

Article

Using AI to optimize management processes and decision-making in large organizations

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Abstract: The article examines the potential of artificial intelligence to optimize management processes and improve decision-making in large organizations. The study is conducted within the framework of a business engineering approach. The analysis is based on data from the Stanford AI Index 2026 database. It evaluates the level of implementation of artificial intelligence-based decision support systems across different industries and business functions. The results reveal statistically significant differences in AI adoption between industries and functional areas (Friedman criterion, $p < 0.05$). The highest level of integration is observed in the technology sector, particularly in IT, software development, marketing, and sales. In contrast, manufacturing and supply chain/inventory management remain the least digitized areas. The study proposes a conceptual AI-based management framework. The framework integrates data sources, analytical models, and decision support systems into a unified adaptive cycle with a feedback mechanism. The findings confirm that the effectiveness of artificial intelligence depends not only on the technological sophistication of the solutions. It also depends on the depth of their integration into management processes and on the development of effective human-AI collaboration models. Finally, the article provides practical recommendations for scaling AI-based solutions in large organizations.

Keywords: artificial intelligence; AI-driven management; decision support systems; organizational performance; digitalization; hospitality industry

1. Introduction

In today's business environment, large organizations face an unprecedented level of complexity of management processes. Growing data volumes, market volatility, global competition, and high stakeholder expectations require executives to make quick, informed and strategically sound decisions. Traditional management approaches, based mainly on experience, intuition or basic analytical tools, are increasingly demonstrating their limitations in the context of Industry 4.0 and digital transformation. In this context, artificial intelligence (AI) appears not only as a technological novelty, but as a strategic tool for optimizing management processes and supporting decision-making [1].

From an engineering perspective, AI is embodied in complex Decision Support

Systems (DSS), which integrate machine learning methods, big data processing, predictive analytics, and optimization algorithms. From a business point of view, such systems can increase operational efficiency, reduce risks and create sustainable competitive advantages. Combining these two perspectives (business and engineering) is key to understanding the real potential of AI in organizations. The article examines this synthesis, focusing on practical implementation mechanisms and measurable results.

According to the McKinsey Global Survey 2025, 88% of organizations already use AI in at least one business function, although only about a third achieve a large-scale enterprise-wide effect [2]. This gap between experimentation and real transformation is especially critical for large organizations, where transaction and data volumes are significant and decision-making errors can have significant financial consequences.

As an illustrative example, we can consider the hospitality industry, a sector characterized by high dynamics of demand, dependence on the human factor and the need for a balance between operational efficiency and personalized service. Hotel chains such as Marriott, Hilton, or InterContinental Hotels Group are actively using AI-driven revenue management systems for dynamic pricing, occupancy forecasting, and resource optimization [3,4]. Such cases demonstrate how engineering solutions (neural networks, predictive modeling) are transformed into business results: RevPAR growth, reduced operating costs, and improved guest satisfaction.

The article is aimed at a comprehensive analysis of the use of artificial intelligence to optimize management processes and support decision-making in large organizations. To achieve this goal, it is envisaged to solve the following tasks: systematization and critical analysis of the existing scientific literature, identification of key problems and challenges, description of methodological approaches to research, presentation of empirical results, discussion of the limitations of the data obtained, as well as formulation of practical recommendations for business practice.

Particular attention is paid to the integration of business and engineering aspects – from the architecture of AI systems and technological solutions to their impact on organizational efficiency and the quality of management decisions.

2. Literature review

Scientific research on the use of AI in management is currently especially relevant. Researchers are actively studying the impact of artificial intelligence on decision-making processes in large organizations. They combine business and engineering approaches.

Many of the papers focus on the practical application of AI. Potwora et al. [5] analyze the role of artificial intelligence in marketing strategies. The authors emphasize process automation, personalization, and forecasting. Such tools help managers make better decisions based on data. Lysenko et al. [6] look at AI in cybersecurity. They show how automating protection and threat detection increases the resilience of organizations. This is important for large companies where data risks are particularly high.

Krap et al. [7] explore digital transformations. They study the impact of new technologies on modern corporate governance methods. The authors note changes in management approaches due to the integration of digital solutions. Sydorchuk et al. [8] analyze the integration of digitalization into public administration. They assess the impact on national security and the economy. Although the work concerns the public

sector, its findings are also applicable to large private organizations. Zhumbei et al. [9] study gamification and motivation. They show how technology supports the emotional resilience of employees. This is true for organizations that are implementing AI and changing workflows.

More global studies confirm the positive impact of AI. Kassa and Worku [1] proves that artificial intelligence increases organizational efficiency through increased employee productivity. The mediating role of productivity is key.

Kumawat et al. [4] conducted a systematic review of 80 empirical articles. They focused on the impact of AI on workers in the hospitality industry. The results show both the benefits and challenges of implementation. McKinsey & Company [2] presented a global survey. 88% of organizations already use AI in at least one function. However, only a fraction of companies achieve a large-scale impact on performance.

Other authors study the technical aspects more deeply. Soori et al. [10] detail AI-based decision support systems in Industry 4.0. They emphasize integration with IoT, cloud computing, machine learning, and predictive maintenance. Such systems streamline operations, reduce costs, and increase efficiency in large organizations. Bokhonko et al. [11] analyze AI-driven DSS in strategic management. Using the examples of Amazon, IBM, and Salesforce, they show the impact on supply chain, HR, and customer relations in large corporations. Lu et al. [12] investigate the impact of AI on organizational management theory. Experiments confirm an increase in the accuracy of decisions up to 92% compared to traditional DSS. Egwuatu [13] examines the transformation of Decision Support Systems into predictive and prescriptive systems. The author focuses on the strategic level of decision-making in business. Aldino and Sujoko [14] conducts a systematic review of AI in Human Resource decision support systems. The results indicate improvements in operational efficiency and process speed. Yandamuri [15] proposes AI-driven DSS for operational optimization in the hospitality industry. The systems support demand forecasting, staff scheduling, and dynamic pricing.

Additional research confirms these trends. Many papers highlight the typical architecture of AI-driven decision support systems, which includes a data layer based on IoT sensors and big data, a machine learning layer using TensorFlow and PyTorch frameworks, and interactive dashboards for managers [10,15,16].

The literature systematically identifies the key challenges of the implementation of artificial intelligence in organizations, among which a special place is occupied by the quality and availability of data, the complexity of integrating AI solutions into existing information systems, the resistance of personnel to technological changes, as well as ethical issues, including algorithmic bias. In response to these challenges, most researchers justify the feasibility of using human-AI collaboration hybrid approaches, which combine the analytical capabilities of algorithms with the expert knowledge of managers.

