand the capabilities and limitations of AI	0.89	0.89	0.83	0.94	0.93	0.89	0.70	0.70
q11[A4]	I have experience in using AI in my company	0.22	0.35	0.35	0.35	0.38	0.33	0.83	0.72
q11[A5]	The level of knowledge about AI in my company is high	0.23	0.23	0.22	0.37	0.36	0.28	0.36	0.49
q11[B1]	I see many advantages to using AI in the company's operations	0.53	0.75	0.74	0.75	0.70	0.70	0.15	0.17
q11[B2]	I increase my productivity thanks to AI	0.50	0.52	0.66	0.59	0.61	0.58	0.67	0.59
q11[B3]	Thanks to AI, I make decisions faster in my company	0.26	0.37	0.48	0.51	0.32	0.38	0.16	0.17
q11[D1]	AI-based systems are trustworthy	0.40	0.26	0.50	0.46	0.38	0.40	0.12	0.10
q11[D2]	AI is capable of generating valuable and reliable recommendations	0.49	0.51	0.70	0.62	0.57	0.58	0.29	0.15
q11[D3]	I trust the results generated by AI	0.33	0.33	0.54	0.44	0.38	0.41	0.13	0.16

Question code	Survey question	Poland	Slovakia	Spain	Italy	Germany	Total	P-value of the Kruskal -Wallis test	ANOVA**
q11[F5]	The ability to use AI at work will be an important asset in the labour market	0.90	0.81	0.94	0.95	0.83	0.88	0.25	0.41
q11[F6]	AI will increase my company's competitiveness	0.60	0.42	0.66	0.66	0.61	0.59	0.06	0.11
q11[F7]	I am in favour of my company investing in AI	0.50	0.5	0.65	0.65	0.56	0.57	0.45	0.49
q11[F8]	My company should implement the latest AI-based solutions	0.50	0.41	0.67	0.66	0.59	0.57	0.04	0.06

*) no significant differences in the multiple comparison test

**) The Shapiro-Wilk normality test shows that the variables do not have a normal distribution

Source: own research

It should be emphasised that the results of the analysis (Table 54) clearly exclude the influence of country on the formation of managers' approach to AI implementation. This approach is universal and statistically indistinguishable in the sample of SMEs surveyed. Some signs of diversity can be seen in question q11[F8] "My company should implement the latest AI-based solutions", but detailed multiple comparison tests ruled out such diversity

4.16.2. Assessment of the diversity of the SME sector's readiness to implement AI and the management styles of managers in the analysed countries

This subsection contains information on the potential differences in the level of preparedness of the SME sector, the use of AI, and the management style preferences of SME managers by country. The assessment of potential differences was based (as in the previous subsection) primarily on the Kruskal-Wallis test. The results were also reinforced by parametric ANOVA where the model assumptions allowed (relatively low deviation from symmetry + homogeneity of distributions). The symbol "-" in the tables indicates that it is not appropriate to use a statistical test. The results of the analysis are presented at 55 and Table 57. Statistical tests conducted on 38 out of 40 variables show that the location (country) of business operations does not differentiate the way SME managers are assessed. This essentially rules out the potential influence of the level of economic development of countries, historical or cultural conditions characterising the countries surveyed. A broader regional analysis is included in earlier sections of this study. Of the 40 variables analysed here, only two show evidence of conditions that differentiate some countries. These are questions marked with the symbols q12[q13] and q20[5], highlighted in bold in the tables. Significant differences in rank (rather than in measurement) were identified in the case of the question "Is the use of AI in the company a bottom-up initiative of employees?" (q12[q13]). A multiple comparison test shows that only Spain and Poland differ, while the other countries are in a kind of intermediate state (see Figure 1). Methodological caution should be exercised when assessing the reasons for this observation. Many (40) variables were tested, which are grouped into thematic and substantive subgroups. A single significant difference, concerning only one pair of countries (Spain and Poland), may be the result of chance or a combination of specific circumstances, which will be discussed further below. There may also be semantic issues: in Poland, a ‘grassroots initiative’ is often only declarative and signalling in nature ( ). Its acceptance depends on the reaction of the superior, so it is an internal feature of the organisation. In Spain, it is more embedded in everyday practice. "Iniciativa de abajo" or "iniciativa de los trabajadores" is more often understood as a natural part of everyday professional activity, accepted by the superior. Employees can introduce innovations on their own, treating it as something natural, which will later be adapted to the formal structure. Hence, research may show that Spaniards value bottom-up approaches more highly in the context of AI: for them, it is part of everyday practice, while in Poland it is more of a postulate that needs to be carefully harmonised with the hierarchy and the manager's approach. The statistical result described above may be reliable, provided that this topic is developed in separate, dedicated quantitative studies. Several explanations are possible, although it cannot be ruled out that the significant difference between Poland and Spain is due to the sample selection.

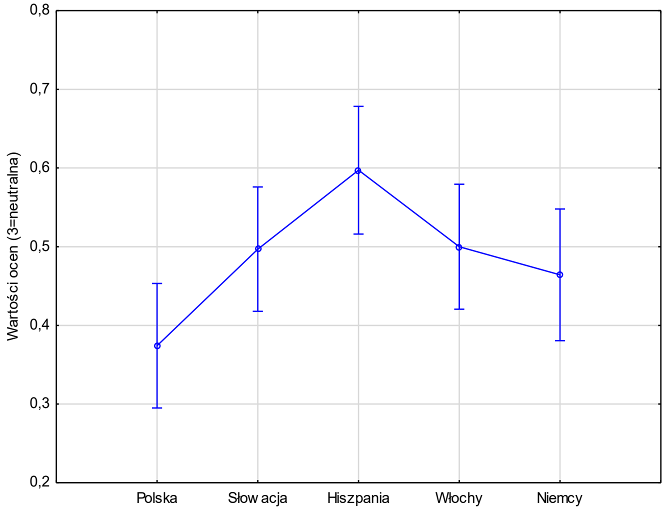

Figure 20. ANOVA Interaction Chart for question q12[13] "Is the use of AI in the company a bottom-up initiative of employees?"

Table 55. Analysis of the impact of country on the degree of preparedness of the SME sector for AI implementation

Question code	Survey question	Homogeneity of variance	Kruskal-Wallis test	Multiple comparison test	ANOVA**
q12[q11]	Are your products or services delivered to foreign customers?	0.000	0.190	-	-
q12[q12]	Does your company use artificial intelligence-based tools?	0.000	0.300	-	-
q12[q13]	Is the use of AI in the company a bottom-up initiative by employees?	0.000	0.004	0.009	-
q12[q14]	Does your company have a formal strategy for implementing AI?	0.001	0.170	-	-
q12[q15]	Does your company have a specialist team/unit for implementing new technologies in the area of IT?	0.256	0.260	-	0.266