Despite significant progress in the development of AI technologies and their active implementation in business practice, there is a shortage of long-term empirical studies assessing their impact on large organizations in an intersectoral context. Most of the available work focuses on either individual functions or technical aspects of the implementation of AI solutions, which limits the possibilities of a comprehensive understanding of their impact on management processes and organizational performance. In this regard, studies that integrate technical analysis with business results and take into account the systemic nature of the implementation of AI-driven

decision support systems remain relevant.

Modern research emphasizes that the implementation of artificial intelligence in organizations goes beyond the automation of individual processes and is transformed into a comprehensive change in management models. Particular attention is paid to the integration of AI into business processes, the development of data-driven decision-making, and the formation of new organizational competencies. At the same time, it is emphasized that the effectiveness of the use of AI largely depends on the ability of organizations to combine technological innovation with management practices and cultural change. The researchers also emphasize the uneven adoption of AI between functions and industries, as well as the difficulty of moving from pilot projects to large-scale use, which creates a significant gap between the potential of the technology and its actual implementation in organizations [17–21].

Despite the significant amount of academic research in the field, a number of aspects remain unresolved. In particular, the main gaps are seen in the formation of effective practical HR strategy and planning, determining the implications for the skills and roles of HR professionals in the workplace, supplemented by artificial intelligence, as well as considering the problem of implementing AI in the HR function compared to other business units. These issues are the focus of the researcher in this article.

3. Materials and methods

The study is based on secondary data from the Stanford Artificial Intelligence Index Report 2026 [22], as well as on a structured database formed on its basis [23]. IBM SPSS Statistics 27 software was used for the analysis. The total sample used in the Stanford AI Index 2026 report covers over 2,000 large organizations from various industries and regions of the world, ensuring a high level of representativeness of the results obtained. At the first stage, descriptive statistics and data visualization (including heatmaps) were used to identify general trends in the use of artificial intelligence in the context of industries and business functions.

To check statistical differences, the nonparametric Friedmann criterion for related samples was used. In cases of significant results, a post-hoc analysis with paired comparisons using the Bonferroni amendment was performed. Additionally, the analysis of the stages of implementation of artificial intelligence (non-use, experimenting, piloting, scaling) was carried out, which made it possible to assess the level of maturity of AI-driven systems in large organizations.

The Stanford AI Index 2026 dataset, presented by Stanford University, used a sample from 2023–2025. The information landscape of the sources selected for the research sample was based on the aspects of quality, accuracy, relevance, bias, reputation and reliability. Attention was paid to methods of assessing the quality, accuracy, relevance, bias, reputation and reliability of the information resources found. Relevant material on the given search topic was selected, with the identification of key points and arguments. Special attention was paid to the importance of consistency in data collection, as well as citation.

A separate stage of the study was the construction of a conceptual framework that summarizes the results of empirical analysis. The diagram reflects the logic of data transformation into management decisions through the integration of data sources, AI analytics, and decision support systems. It is developed on the basis of identified functional differences, levels of AI adoption, and the feedback loop principle, which ensures the adaptability of AI-driven decision support systems.

4. Results

This section presents the results of an empirical analysis of the use of artificial intelligence in large organizations with a focus on its role in optimizing management processes and supporting decision-making. The analysis is based on data from the Stanford AI Index 2026 and combines descriptive and statistical methods in order to identify patterns in the implementation of AI-driven management and decision support systems in various industries and business functions. Particular attention is paid to cross-industry differences, functional differentiation, as well as levels of maturity of AI adoption – from experimentation to large-scale use. This approach allows not only to capture the current state of AI use, but also to assess the depth of its integration into organizational processes and the potential impact on organizational performance, in particular in sectors related to the hospitality industry.

Let's consider the dynamics of AI adoption in large organizations by region of the world. Data from the Stanford AI Index 2026 (**Figure 1**) shows a rapid increase in the use of artificial intelligence in business during 2023–2025 [23].