Question code	Survey question	Homogeneity of variance	Kruskal-Wallis test	Multiple comparison test	ANOVA**
q12[q16]	Do your company's employees participate in AI training?	0.098	0.290	-	0.300
q12[q17]	Would you like to participate in such training in the near future?	0.000	0.012	0.065	-
q12[q18]	Does the company create databases with a view to using AI in company management?	0.479	0.140	-	0.143
q12[q19]	Have you obtained a grant or funding for implementing AI in your company?	0.000	0.021	0.100	-
q12[q110]	Do you collaborate with an external AI technology provider?	0.001	0.13	-	-
q12[q111]	Has the company previously conducted technology readiness assessments?	0.007	0.140	-	-
q12[q112]	Does your company cooperate with international partners in implementing new technologies?	0.512	0.404	-	0.405
q12[q113]	Has your company applied for financial support for the implementation of AI technology?	0.001	0.250	-	-
q12[q114]	Has your company received financial support for the implementation of AI technology?	0.000	0.150	-	-
q12[q115]	Has your company applied for support for the implementation of AI technology in the form of: grants	0.031	0.530	-	-
q12[q116]	Has your company applied for support for the implementation of AI technology in the form of: a low-interest loan	0.000	0.004	0.069	-
q12[q117]	Has your company applied for support for the implementation of AI technology in the form of: public services (consulting)	0.000	0.120	-	-
q12[q118]	Has your company received support for the implementation of AI technology in the form of: grants	0.070	0.580	-	0.582

Question code	Survey question	Homogeneity of variance	Kruskal-Wallis test	Multiple comparison test	ANOVA**
q12[q119]	Has your company received support for the implementation of AI technology in the form of: a low-interest loan	0.000	0.038	0.194	-
q12[q120]	Has your company received support for the implementation of AI technology in the form of: public services (consulting)	0.000	0.062	-	-
q12[q121]	Does your company plan to support the implementation of AI in the form of subsidies?	0.278	0.820	-	0.830
q12[q122]	Does your company plan to apply for support for AI implementation in the form of: a low-interest loan	0.066	0.740	-	0.741
q12[q123]	Does your company plan to apply for support for the implementation of AI in the form of public services (consulting)?	0.012	0.390	-	-
q12[q124]	Has your company ever paid for/purchased an AI-related service/product?	0.390	0.880	-	0.885

**)The Shapiro-Wilk normality test shows that the variables do not have a normal distribution

Source: own research

Table 56. Analysis of the impact of country on the management styles of SME managers

Question code	Survey question	Homogeneity of variance	Kruskal-Wallis test	Multiple comparison test	ANOVA**
q20[1]	He makes the decision himself and then informs his superiors about it	0.478	0.180	-	0.124
q20[2]	I allow people to work independently, even if they may make mistakes	0.090	0.560	-	0.295
q20[3]	I believe that the workplace exists primarily to achieve production targets	0.116	0.032	0.258	0.035

Question code	Survey question	Homogeneity of variance	Kruskal-Wallis test	Multiple comparison test	ANOVA**
q20[4]	Discussions are helpful in the development of subordinates	0.639	0.070	-	0.067
q20[5]	**Subordinates perform their work properly without being instructed by their manager**	**0.012**	**0.004**	**0.045**	**-**
q20[6]	Employees need to be provided with conditions conducive to their development	0.009	0.630	-	-
q20[7]	The most important thing in the workplace is good interpersonal relations.	0.598	0.660	-	0.634
q20[8]	Subordinates should participate in decision-making	0.667	0.300	-	0.444
q20[9]	I set a strict work schedule	0.282	0.850	-	0.770
q20[10]	The most difficult tasks should always be assigned to the most experienced employees	0.108	0.470	-	0.466
q20[11]	Never make concessions that compromise the effectiveness of your work	0.392	0.670	-	0.889
q20[12]	If necessary, most subordinates could perform their duties without the manager's assistance.	0.584	0.590	-	0.609
q20[13]	As many powers as possible should be delegated to subordinates	0.522	0.360	-	0.305
q20[14]	Caring for the improvement of the general and professional knowledge of subordinates, even when it is not necessary in the current situation, is the responsibility of the manager.	0.418	0.307	-	0.364
q20[15]	Work discipline should be strengthened	0.613	0.319	-	0.211
q20[16]	Changes to objectives and methods should be agreed with subordinates	0.507	0.110	-	0.119

**)The Shapiro-Wilk normality test shows that the variables do not have a normal distribution.

Source: own research

The results of this study show that the overall level of AI implementation in Spanish companies is higher (according to this study, 12% use AI) than in Poland (9.3%). This in itself promotes the acceptance of grassroots initiatives (experiments with technology) by employees. In turn, according to Eurostat statistics for 2024, the EU average is 13.5%, but Poland is among the weakest in the EU (3.7% in 2023; in 2024 approx. 5.9%), which means a poorer ecosystem of tools and practices, where spontaneous employee initiatives are more difficult to come by. Secondly, the literature on organisational culture points to differences that favour bottom-up approaches in Spain compared to Poland. The profile of AI applications in Spain (administration, sales/marketing, cybersecurity) coincides with areas where employees often test tools themselves (e.g. text assistants, CRM automation) and only then are they formalised by IT or management. Why is there no difference in comparisons with Germany, Italy or Slovakia? It is possible that other implementation paths dominate in these countries (e.g. top-down in large German companies), which means that the perception of "bottom-up" does not differ statistically from Poland, even though the overall level of AI implementation is sometimes higher. It is also possible that these exceptions confirm that the differences result from the specific nature of the study and do not characterise the population.

The second question in which differences in rank were identified (note: there is no difference in the average values of the ratings) is q20[5] "Subordinates do their job properly without being told to do so by their manager". In this case, multiple comparison analysis showed that there are significant differences between Italy (where the rank of this statement is lower) and Poland and Germany. At the same time, there is no statistically significant difference between neighbouring Poland and Germany (Figure 2). The methodological reservations are the same as for question q12[13]. In this case, too, the study should be expanded to include a more in-depth quantitative analysis, as other questions describing the sphere of employee inclusion, trust and forms of cooperation within the team do not confirm these differences. However, the convergence of assessments in Poland and Germany, as countries with strong economic and cultural integration, speaks in favour of the correlations diagnosed here. This convergence indicates a stable pattern that is unlikely to be a random observation. The difference compared to Italy also fits well with the well-known, almost commonplace typologies of "German" and "Italian" work cultures. Therefore, the difference indicated in the tests can be preliminarily treated as a justified cultural effect rather than a random statistical deviation. Based on the convergence of Poland and Germany, against the backdrop of Italy's clear deviation (in the negative), a cautious diagnosis can be made: in Poland and Germany, the emphasis is usually placed on self-discipline, established forms of cooperation, diligence, and formalised procedures. Supervision is important as an element of the structure, but it does not define the quality of work itself, which is determined by the established form and culture of work. Employees "know what to do and how to do it", and their superiors do not have to constantly remind them of their duties. In Italy, the manager plays a greater role in the process of motivation and organisation, where supervision and guidance are treated as natural components of work, rather than an expression of a lack of independence. This is probably due to a slightly different understanding of the manager-subordinate relationship. Italian organisational culture is characterised by a higher level of relationality and contextuality. A manager is expected to be not only a superior, but also an active participant in the work process. Someone who, through frequent interaction, guidance and supervision, ensures the consistency of the team's actions. This does not mean a lack of responsibility on the part of employees, but rather a different understanding of "proper performance" (as in the previous question, this concerns the understanding of the concepts contained in the survey question). Italian research on leadership styles indicates that a leader acts as a mediator and coordinator, not just someone who gives orders. Hence, in the perception of Italian respondents, working without orders is not an ideal model, but an incomplete situation, lacking the relational element and therefore considered less important from a manager's point of view.