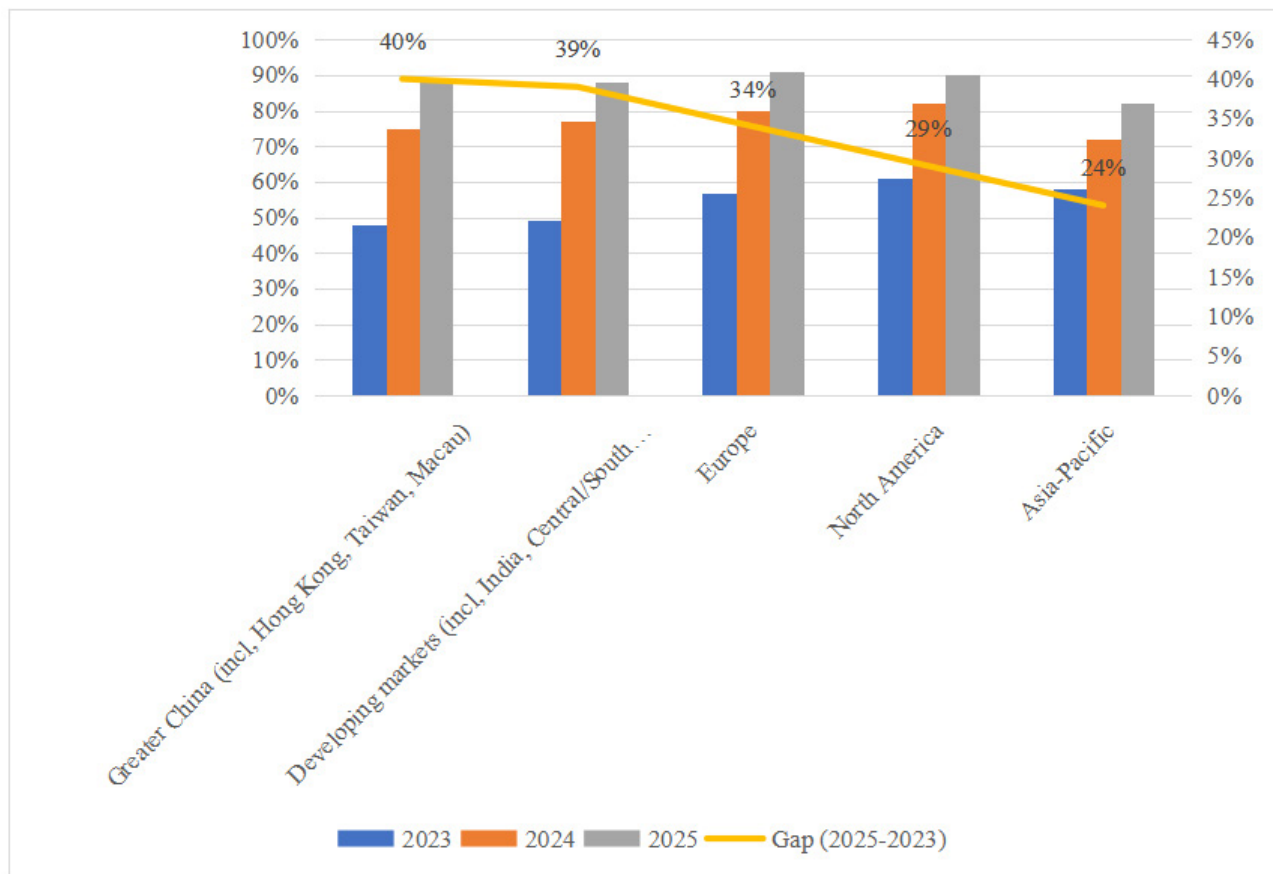


Figure 1. Share of organizations using AI in at least one business function, by region, 2023–2025 (%).

Source: Stanford University [23].

Data analysis shows a significant acceleration in AI adoption in large organizations around the world. The growth leaders were Greater China (+40% in three years) and developing countries (+39%). Europe has the highest level of AI penetration in 2025 – 91% of organizations use artificial intelligence in at least one business function. North America also scores high (90%).

The data obtained confirm that AI is rapidly moving from the experimental

phase to a full-fledged tool for optimizing management processes and supporting decision-making on a global scale. The highest growth rates are observed in regions that previously had a lower penetration rate, indicating an active catch-up process.

Before conducting further analysis, it is advisable to conduct a visual study of the use of AI in various industries and business functions. For this purpose, a heat map has been used, which allows you to assess the level of integration of AI-driven management and decision support systems into key management processes of large organizations. This approach is in line with the business engineering logic of the study, as it allows you to identify practical patterns of technology use, identify functional areas with the greatest impact of AI on organizational performance, as well as compare the level of digital maturity between industries. Particular attention is paid to sectors related to the hospitality industry in order to assess their positioning in the overall structure of the implementation of artificial intelligence (**Figure 2**).

Function \ industry	Advanced industries	Business, legal and professional services	Consumer goods and retail	Energy and materials	Financial services	Health care, pharma and medical products	Media and telecom	Technology
Human resources	18	20	22	22	17	25	28	28
IT	40	21	32	39	36	30	38	56
Knowledge management	29	58	28	33	38	46	34	46
Manufacturing	26	1	13	21	0	11	5	9
Marketing and sales	29	46	51	33	36	38	45	49
Product and/or service development	30	33	21	28	28	36	32	49
Risk, legal, and compliance	7	15	11	17	43	13	17	18
Service operations	22	32	34	32	38	25	46	45
Software engineering	32	13	19	30	23	21	33	58
Strategy and corporate finance	16	22	9	20	12	18	17	20
Supply chain/ inventory management	25	4	22	19	3	21	6	10

Figure 2. Heatmap of AI usage by industries and functions, 2025.

Source: Stanford University [23].

The heatmap demonstrates the uneven distribution of AI usage across industries and business functions. The highest values are observed in the Technology sector, in particular in IT (56%), software engineering (58%), product development (49%) and marketing and sales (49%), which confirms its leadership position in the implementation of AI-driven management. The media and telecom sector demonstrates similarly high indicators: service operations (46%), marketing and sales (45%) and IT (38%). In the Financial services sector, the function of risk, legal and compliance (43%), as well as service operations (38%) and knowledge management (34%) stands out, which reflects the specifics of the regulatory environment and the need for analytical solutions.

The Consumer goods and retail (which includes the hospitality industry) and Business, legal, and professional services show moderate values: for example, marketing and sales (51% and 46%, respectively) and service operations (34% and

32%), indicating an active, but not dominant, use of AI. On the other hand, the lowest indicators are observed in the manufacturing functions (from 0% in Financial services to 26% in Advanced industries) and supply chain management (for example, 3% in Financial services and 4% in Business services), which indicates the limited adoption of AI in operational-traditional processes.

In general, visual analysis taking into account quantitative values indicates the presence of intersectoral differences, but their statistical significance requires additional verification.

For this purpose, the Friedmann criterion was applied for linked samples. The test results confirm the presence of statistically significant differences between industries (Sig. = 0.044 < 0.05), which makes it possible to reject the null hypothesis of the sameness of distributions. Further post-hoc analysis using the Bonferroni amendment showed that a statistically significant difference was observed only between the Financial services and Technology sectors (Adj. Sig. = 0.047), while other pairwise comparisons were not significant (Appendix A).

These results are consistent with the visualization of pairwise comparisons (Figure 3), where the Technology sector shows the highest average rank and the most marked deviation from other industries. Figure 3 shows significant differences with the Bonferroni correction in blue. At the same time, a limited number of significant differences indicates a gradual convergence of levels of AI adoption between most sectors, which is a characteristic feature of the current stage of development of AI-driven decision support systems in large organizations.