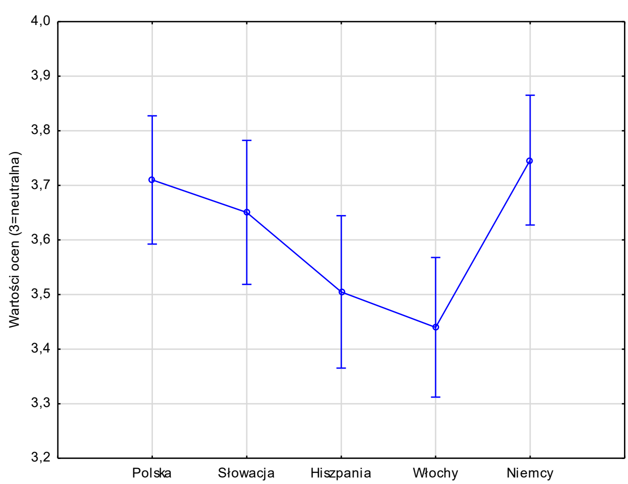

Figure 21. ANOVA Interaction Chart for question q20[5] "Subordinates do their job properly without orders from their manager."

Therefore, it is impossible to speak of a significant impact on the values of variables and the way respondents rank statements by such general factors as historical and economic conditions, the date of accession to the EU, etc. As has been shown, there are practically no differences in the values of variables in terms of country affiliation. It is therefore futile to look for the influence of external factors describing the state of countries where the variables do not differ. Any influence on the two variables described above is subtle and difficult to measure. This is because it concerns aspects of interpersonal relations and the propensity for grassroots initiatives.

5. Conclusions and recommendations

5.1. Key findings from the study

Managers who use AI tools are characterised by a higher level of innovation orientation, openness to technology and flexibility in decision-making.

In companies where management uses generative AI, there is a more open attitude towards implementing new solutions and a willingness to implement new processes. These attitudes cover both strategic and operational areas. These managers are more likely to see technological change as an opportunity rather than a threat. A higher level of acceptance for innovative solutions allows for better use of available information, which promotes faster response to market challenges. This group of managers is more willing to use data analysis tools, which translates into analysis-based decisions.

The use of AI is associated with a greater emphasis on process efficiency, streamlining and teamwork discipline.

Managers who use artificial intelligence tools tend to shorten decision-making processes and eliminate decision-making procedures within the team. They perceive automation as an element that increases productivity. This way of thinking allows them to better manage the team's time and resources, as well as increase the pace of project implementation. There is also a greater willingness to entrust some analytical tasks to systems rather than people. At the current stage of implementation, this does not exclude but rather stimulates cooperation and interaction within the organisational structure; it potentially allows for a focus on tasks that require creativity and interpersonal interaction.

Companies using AI have a basis for better risk management thanks to greater precision in analysis and forecasting.

Some survey questions touch on the aspect of risk, task delegation and responsibility. Based on these, it can be argued that managers using AI solutions are more likely to consider a wider set of variables in their decision-making processes. According to their statements, they emphasise greater discipline in the execution of tasks, while demanding the same from others. This potentially reduces the risk of wrong decisions. There is a tendency here to use data-driven methods instead of intuitive decision-making. In the future, this may translate into more predictable and stable business results.

There are noticeable differences in the approach to communication between AI users and those who do not use these tools.

Managers who use AI place greater emphasis on clarity of communication and selective sharing of information. Given the potential risks (e.g. excessive fragmentation of information), this can lead to more effective data exchange within teams. Those who do not use AI are more likely to rely on direct interactions and traditional, conservative forms of communication, which helps to maintain the established model of relationships but can prolong processes. It should be emphasised that no reduction in the importance of interpersonal relationships was observed in the group of AI managers.

The use of instant messaging significantly affects the dynamics of teamwork.

Managers who make intensive use of instant messaging prefer quick and direct contact. At the same time, they emphasise that they value less formal forms of communication and cooperation. However, they maintain a higher level of discipline and care for the quality of their work. They are also focused on the humanistic aspect of the team's activities.

The combination of AI and instant messaging creates a profile of a manager who is focused on quick responses but requires a high level of self-discipline in information management.

Managers who combine both types of tools reap the greatest benefits in terms of flexibility and teamwork efficiency. AI certainly enables them to better filter, verify and analyse data, while instant messaging provides immediate contact. These managers are also committed to the responsibility of pursuing the company's formally set goals. There are indications that the use of both tools is a bottom-up, informal initiative. Therefore, in practice, combining these types of tools in the future will require the development of procedures to minimise the multitude of messages. This seems to be a challenge for the SME sector, which largely operates in less formalised and more horizontal organisational structures.

Regional differences affect SMEs' readiness to implement AI.

The analysis revealed clear differences between regions in terms of the formal basis for implementing artificial intelligence solutions. This applies in particular to elements such as the development of a coherent implementation strategy or establishing relationships with external technology providers.

In regions where readiness is higher, better organisation of processes, greater formalisation and a higher degree of openness to cooperation can be observed. On the other hand, areas with lower levels of these indicators may encounter barriers in accessing expert knowledge, tools and funding. This is an obstacle in these regions, primarily directed against the development of skills and human capital. Such diversity suggests that (at least in some areas) the development of AI across Europe will not be uniform and that the benefits of implementation will first be reaped by those regions that are already investing in organisational capital and the institutional foundations for digital transformation.

Relationships with external technology providers can influence the pace and cost of AI implementation.

External technology providers play a key role in the AI implementation process. Differences between regions may indicate that where such cooperation is more frequent, organisations move more quickly from the planning stage to actual implementation. It can be expected that a higher frequency of such relationships is associated with better knowledge transfer, access to modern tools and the opportunity to benefit from the experience of partners with an international reach. The lack of such links in some regions may limit the pace of competence development. It also prolongs the process of technology adaptation and may increase implementation costs (due to lower supply).

Technological maturity is a factor stimulating the adaptation of AI.

Another factor differentiating regions is the degree of technological readiness in companies. Organisations that focus on increasing their "technological resources" are clearly better prepared for implementation. Readiness analysis allows gaps in infrastructure, human resources and processes to be identified. It constitutes a knowledge resource, the lack of which is reported by a large proportion of the companies surveyed. This knowledge enables the development of an implementation plan. The lack of this type of knowledge about a company's technological advancement can result in decisions being made based on intuition, incomplete information, and bottom-up but uncoordinated actions. The results of the study suggest that the practice of assessing technological maturity, especially in regions with a lower degree of digitisation, could significantly shorten the path to AI adoption.

Integrated management systems form the basis for the formal implementation of AI in SMEs.