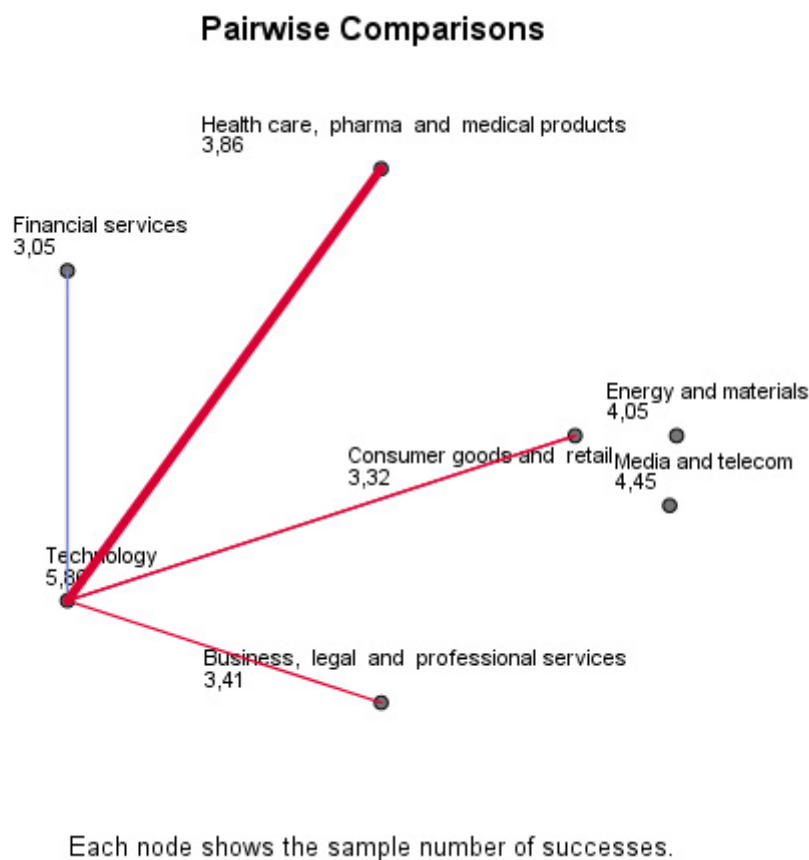


Figure 3. Paired comparisons of the level of AI use between industries (Friedman post-hoc analysis, Bonferroni adjusted).

Source: calculated by authors based on Stanford University [23].

The results of hypothesis testing using the Friedman criterion indicate the presence of statistically significant differences between the levels of artificial intelligence use in various business functions of large organizations. The obtained significance value Sig. = 0.000 ($p < 0.05$) allows us to reject the null hypothesis of the sameness of distributions.

A meaningful interpretation of this result indicates that the implementation of artificial intelligence in organizational processes is uneven. This is consistent with the logic of digital transformation, where different functional units have different levels of technological maturity, access to data, and readiness for automation. From an engineering point of view, this reflects the difference in the complexity of process algorithmization, and from a business point of view, it reflects the different potential for creating added value through analytics and automation.

Further post-hoc analysis using the Bonferroni amendment made it possible to clarify which functions have statistically significant differences. The most pronounced discrepancies are observed between Manufacturing and a number of other functions, including IT (Adj. Sig. = 0.003), Knowledge Management (Adj. Sig. = 0.003), Marketing and Sales (Adj. Sig. = 0.001) and Service Operations (Adj. Sig. = 0.038) (Appendix B, **Figure 4**). In all these cases, the value of the adjusted significance is lower than 0.05, which indicates a systematically lower level of AI use in production processes compared to more digitized units. This can be attributed to the higher proportion of physical operations, the complexity of integrating IoT solutions, and the relatively slower digital transformation of the production environment (**Figure 4**).

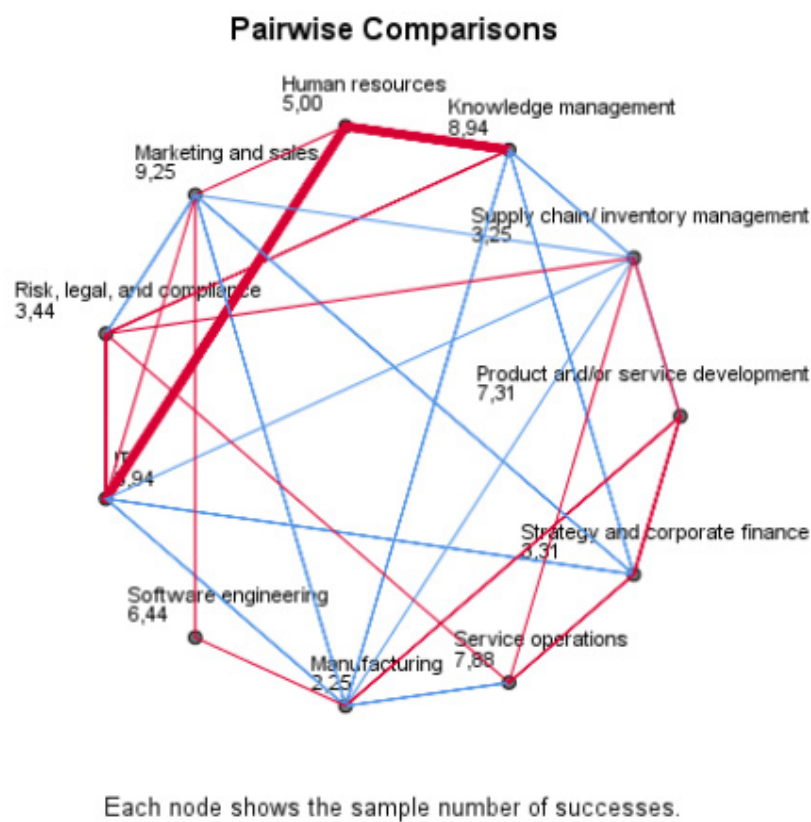


Figure 4. Paired comparisons of the level of AI use between business functions (Friedman post-hoc analysis, Bonferroni adjusted).

Source: calculated by authors based on Stanford University [23].

A similar, though somewhat less pronounced, pattern is observed for the Supply Chain and Inventory Management function, which also shows statistically significant differences with IT (Adj. Sig. = 0.033), Knowledge Management (Adj. Sig. = 0.033), and Marketing and Sales (Adj. Sig. = 0.016). This indicates that, despite the high optimization potential through predictive analytics and AI-based DSS, the level of actual implementation of such solutions in logistics processes remains uneven and does not yet reach the level of leading digital functions.

The Strategy and Corporate Finance function also shows a number of significant differences, in particular compared to IT (Adj. Sig. = 0.038), Knowledge Management (Adj. Sig. = 0.038) and Marketing and Sales (Adj. Sig. = 0.019). This indicates a gradual but not yet fully completed process of integrating AI into strategic management decisions, where analytical models are increasingly used, but their systematic integration into corporate governance is still taking shape.

Similarly, in the Risk, Legal and Compliance function, a statistically significant difference is observed with Marketing and Sales (Adj. Sig. = 0.025). This shows that even within risk management and compliance, where analytical tools are actively used, the level of AI adoption still lags behind more customer-centric and digitally mature functions.

At the same time, no significant differences were found between such functions as IT, Knowledge Management, Marketing and Sales, Software Engineering and Product Development. This allows them to be interpreted as an established core of high AI maturity within organizations, where artificial intelligence is already an integrated element of operational and management processes.

Thus, the results of statistical analysis confirm that the implementation of artificial intelligence in large organizations is structurally heterogeneous, which forms the need for differentiated digital transformation strategies depending on the specifics of each business function and its role in creating organizational efficiency.

An additional dimension of AI adoption analysis is provided by assessing the stages of use of AI solutions in different business functions, which allows you to move from a static slice (usage level) to a dynamic understanding of the maturity of technology implementation.

The relevant data shows the distribution of organizations by stages of AI implementation: from lack of use to the scaling stage. Overall, the results indicate that most business functions are still in the early stages of AI integration (**Figure 5**). In particular, the share of companies that do not use AI at all remains dominant, ranging from 66% in Knowledge Management to 91% in Manufacturing. This confirms the conclusions of the previous analysis regarding the unevenness of digital transformation.

At the same time, a deeper analysis shows significant differences between the functions in terms of technological maturity.

The most advanced are IT, Knowledge Management, and Marketing and Sales. There is a relatively higher level of experimentation and scaling in these functions, with the proportion of organizations in the experimenting, piloting, or scaling stages being approximately 21–25%. This indicates the formation of the core of AI-driven management, where technologies are already being integrated into operational processes and decision support.

The Service Operations and Product Development functions occupy an intermediate position. There is also an active testing phase (experimenting and piloting), but the level of scaling remains limited. This indicates that there is potential

for further engineering integration of AI-based decision support systems, especially in the context of optimizing operations and product lifecycle management.

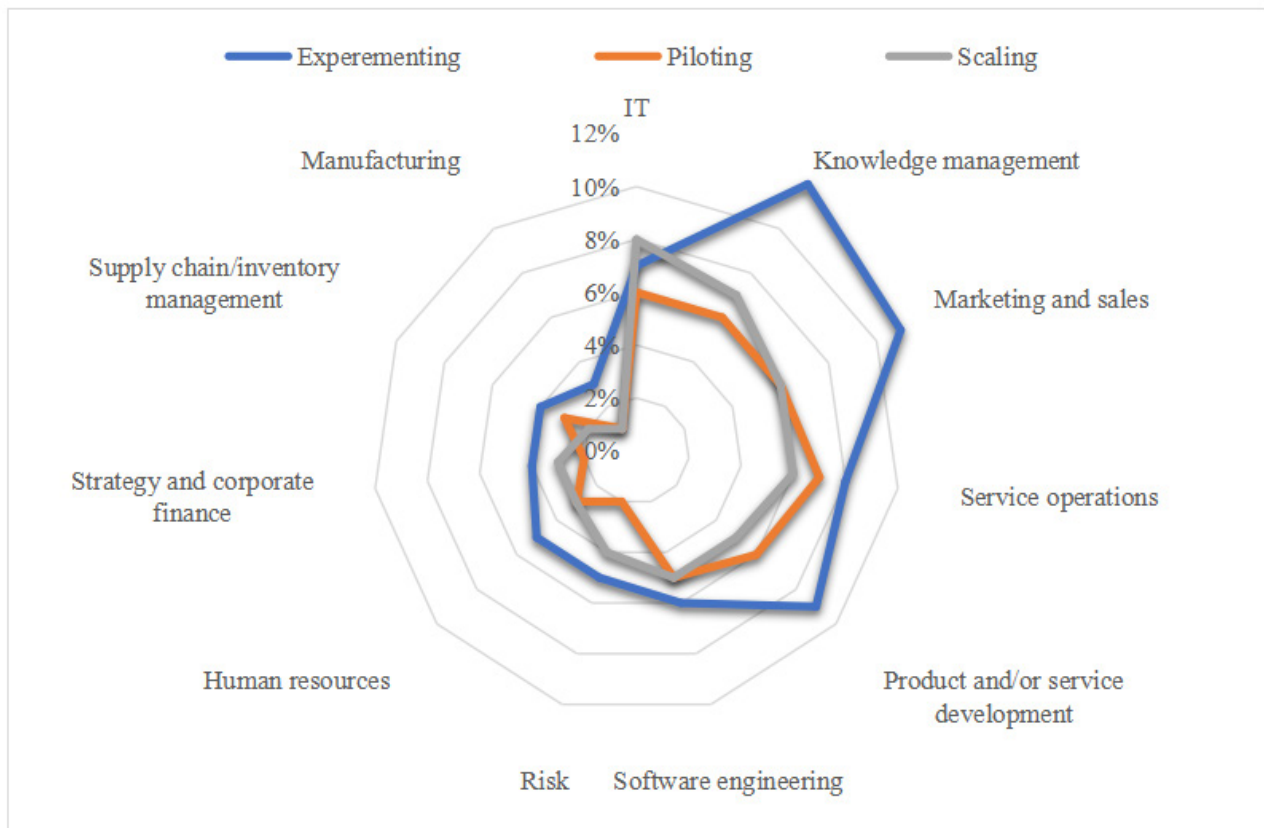


Figure 5. Levels of AI adoption by business functions: stages of experimentation, piloting, and scaling.

Source: calculated by authors based on Stanford University [23].

On the other hand, the Risk, Human Resources, and Strategy and Corporate Finance functions are characterized by a much lower level of adoption. The share of organizations that do not use AI exceeds 80%, and the level of scaling remains minimal (2–4%). This may be due to high requirements for accuracy, regulatory constraints, and the complexity of formalizing management decisions in these areas.

Supply Chain and Manufacturing remain the least digitized, where about 90% of organizations do not use AI. Even the stages of experimentation and piloting are minimally represented here. From an engineering standpoint, this is due to the difficulty of integrating AI solutions into physical processes, reliance on IoT infrastructure, and high capital expenditures.

Thus, the combination of the results of the Friedman criterion (which records statistical differences) and the analysis of implementation stages (which reflects the level of maturity) allows for a deeper understanding of the digital transformation process. If the first approach answers the question “where is AI used more/less”, then the second is “how mature is this use”.

Taken together, these results confirm that the implementation of AI-driven decision support systems in large organizations has not only cross-functional differences, but also different speed of transition from experimentation to large-scale use. This reinforces the need for differentiated AI adoption strategies, taking into account both the technological and business characteristics of each function.

5. Discussion

The results obtained indicate that the implementation of artificial intelligence in large organizations has a structurally heterogeneous, but at the same time convergent nature, which manifests itself both at the level of industries and at the level of business functions. Such a dual nature reflects the current stage of development of AI-driven management, when the technology is already widespread, but has not yet reached full maturity in all areas of activity.

From an industry perspective, it is found that the Technology sector demonstrates a statistically higher level of AI use compared to Financial services, which is confirmed by the results of the post-hoc analysis with the Bonferroni correction. At the same time, the absence of significant differences between most other industries indicates a gradual alignment of AI adoption levels (convergence effect). This means that artificial intelligence is moving from the category of differentiating innovation to a basic element of the operational and strategic activities of organizations, regardless of their industry affiliation. The results are particularly indicative for sectors related to the hospitality industry (consumer goods and retail), which demonstrate an average level of AI use, but at the same time have significant growth potential due to a high dependence on demand, customer experience, and operational efficiency.