One of the key indicators of readiness for AI implementation is the use of sophisticated, integrated systems that support enterprise process management. Companies using such tools have achieved a high level of data integration. They also have a much better starting point for implementing intelligent solutions. These systems reduce the phenomenon of "information islands" and promote the consistency and quality of data used in AI. This, in turn, reduces risks and builds trust in the technology. Slight but noticeable regional differences in this area may reflect the overall level of digitisation of the local economy and the willingness to invest in modern IT tools. Areas with a lower level of implementation of such systems will require greater expenditure on infrastructure preparation.

The actual implementation of AI tools in operational practice.

A very interesting result of the study is the lack of statistically significant differences between regions in the current use of AI tools. The results indicate that the level of their adaptation remains relatively low. This may mean that the implementation of AI is at a similar early stage of development regardless of geographical location. However, in light of the research, it appears that the key differences between regions are not so much about the possession of the technology itself, but rather the degree of organisational preparedness and the strategy for reaching the point of implementation. Here, the differences are already clearly outlined. In practice, this means that in the coming years, there may be differences in the dynamics of AI adoption growth. It will be faster in regions that are prepared and slower in those where the process of building competencies is just beginning.

The competencies of management staff influence the effectiveness of AI adaptation by focusing on the development of employees' digital competencies.

The analysis reveals that one of the factors determining the effectiveness of AI implementation is the level of technological knowledge and awareness of managers. This is articulated in both the declared needs, barriers and review of data on management style. The need to improve AI skills is so strong that it even equals the need to finance the digital transformation towards AI. In organisations where managers have the ability to assess the potential of AI tools and understand their limitations, the implementation process will run more smoothly and with potentially less risk of misguided investments. This is because managers prefer a rational implementation model of knowledge->experience->investment. Managers with high digital skills are more likely to engage in employee education, build a culture of openness to innovation, and are likely to skilfully integrate new technologies into existing processes. Where these competencies are limited, implementations may take on an experimental character, unsupported by strategic consistency and the commitment of the entire company structure. This increases the likelihood of fragmented or short-lived effects. The results of the study indicate the need to develop management and technological skills in parallel as the foundation for effective transformation.

Acceptance and inclusion are prerequisites for successful AI implementation….

The level of an organisation's readiness to adapt AI depends not only on infrastructure and strategy, but also on the attitudes of the employees themselves. Research shows that where there is a high level of acceptance of new technologies, the implementation process is more advanced. Acceptance involves, among other things, a greater belief in the benefits of automation. A sense of job security and a clear understanding of how AI can affect daily duties are also expected. This requires not only bottom-up initiatives, but also a formalised approach and conscious management of the (formal) implementation of AI. On the other hand, low levels of trust or fears of job losses can effectively slow down the pace of implementation, although they will certainly not stop it. The benefits seem to outweigh the disadvantages. This result emphasises that the implementation strategy should include communication activities, transparent information about objectives, training programmes and building employee competencies. It is therefore crucial to involve employees in the transformation process, rather than simply imposing ready-made solutions on them.

A synthetic assessment of SMEs' readiness to implement AI in regions and at different levels of technological development.

The readiness of small and medium-sized enterprises (SMEs) to implement artificial intelligence largely depends on regional conditions and the level of technological development of the environment in which they operate. In regions with a documented higher degree of economic digitisation, developed ICT infrastructure and easy access to know-how, the barriers to entry into AI technologies will be lower. Above all, companies there can benefit from local IT service providers, technology partners, innovation support networks (consultants, training services, etc.) and, what seems to be a significant factor, an established standard of cooperation in the field of IT. These are the foundations for faster adaptation of new tools. In such regions, there is greater competitive pressure resulting from the prevalence of data-based solutions, but this encourages SMEs to invest in AI in order to maintain or strengthen their market position. The opposite situation occurs in regions with lower levels of technological development, where infrastructure limitations are less significant, but the lack of qualified personnel and weaker links to innovation ecosystems are likely to slow down the process of AI implementation to a greater extent. The lack of internal know-how in companies is particularly noticeable. It can be expected that companies are also concerned about investment risk, the unpredictable return on investment at the current stage of AI implementation, and the difficulty of integrating new solutions with existing, often traditional, company systems and operating models. This explains the previously mentioned expectation that investment should be preceded by knowledge and experience. The lack of local examples of successful formal implementations may further reduce the willingness to experiment with the technology. Regional conditions may also have a cultural, organisational and institutional dimension. In regions with a tradition of cooperation between science and business, modern management models and active support from public administration, there is a clearly higher level of openness to AI. We can see this when comparing Western European countries with Central European countries. Although the differences are not dramatic, they are nevertheless visible. In less technologically developed environments, on the other hand, decisions to implement AI are more often made only after external impulses or as a result of informal grassroots initiatives. Companies are less likely to have formal strategies in this area. Some companies use external funding for AI-related purposes, and the process of applying for funds requires strategy and planning. Therefore, in addition to its financial dimension, the grant system can also have an impact on strategic and technological readiness. The lack of prior technological readiness analyses, the relatively low rating of the grant system, the involvement of the public sector and limited (at least in the SME sector) cooperation with international partners may result in a more cautious formal decision-making process regarding implementations. As a result, the readiness of SMEs to adapt AI in such countries is a combination of available, albeit modest, resources and can be considered slightly lower. Ultimately, it can be concluded that the readiness of SMEs to implement AI is not solely based on the individual strategy of the company, but is largely determined by the regional environment and the availability of technological resources. Regions with a higher level of development have the capacity to create ecosystems that support innovation, while in technologically weaker areas it is necessary to implement support measures such as educational programmes, cooperation networks or easier access to financing with formal requirements conducive to the development of strategies and planning for AI implementation.

In light of the research, management style plays a significant role in the implementation of both AI tools and Big Data solutions, with this impact manifesting itself in several interrelated dimensions. In companies where management styles based on high employee autonomy, participation in decision-making and the promotion of innovation, cooperation with care for the well-being and education of employees prevail, the implementation of new technologies is more advanced (especially in relation to communication, AI and Big Data). The data shows that managers with this approach are more likely to give high priority to digital solutions (including AI). They recognise their strategic value, trust AI results and are willing to invest in their implementation. This management style is also associated with the development of employees' AI skills, which also promotes effective implementation. Managers with this approach see AI and Big Data as tools that support decision-making processes, rather than a substitute for teamwork or team interaction. Their assessments in this study show that, in the opinion of AI managers, technology does not replace humans, but enhances their capabilities. This perception facilitates the acceptance of new solutions among teams. An alternative management model revealed by the study is a more centralised, controlling model based on more rigid procedures. In this case, the implementation of AI and Big Data is somewhat slower. In such organisations, new technology may be treated more as a tool for supervision or cost optimisation than as a catalyst for innovation and work efficiency. The results also suggest that in these companies, managers are more likely to perceive analytical technologies as costly and involving organisational risk, which may result in greater investment caution and slightly slower implementation. As the research shows, there are grounds for concluding that managers with a participatory and open style are more willing to involve employees in decision-making processes concerning the selection and implementation of digital solutions, while emphasising discipline and quality of analysis. In hierarchical organisations, where communication is one-way (usually top-down), acceptance tends to be lower and implementation is more formal and administrative in nature. An important factor differentiating the effectiveness of implementation is managers' focus on employee development. A leadership style that invests in improving staff qualifications , creating paths for digital competence development and systematic training translates into greater implementation efficiency and a faster pace of adaptation of Big Data and AI tools. Managers report these areas as requiring intensive intervention and define them as needs.