At the level of business functions, the results confirm the presence of a clear functional asymmetry in the implementation of AI. In particular, a core of functions with a high level of AI maturity (IT, Knowledge Management, Marketing and Sales, Software Engineering, Product Development) has been formed, between which no statistically significant differences have been found. This allows them to be interpreted as core layer AI-driven decision-making, where artificial intelligence is already integrated into day-to-day operations, analytics, and decision support systems. It is in these functions that AI goes from being an auxiliary tool to a key element of value creation.

On the other hand, features such as Manufacturing and Supply Chain/Inventory Management demonstrate a systemically lower level of AI usage, which is confirmed by statistically significant differences in the results of the Friedman criterion and post-hoc analysis. This reflects the engineering limitations associated with integrating AI solutions into physical processes, reliance on IoT infrastructure, and the high costs of digital transformation. Similarly, the Strategy and Corporate Finance, Risk, and Human Resources functions are characterized by a limited level of implementation, which is explained by the complexity of formalizing decisions, high requirements for accuracy, and the impact of the regulatory environment.

An important addition to static analysis is the assessment of the stages of AI implementation, which allows you to reveal the dynamic aspect of digital transformation. The results show that most organizations, even in functions with relatively high levels of AI use, are in the experimentation and piloting phases. The share of full-scale implementation (scaling) remains limited, which indicates that there is a gap between adoption and enterprise-wide integration. This is consistent with global research and highlights that the key challenge is not the adoption of technologies as such, but their scaling and integration into management processes.

The generalization of the results obtained is the proposed framework (**Figure 6**), which reflects the system logic of the functioning of AI-driven decision support systems in large organizations. Unlike traditional approaches that consider AI as a separate analytics tool, this framework interprets it as a multi-layered integrated architecture that combines data sources, analytical models, decision support systems,

and business processes.

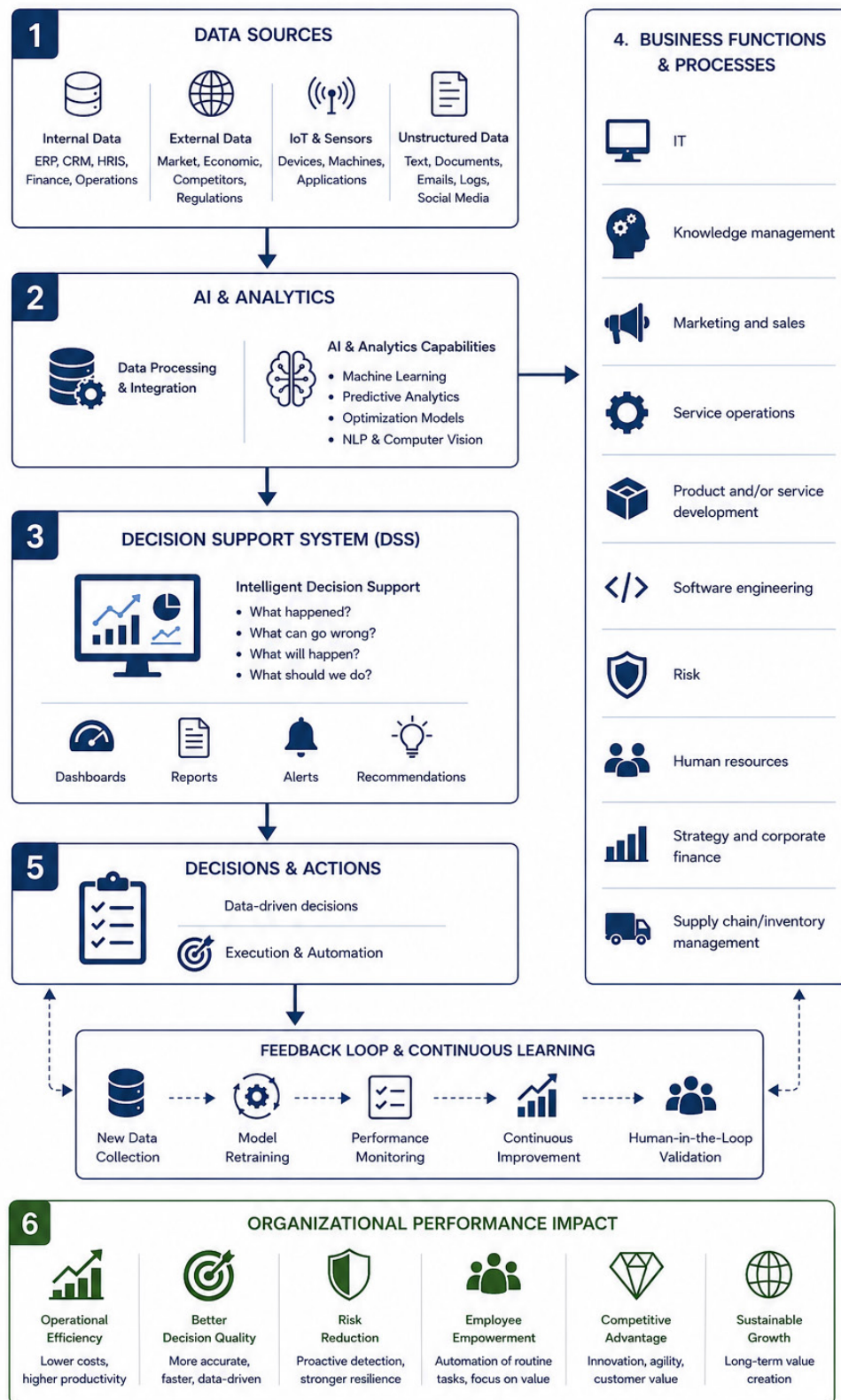


Figure 6. AI-based decision support framework in the context of business functions of large organizations.

Source: developed by the authors on the basis of a generalization of the results of research and analysis of scientific literature on the use of artificial intelligence in management processes and decision support systems; The visualization was created using artificial intelligence tools.