The management style in SMEs influences how and at what pace AI and Big Data solutions are implemented. Participatory and developmental leadership models foster a culture of innovation and full exploitation of the potential of technology. Conservative, controlling and somewhat conservative styles may limit the dynamics of transformation, although it must be admitted that they can provide greater control over the risks and threats associated with the use of AI.

Financial, organisational and technical barriers as a deterrent to the implementation of AI in SMEs.

Economic barriers, such as high implementation costs (from the point of view of SMEs), lack of funds for investment or limited access to external financing, mean that some companies, despite expecting benefits, are postponing decisions on AI implementation until the future. This is particularly true in less developed economies, such as Poland and Slovakia. In SMEs, where investment budgets are more limited, the risk of implementation failure is certainly perceived as much greater than in large enterprises, which further weakens the willingness to take action. Secondly, organisational barriers such as a lack of specialist skills, insufficiently developed technical infrastructure, a lack of formal ERP systems, conservative management styles or business processes that are not aligned with the requirements of the technology can limit the possibility of effective AI implementation. In companies where there is no culture of data analysis and experimentation with new tools, AI is often treated as a curiosity rather than an element of digital transformation. This is why AI, instant messaging and big data analytics are used much less frequently in companies in Central European countries. As a result, even if implementation does take place, the technology is likely to be used in a fragmented manner and without full synergy. Thirdly, barriers such as employee fears of job losses, lack of trust in automated recommendations or low acceptance of change can cause AI projects to encounter resistance at the team level. Managers who fear conflict or a decline in employee morale may either limit the scale of implementation by choosing less invasive projects or introduce the technology covertly, which not only reduces its strategic importance but also increases the distrust of employees who are not involved in the adaptation process. The combined impact of these barriers can result in one of the pessimistic scenarios described earlier (see chapter 4.2). The lack of competence and infrastructure potentially limits the effectiveness of initial implementations, leading to weaker results, which in turn increase scepticism and reluctance to make further investments. As a result, SMEs may remain at the technological "tail" of the market, losing their competitive advantage to companies that have already overcome these barriers. These scenarios seem realistic: the results show that many companies do not have coherent plans or strategies for integrating AI into their business processes. Therefore, there are no clearly defined goals for this technology to achieve or expected results to be achieved. The lack of such documents/strategies may result in incomplete implementations. This situation is likely due to the lack of specialist knowledge highlighted in the study: in the SME sector, access to specialist know-how and resources is limited. This applies to human, technical and financial resources. In companies where there are no qualified IT teams or AI experts, implementation processes are significantly prolonged, becoming an obstacle already at the planning stage. The data indicates that companies report a need for training to improve their employees' skills in new technologies, as they face difficulties in adapting tools and using them effectively. An obvious obstacle, although not a primary one, is the lack of access to external financing, grants or technology partnerships, which reduces the ability of companies to cover the high initial costs associated with AI implementation. The barriers identified in the study therefore form a complex network of constraints in which organisational, resource and cultural factors reinforce each other. However, they should not be seen as a factor that precludes the implementation of AI. This process will take place, but in the case of companies with shortages, it will be much slower and perhaps less effective. The lack of strategy and readiness analysis should be viewed in a similar light: it limits the accuracy of investments. All these factors slow down the pace of implementation, which, combined with conservative management styles, reduces openness to experimentation and innovation. Overcoming these barriers therefore requires a systemic approach – combining strategic planning with competence development, partnership building and the development of an SME organisational culture. These initiatives will foster inevitable technological change.

5.2. Recommendations for SMEs regarding the implementation of AI

The research conducted has allowed us to formulate reasonable conclusions regarding the implementation of AI in SMEs.

1. The level of AI implementation in SMEs in the EU is low and varies significantly from region to region The survey and literature review confirm the continuing "digital divide" between EU countries. Northern and Western European countries (Denmark, Sweden, Germany) have a significantly higher level of AI adoption than Central and Eastern European countries (Poland, Slovakia) and some southern countries (Spain, Italy). These differences exceed 20 percentage points and are structural in nature. The vast majority of surveyed companies do not use AI systematically. Where AI is used, it is ad hoc and tool-based (e.g., content generation, simple data analysis) rather than integrated into the company's development strategy. Our study confirms this: although 49% of SMEs surveyed report some use of AI tools, only 32.9% of companies have a formal AI implementation strategy. This means that more than 1/3 of companies using AI do so in an ad hoc and uncoordinated manner, without embedding the technology in the organisation's development strategy.

2. SMEs' readiness to implement AI remains insufficient In most of the countries surveyed, SMEs assess their financial, technical, and competence resources as insufficient for the full implementation of AI. Particularly evident is the deficit in digital and managerial competences in the strategic use of AI, not just in point tools (e.g., process automation). Managers and owners of SMEs in most countries recognise the potential benefits of AI (efficiency, time savings, decision support, competitive advantage), but at the same time assess their own organisational and competence readiness as insufficient for real implementation. Analysis of the survey results on the Likert scale indicates a moderate level of confidence and readiness for implementation, with values slightly positive rather than high. This means that a cautious attitude prevails over a proactive one.

3. The adaptation of AI is strongly correlated with the level of economic development in a given country.

A comparative analysis showed a significant correlation between GDP per capita and the level of AI use in enterprises. Countries with higher productivity and digital maturity are implementing AI more quickly, further strengthening their competitive advantage and deepening development inequalities in the EU. The survey results clearly show that the key limitation is not access to AI tools, but rather:

- the lack of digital skills among management staff,
- low level of understanding of how AI works,
- difficulty in assessing the cost-effectiveness of implementations.

Technological and infrastructural barriers are therefore secondary. Although 68.7% of respondents have a university degree and 60% declare a technical profile, the survey revealed apparent deficits in the practical use of AI in companies. Companies point to the need for training and competence support as a prerequisite for effective implementation, underscoring the gap between formal education and operational readiness to deploy AI.

4. The most common applications of AI in SMEs are operational rather than strategic.

SMEs use AI mainly for data analysis, automating simple processes, content generation, image recognition, and operational decision support. AI is less often part of a long-term development strategy, product innovation, or business model transformation. The costs of AI implementation are perceived as a significant investment risk. Respondents, especially in SMEs from Central and Eastern Europe, point to concerns about implementation costs, uncertainty about return on investment, and limited access to dedicated financing as significant factors inhibiting decisions to implement AI. A substantial proportion of SMEs cite lack of access to external funding, grants, and technology partnerships as a factor inhibiting AI implementation. Although this is not a dominant barrier, high initial costs and investment risk effectively slow down the adaptation process, especially in SMEs without their own IT teams.

5. The barriers to AI implementation are multidimensional and include:

- financial (implementation costs, lack of access to capital),
- competence (shortage of specialists, low managerial awareness),
- organisational (lack of digital strategy, resistance to change),
- institutional and regulatory (legal uncertainty, complexity of regulations).

6. Mental barriers and lack of trust in AI are particularly evident in SMEs in Central and Eastern European countries. Lower level of actual AI use as an indirect indicator of mental barriers in the Central and Eastern European countries covered by the study (Poland, Slovakia), the percentage of SMEs using AI is significantly lower than in Western European countries and Germany:

- Poland: 5.9% of SMEs use AI
- Slovakia: approx. 7–8% of SMEs
- Germany: 19% of SMEs
- Spain: 9–10% of SMEs
- Italy: approx. 12% of SMEs

The difference between Poland and Germany is over 13 percentage points, which – given comparable access to basic digital tools – indicates not only economic barriers but also lower confidence and greater caution in decision-making among SME managers in Central and Eastern Europe.

A declarative attitude towards AI was obtained with a predominance of neutral and cautious responses. In the survey (Likert scale −2 to +2):

- the average ratings for trust in AI and readiness for implementation are close to neutral (0),
- there is no dominance of "definitely yes" responses,
- in Central and Eastern European countries, the following responses are more common: *"rather no" and "I have no opinion"*.

This means that cognitive and affective attitudes towards AI are clearly more conservative, which the authors of the report interpret as a manifestation of mental barriers rather than a lack of awareness of the technology's existence.

Thus, mental barriers and lack of trust in AI in SMEs are particularly evident in Central and Eastern European countries, which is reflected in the lower level of actual AI use (Poland 5.9% vs Germany 19%), the predominance of neutral and cautious attitudes in the survey, and the lack of systemic strategies for implementing AI despite the relatively high level of education of management staff.

7. Management style and managerial attitudes significantly influence decisions to implement AI.

The study confirms that managers who are more open to innovation, risk-taking, and a strategic orientation are more likely to implement AI. Management style differentiates the approach to AI as strongly as economic or technological factors

Analysis of survey responses confirms that managers with the following styles:

- more innovative,
- proactive,
- strategically oriented

They are significantly more likely to declare their readiness to implement AI and have a positive attitude towards this technology. A conservative, strongly hierarchical style correlates with a reluctance to adopt AI.

Survey data confirm that SMEs managed in an innovative, proactive, and strategic manner are more likely to declare their readiness to implement AI, as reflected in a higher percentage of companies with an AI strategy (32.9%) and bottom-up initiatives (35.7%). On the other hand, the conservative and hierarchical style, which is dominant in over 60% of the SMEs surveyed, correlates with a lack of an AI strategy and reluctance to implement AI at scale.

8. There are apparent regional differences and differences resulting from the length of EU membership between the countries covered by the survey:

- SMEs in Germany more often declare actual implementations and a higher level of organisational maturity,
- SMEs in Poland and Slovakia more often point to competence and financial barriers,
- Spain and Italy occupy an intermediate position – more open than Central Europe, but lacking systematic implementation.

9. AI is not yet seen as a key element of SME competitive strategy

Although 49% of companies use AI, only one in three (32.9%) has a strategy for its implementation. This means that for most SMEs, AI remains only an operational or experimental tool, rather than an integral part of their business model and long-term competitiveness. Literature reviews and our own research indicate a gap between the ambitions of EU policies and the real capabilities of SMEs. The EU's objectives set out in strategic documents such as Digital Decade 2030 and the EU SME Strategy envisage the mass implementation of AI in enterprises. Still, without more intensive financial, training, and advisory support, SMEs will not be able to achieve them. This is particularly true for peripheral regions and economies in Central and Eastern Europe.

10. AI should be treated as a tool for cohesion, not just innovation

The even adaptation of AI in SMEs should become an instrument for strengthening the economic and social cohesion of the EU. The lack of coordinated action risks further technological fragmentation of the Union and weakening its global competitiveness. EU policy on supporting the implementation of AI should be differentiated and tailored to the needs of individual countries and regions, as **there are apparent differences between the countries covered by the study:**

– SMEs in Germany report the highest level of AI implementation and competence in this area,
– SMEs in Poland and Slovakia have the lowest level of AI implementation and competence in this area,
– SMEs in Spain and Italy are in the middle, with relatively greater openness but limited systematic implementation.

In summary, the research results confirm the assumptions made in the project grant application, as specified in the objectives and all research hypotheses.

Based on the results of the research, the following recommendations for SMEs in the field of AI implementation were formulated:

1. Transition from ad hoc implementations to a strategic approach

SMEs should treat AI not as a single operational tool, but as part of a long-term strategy for development and competitiveness. It is recommended to develop a simple but formal AI strategy that defines business objectives, areas of application, implementation stages, and performance measures. The lack of such a strategy encourages fragmented and ineffective implementations.

2. Gradual implementation of AI in key business processes

   Instead of attempting a comprehensive transformation, SMEs should start with pilot implementations in areas with the most significant potential for return, such as data analysis, management decision support, administrative process automation, marketing, and customer service. This allows them to reduce risk and build trust in the technology.

3. Investing in managerial and employee AI skills

   The key barrier to AI implementation is a lack of skills, not a lack of technology. SMEs should invest in training for management and key employees, focusing not only on using the tools but also on understanding the capabilities, limitations, and business implications of AI.

4. Strengthening the role of the manager as a leader of digital transformation

   Research shows that management style significantly impacts AI implementation. It is recommended to develop an innovative, proactive, and strategic management style based on openness to experimentation, learning, and the acceptance of controlled risk.

5. Leveraging bottom-up initiatives from employees

   SMEs should create conditions conducive to bottom-up initiatives, encouraging employees to test AI tools and submit ideas for their application. This approach increases acceptance of the technology, reduces mental barriers, and accelerates implementation.

6. Building an organisational culture based on data and trust in technology

   Effective AI implementation requires the development of an organisational culture in which decisions are based on data and technology is seen as support rather than a threat. It is recommended to conduct internal communication to explain the role of AI and its impact on teamwork.

7. Using external support and technology partnerships

   Due to SMEs' limited resources, it is advisable to engage external technology providers, consultants, and support institutions, including innovation centres and public programmes. Partnerships reduce entry costs and shorten implementation time.

8. Taking ethical and regulatory aspects into account at the planning stage

SMEs should consider data protection, liability, and compliance with EU AI regulations from the outset. Early consideration of these aspects reduces legal risk and strengthens customer and employee confidence.

9. Systematic evaluation of the effects of AI implementation

It is recommended to regularly monitor the results of AI implementations in terms of effectiveness, cost savings, and impact on competitiveness. This allows for adjusting activities, scaling practical solutions, and discontinuing tools with low added value. Communicating the positive effects of AI implementation to employees will increase their motivation to use it, enhance their understanding of its importance and purpose, and stimulate creative attitudes towards its use.

5.3. Recommendations for public institutions and EU policy

Based on the research conducted and the conclusions drawn, recommendations for public institutions and policymakers at the national and EU levels have been developed. The following is recommended:

1. Focusing public policies on the real needs of SMEs, rather than solely on the strategic objectives of the EU

Public institutions should adapt AI support instruments to the actual level of SME readiness. The current gap between the EU's ambitious goals and the SME sector's real capabilities requires more pragmatic, phased solutions that account for companies' organisational and competence limitations.