Artificial intelligence-based decision support systems (AI-DSS) are transforming the management of large organizations, shifting the focus from hierarchical control to predictive analytics and decentralized response. They act as “cognitive amplifiers”, reducing the cognitive load of managers and increasing the speed and quality of real-time decisions. The integration of AI into various business functions is deeply explained through key organizational theories:

- the theory of Bounded Rationality: decision makers (DRMs) are physically unable to process the entire amount of information, so they look for a “satisfactory” option rather than an optimal one; the role of AI is as follows: AI-DSS overcome human cognitive limitations by instantly scanning millions of data points, detecting hidden patterns and generating optimal (or best-case) scenarios, which turns the process into a truly scientifically sound one;

- Information Processing Theory: organizations are data processing systems, their effectiveness depends on the ability of the structure to collect, interpret and disseminate information to reduce uncertainty; the role of AI is as follows: AI acts as the main driver, breaks down information barriers (silos) and provides universal access to operational data, which allows different departments to act in a coordinated manner in turbulent conditions;

- Contingency Theory: there is no single best way to manage an organization, the structure and management style must adapt to internal and external conditions; the role of AI is as follows: the implementation of AI contributes to the decentralization of authority, and thanks to AI assistants, line managers and the front office receive real-time analytics and can make autonomous decisions without waiting for approval from senior management [24,25].

These theoretical positions are based on classical works: the concept of bounded rationality by Simon (1955), the theory of information processing in organizations by Galbraith (1974), and the situational theory by Lawrence & Lorsch (1967).

In particular, the empirically identified functional differentiation is reflected in the Business functions & processes block, where different levels of AI adoption correlate with different degrees of integration in the decision-making cycle. Functions with a high level of AI maturity are actually integrated into the core of the system, while less digitized areas occupy a peripheral position, reflecting their limited level of involvement in AI-driven decision-making processes.

The key element of the framework is to display the full cycle of data transformation into management decisions: from Data Sources through AI & Analytics to the Decision Support System and further Decisions & Actions. This is consistent with the results of the study, which showed that the effectiveness of using AI is determined not only by the presence of algorithms, but by the level of their integration into organizational processes and management practices.

A special role is played by the feedback loop, which ensures continuous model learning, system adaptation, and increased decision accuracy. The results of the analysis of the implementation stages confirm that most organizations are at the stage of forming this cycle, which limits the full realization of the potential of AI-driven DSS. Thus, **Figure 5** performs not only an illustrative, but also a conceptual and analytical function, combining the results of statistical analysis with the business engineering logic of the functioning of decision support systems.

In general, the results of the study confirm that the implementation of artificial intelligence is a multidimensional process that depends on the industry specifics, functional role, and level of digital maturity of the organization. This underscores

the need to develop differentiated AI transformation strategies focused not only on technological aspects but also on integration into management processes. In this context, the development of human-AI collaboration approaches, which combine the analytical capabilities of algorithms with the expert knowledge of managers, ensuring an increase in the quality of management decisions and organizational performance, is especially promising.

5.1. Discussing the implications for HR

According to the empirical data obtained, the HR function belongs to the group with a low level of AI implementation - more than 80% of large organizations in this area do not use artificial intelligence at all (**Figure 5**). Such a gap between HR and digitally mature functions (IT, marketing, knowledge management) emphasizes the need for targeted programs to develop digital competencies of HR specialists, as well as the implementation of change management models that can overcome organizational resistance. That is why the new roles proposed in this section (“AI Workflow Architect”, “AI Steward”, “Human Resources Analytics Leader”) directly follow from the identified patterns: the low maturity of the HR function requires specialists who are able to integrate analytical tools into the processes of selection, assessment and development of personnel, while ensuring ethical control of algorithms.

Artificial Intelligence (AI) is not replacing HR professionals, but rather transforming them by automating routine tasks and increasing productivity. This is transforming HR professionals from administrators to strategic partners whose work is based on data, empathy and adaptation to technology. The role of the specialist is transforming into hybrid positions that combine business, analytics and technology:

- AI Work Architect in HR (AI Work Architect): Defines business objectives, forms success criteria and decides which processes to delegate to AI and which to leave under human control;
- AI Steward: Checks the solutions proposed by the algorithm for reality, monitors algorithmic bias and monitors ethical issues What is the future of work? Defining roles for humans and AI;
- People Analytics Lead: Interprets data from systems to predict employee turnover and develop talent development strategies;
- Employee Experience Architect: Uses the freed-up time to build corporate culture, deep onboarding, mental health, and coaching that machines cannot replicate.

In addition to basic communication and management skills, new competencies are becoming critical:

- Digital and AI Literacy: Understanding how algorithms work (LLM), the ability to create precise queries (prompts), and integrate AI into HR systems;
- Data Literacy: The ability to read analytical reports, identify patterns, and make decisions based on numerical information, not just intuition;
- Ethical Management and Data Protection: Knowledge of legal and ethical constraints (particularly around privacy and AI bias in hiring);
- Leadership and Empathy: Developed emotional intelligence to manage change, resolve conflict and support employees How AI Is Transforming the Future of HR Roles.

The implementation of artificial intelligence (AI) in the field of human resources (HR) faces fundamental difficulties: if in logistics, IT or finance AI solutions focus on objective data and process optimization, then in HR the main object is the person. This makes the integration of AI socially sensitive and complex. The main problems

of integrating AI in HR compared to other business units:

- Ethical risks and algorithmic bias - unlike marketing or analytics, where an AI error costs lost money, an algorithmic error in HR (for example, when selecting candidates or promoting) violates human rights, causes discrimination based on gender, age or origin;
- In IT development or operations, bias is resolved by retraining on high-quality technical data sets, while human behavior and historical biases in HR data are difficult to standardize;
- Protection of confidential data – working with highly sensitive personal information of employees (medical data, performance evaluation, personal financial needs) requires unprecedented cybersecurity measures, financial or logistics departments also work with confidential information, but in HR, a data leak can lead to serious legal consequences and huge reputational losses;
- The “black box effect” and transparency of decisions – employees and candidates demand clear explanations why the system rejected their resume, lowered the KPI score or denied a raise; In manufacturing or IT, the results of AI work are more predictable (demand forecasting, code optimization, routing), the explainability of decisions there does not require social or psychological delicacy;
- Loss of empathy and human approach – HR management is based on trust, emotional intelligence and personal contact; automation of onboarding, conflict resolution or communication about dismissal using chatbots can lead to demotivation of staff;
- Difficulty in measuring profitability (ROI) – measuring the effectiveness of AI implementation (for example, whether AI really selected the “best” leader for the company) is difficult.

It is considered expedient to adhere to an approach where technology plays the role of an assistant (automation of routine and market analytics), and final decision-making and accountability remain with human managers (“human-in-the-loop”) [26-31].