2. Prioritise competence support over technological support

Research results indicate that the main barrier to AI implementation in SMEs is a lack of knowledge and competence, rather than access to tools. It is recommended to develop programmes for:

- management training in the strategic use of AI,
- practical training for SME employees,
- AI literacy programmes aimed at business owners.

These programmes should be easily accessible, short and practical, and financed from public funds.

3. Strengthening the role of intermediary institutions and SME support ecosystems

Institutions such as technology parks, chambers of commerce, and development agencies should act as “translators” of AI technology into the language of SME business. The following is recommended:

- increasing funding for their advisory activities,
- standardising AI support services for SMEs,
- developing regional first contact points for companies.

4. Differentiating support instruments according to the level of maturity of regions

EU and national policies should take greater account of the differences between Central and Eastern Europe and Western Europe. In regions with a lower level of AI adaptation (e.g., Poland, Slovakia), the following are necessary:

- simpler grant instruments,
- pilot and demonstration support,
- programmes to reduce mental barriers and investment risk.

A uniform approach for the entire EU deepens the existing technological gap.

5. Support for pilot and demonstration implementations in SMEs

Public institutions should promote financing for small-scale AI pilot projects, enabling SMEs to test solutions without requiring a complete transformation. This approach lowers the entry threshold, builds trust in the technology, and accelerates adoption.

6. Integration of AI policies with SME development and cohesion policies

AI should be treated not only as an area of innovation, but also as a tool for economic and regional cohesion. It is recommended that AI policies be more closely linked to:

- EU cohesion policy,
- regional development strategies,
- SME and entrepreneurship support programmes.

7. Simplifying SME access to financing for AI implementation

National and EU institutions should:

– reduce the complexity of grant procedures,

– introduce mixed instruments (grant + consultancy),

– develop preferential loans and guarantees for AI projects in SMEs.

It is imperative to support companies without their own IT teams.

8. Building trust in AI through clear and proportionate regulations

EU regulatory policy (including the AI Act) should be implemented in a way that is easy for SMEs to understand. It is recommended to:

– developing practical guidelines for SMEs,

– providing advisory support on regulatory compliance,

– avoiding excessive administrative burdens for SMEs.

9. Supporting a change in managerial attitudes towards AI

Public institutions should promote a narrative in which AI is seen as a tool to support decision-making and competitiveness, rather than a threat. It is recommended to conduct information campaigns, showcase case studies, and promote good practices demonstrating the real benefits of AI implementation in SMEs. Tools such as national and international competitions, inter-institutional and inter-sectoral workshops, etc., would be helpful.

10. Continuous monitoring of AI readiness and implementation in SMEs

It is recommended to continue and develop comparative research at the national and EU levels, enabling:

– assessing the effectiveness of public policies,

– identify regional barriers,

– update support instruments based on empirical data.

The research should be ongoing, conducted by international research teams, taking into account responses to changes at the national and EU levels. Such teams should have permanent multi-year public funding obtained through a competitive process.

6. Scientific publications and conferences related to the project

6.1. Published scientific articles

The following scientific articles have been/will be published as part of he project:

1. BARRIERS TO THE IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE IN SMALL and MEDIUM-SIZED ENTERPRISES IN SELECTED EUROPEAN UNION COUNTRIES, Nunzio Casalino, Aneta Bełdycka-Bórawska, Ireneusz Żuchowski, Tomasz Bernat, Journal "Economics and Environment", in No. 2(101)/2027. e-ISSN 2957-0395, ISSN 2957-0387
2. ARTIFICIAL INTELLIGENCE AS A COMPETITIVENESS FACTOR FOR SMES: A MULTIDIMENSIONAL PERSPECTIVE INTEGRATING TECHNOLOGICAL, ORGANISATIONAL and COMPETENCY DIMENSIONS, Ireneusz Żuchowski, Nunzio Casalino, Radovan Savov, Anna Strychalska-Rudzewicz, Jesús Adolfo Guillamón Ayala, Iildefonso Mendez, Tomáš Michalička, Agnieszka Brelik, European Research Studies Journal XXIX, Issue 1, 2026, pp. 53-75
3. RESEARCH PROJECT ON THE PREPARATION and LEVEL OF USE OF ARTIFICIAL INTELLIGENCE IN SMALL and MEDIUM-SIZED ENTERPRISES IN EUROPE, Jesús Adolfo Guillamón-Ayala, Ildefonso Méndez Martínez – submitted to the publisher
4. MANAGERIAL READINESS FOR ARTIFICIAL INTELLIGENCE AND THE GAP BETWEEN ATTITUDES AND IMPLEMENTATION: EVIDENCE FROM EUROPEAN SMES, Anna Strychalska-Rudzewicz, Ireneusz Żuchowski, Nunzio Casalino, Radovan Savov, Jesús Adolfo Guillamón Ayala – submitted to the publisher
5. THE USE OF ARTIFICIAL INTELLIGENCE IN SMALL AND MEDIUM-SIZED ENTERPRISES IN SLOVAKIA – A PILOT STUDY, Tomáš Michalička, Radovan Savov – submitted to the publisher

6.2. Conference presentations

As part of the project, the research results were presented at scientific conferences:

1. 25th INTERNATIONAL SCIENTIFIC CONFERENCE GLOBALISATION and ITS SOCIO-ECONOMIC CONSEQUENCES 2025, Slovak Republic, Rajecke Teplice, organised by the University of Žilina, 8–9 October 2025
   Title of the presentation: *The Use of Artificial Intelligence in Small and Medium-Sized Enterprises in Slovakia – A Pilot Study.*
   Participants: Tomáš Michalička & Radovan Savov
2. "XXIX CONGRESO DE SOCIOLOGÍA DE CASTILLA-LA MANCHA", 14-16 November 2025, Ciudad Real, Spain, organised by ASOCIACIÓN CASTELLANO MANCHEGA DE SOCIOLOGÍA
   Title of presentation: *Preparation and level of utilisation of AI in SMEs.*
   Participants: Jesús Adolfo Guillamón-Ayala, Ildefonso Méndez Martínez
3. International Scientific Conference "Science and Business – Common Challenges", 20 November 2025, Krakow, organised by AGH University of Science and Technology
   Title of presentation*: Level of readiness, conditions for implementation, and level of implementation of AI in SMEs*.
   Participants: Ireneusz Żuchowski
4. 21st National Congress of Economists 1–4 June 2025, Miedzyzdroje, organised by the University of Szczecin
   Title of presentation: *Artificial intelligence in SMEs – opinions of management staff.*
   Participants: Ireneusz Żuchowski
5. International Scientific Conference "Agriculture in the 21st century – challenges, prospects, directions of development" 26–29 May 2025, organised by the International Academy of Applied Sciences in Łomża
   Title of presentation: *Artificial intelligence in SMEs – opportunity or threat.*
   Participants: Ireneusz Żuchowski

6. 4th International Forum of Young Scientists, 17 January 2026, organised by the International Academy of Applied Sciences in Łomża
   Title of presentation: ‘*Preparation and level of use of artificial intelligence in SMEs – key findings from research’*.
   Participants: Ireneusz Żuchowski

Summary

The report is a comprehensive study on the level of preparedness and degree of utilisation of artificial intelligence (AI) in the small and medium-sized enterprise (SME) sector in selected European countries: Poland, Slovakia, Spain, Italy, and Germany. The study was carried out as part of an international research project, the aim of which was not only to diagnose the current state of AI implementation in SMEs, but also to identify key barriers, enabling factors, and the role of management styles and national conditions in technological adaptation processes. An important element of the report is also a set of recommendations addressed to enterprises, public institutions, and policymakers at the national and EU levels.

An analysis of the economic and institutional context clearly shows that the implementation of artificial intelligence in the European Union remains uneven and highly regionally diverse. Statistical data and empirical research confirm the existence of a clear ‘digital divide’ between countries with high levels of technological development and those of Central and Eastern Europe. Germany, as the EU’s economic leader, shows a significantly higher level of digital maturity and greater AI use than Poland or Slovakia, while southern European countries (Spain and Italy) occupy an intermediate position. These differences are closely correlated with GDP per capita, the availability of digital infrastructure, human capital, and public support instruments.

The report highlights the strategic importance of the SME sector for the European Union’s economy. These enterprises account for the vast majority of jobs, a significant share of added value, and play a key role in maintaining the socio-economic cohesion of regions. At the same time, SMEs face the greatest difficulties in implementing advanced technologies, including artificial intelligence. For this reason, their ability to adapt AI is fundamental to achieving the EU objectives set out in documents such as the Digital Decade Policy Programme 2030, the EU SME Strategy, and the European Green Deal.

The empirical part of the report, based on a survey of 1,000 SME managers and in-depth interviews, provides a detailed diagnosis of enterprises’ technological readiness. The results indicate that although awareness of the potential benefits of AI is relatively high, the actual use of these technologies

remains limited. The most commonly used AI solutions include automating administrative processes, data analysis, customer service support (chatbots), and CRM and ERP system features. More advanced applications, such as predictive decision-making models and advanced Big Data analytics, remain rare.

The research identified three main groups of barriers hindering the implementation of artificial intelligence in SMEs. Technological barriers include insufficient data quality, a lack of interoperable IT systems, and limited access to advanced digital infrastructure. Organisational barriers mainly concern competence deficits, low levels of managerial knowledge about AI, employee resistance to change, and an organisational culture that is not conducive to innovation. Financial barriers, on the other hand, are associated with high implementation costs, uncertainty about returns on investment, and limited access to dedicated financing instruments, especially for smaller entities.

An important contribution of the report is its analysis of the impact of managers’ management style and personality traits on decisions regarding AI implementation. The results of the study indicate that companies managed in a more participatory manner, open to innovation and organisational learning, are more ready to implement artificial intelligence. Managers who are more risk-taking, have greater trust in technology, and are strategically oriented are more likely to see AI as a tool for enhancing competitiveness rather than a threat.

In summary, the report provides an in-depth, multidimensional analysis of the process of implementing artificial intelligence in Europe’s SME sector. Its value lies in combining theoretical, empirical, and applied perspectives and in formulating practical recommendations that can serve as a basis for further research, support programmes, and the development of public policies conducive to the responsible and inclusive digital transformation of the European economy at the EU and Member State level. However, it should be noted that implementation policies at the EU and national levels should take into account the internal diversity and specific characteristics of EU countries and regions.

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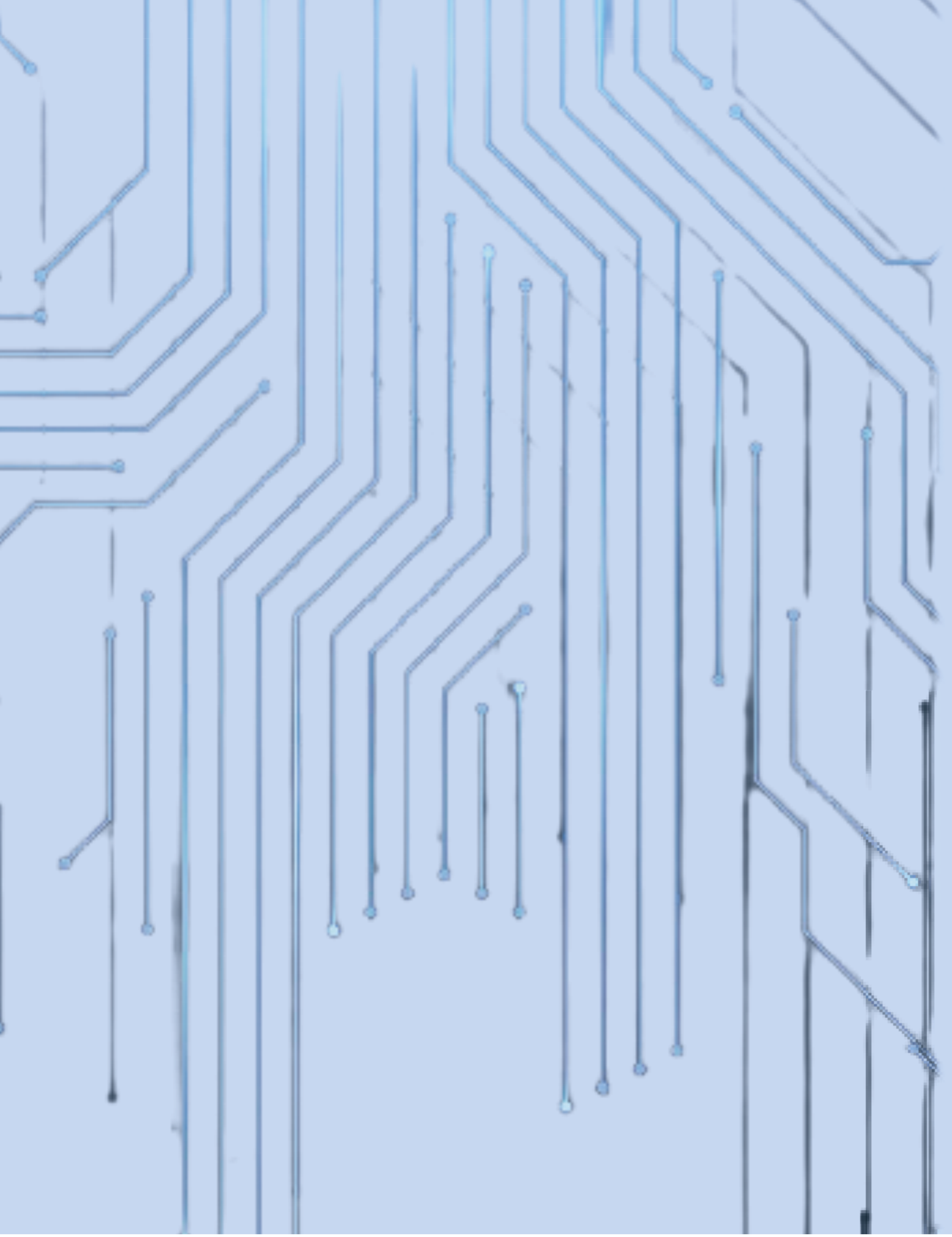

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