Uneven adoption occurs when technologies are purchased but not used. To bridge this gap, organizations must approach change management from an AI Readiness perspective, not just a change in habits: aligning business goals and employee needs (a clear business case: why AI is needed, and communicating the benefits not only to the business but also to each individual employee), changing the approach to performance evaluation (abandoning traditional metrics such as hours worked, shifting instead toward assessments of quality, creativity, problem-solving, and algorithm management skills), ethics and vendor management (protecting against bias – organizations are responsible for algorithms, even if they are provided by third-party vendors, which requires coordination with the IT department and the legal department to audit AI tools for discrimination and privacy violations).

6. Conclusion

The results of the study confirm that artificial intelligence is becoming a strategic tool for optimizing management processes and improving the quality of decision-making in modern large organizations. The uneven, but progressive nature of the implementation of AI-driven decision support systems is revealed, with clearly defined leaders (technology sector, IT, marketing) and lagging functions (manufacturing, supply chains).

The conceptual framework proposed in the paper illustrates the transition from

the fragmented use of individual AI tools to a complex integrated system that covers the entire cycle of data transformation into management decisions with a mandatory feedback loop.

Key takeaways:

- the introduction of AI has a clearly expressed functional and sectoral nature;
- the greatest effect is achieved when moving from pilot projects to enterprise-wide scaling;
- a critical success factor is the development of human-AI collaboration models.

Prospects for further research are an empirical assessment of the long-term impact of AI systems on the financial results of organizations in various industries, as well as the development of industry reference models.

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References

1. Kassa BY, Worku EK. The impact of artificial intelligence on organizational performance: The mediating role of employee productivity. *Journal of Open Innovation: Technology, Market, and Complexity*. 2025;11(1):100474. doi:10.1016/j.joitmc.2025.100474
2. McKinsey & Company. *The state of AI in 2025: Agents, innovation, and transformation* [Internet]. 2025 [cited 2026 May 26]. Available from: <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai>
3. Zahidi F, Kaluvilla BB, Mulla T. Embracing the new era: Artificial intelligence and its multifaceted impact on the hospitality industry. *Journal of Open Innovation: Technology, Market, and Complexity*. 2024;10(4):100390. doi:10.1016/j.joitmc.2024.100390
4. Kumawat E, Datta A, Prentice C, Leung R. Artificial intelligence through the lens of hospitality employees: A systematic review. *International Journal of Hospitality Management*. 2025;124:103986. doi:10.1016/j.ijhm.2024.103986
5. Potwora M, Vdovichena O, Semchuk D, Lipych L, Saienko V. The use of artificial intelligence in marketing strategies: Automation, personalization and forecasting. *Journal of Management World*. 2024;(2):41–49. doi:10.53935/jomw.v2024i2.275
6. Lysenko S, Bobro N, Korsunova K, Vasylychshyn O, Tatarchenko Y. The role of artificial intelligence in cybersecurity: Automation of protection and detection of threats. *Economic Affairs*. 2024;69(Special Issue):43–51. doi:10.46852/0424-2513.1.2024.6
7. Krap A, Bataiev S, Bobro N, Kozub V, Hlevatska N. Examination of digital advancements: Their influence on contemporary corporate management methods and approaches. *Multidisciplinary Reviews*. 2024;7:e2024spe026. doi:10.31893/multirev.2024spe026

8. Sydorhuk O, Bashtannyk V, Terkhanov F, Kravtsov O, Akimova L, Akimov O. Integrating digitization into public administration: Impact on national security and the economy through spatial planning. *Edelweiss Applied Science and Technology*. 2024;8(5):747–759. doi:10.55214/25768484.v8i5.1740
9. Zhumbel M, Apelt H, Savchuk N, Akimov O, Tsymbal I. Leveraging gamification to sustain student motivation and emotional resilience in higher education during wartime: Case studies from Ukraine. *LatIA*. 2025;3:345. doi:10.62486/latia2025345
10. Soori M, Karimi Ghaleh Jough F, Dastres R, Arezoo B. AI-based decision support systems in Industry 4.0, a review. *Journal of Economy and Technology*. 2026;4:206–225. doi:10.1016/j.ject.2024.08.005
11. Bokhonko I, Kubasiak M, Oleksa-Kaźmierczak A. AI-driven decision support systems in strategic business management: A case-based analysis. *Scientific Papers of Silesian University of Technology. Organization and Management Series*. 2025;(230):49–61. doi:10.29119/1641-3466.2025.230.3
12. Lu X, Hu N, Zou J. Artificial intelligence in decision support systems: Impact on organizational management theory. In: *Proceedings of the 9th International Conference on Electronic Information Technology and Computer Engineering (EITCE '25)*. 2025:335–340. doi:10.1145/3766671.3766731
13. Egwuatu OV. AI-driven decision support systems for business strategy. *World Journal of Advanced Research and Reviews*. 2025;27(2):1752–1769. doi:10.30574/wjarr.2025.27.2.3065
14. Aldino B, Sujoko S. Leveraging artificial intelligence in decision support systems for strategic human resource management: A systematic literature review. *American Journal of Open Research*. 2025;4(4):1–23. doi:10.58811/opsearch.v4i4.185
15. Yandamuri US. AI-driven decision support systems for operational optimization in hospitality technology. *Metallurgical and Materials Engineering*. 2024;30(4):950–958. doi:10.63278/mme.v30i4.1918
16. Mahamad S, Chin YH, Zulmuksah NIN, Haque MM, Shaheen M, Nisar K. Technical review: Architecting an AI-driven decision support system for enhanced online learning and assessment. *Future Internet*. 2025;17(9):383. doi:10.3390/fi17090383
17. Bughin J, Seong J, Manyika J, Chui M, Joshi R. *Notes from the AI Frontier: Modeling the Impact of AI on the World Economy* [Internet]. McKinsey Global Institute; 2018 [cited 2026 May 26]. Available from: <https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy>
18. Kolbjørnsrud V, Amico R, Thomas RJ. Partnering with AI: How organizations can win over skeptical managers. *Strategy & Leadership*. 2017;45(1):37–43. doi:10.1108/SL-12-2016-0085
19. Lichtenhaler U. Extremes of acceptance: Employee attitudes toward artificial intelligence. *Journal of Business Strategy*. 2020;41(5):39–45. doi:10.1108/JBS-12-2018-0204
20. Mikalef P, Boura M, Lekakos G, Krogstie J. Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*. 2019;30(2):272–298. doi:10.1111/1467-8551.12343
21. Verhoef PC, Broekhuizen T, Bart Y, Bhattacharya A, Dong JQ, Fabian N, et al. Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*. 2021;122:889–901. doi:10.1016/j.jbusres.2019.09.022
22. Stanford University. *Artificial Intelligence Index Report 2026* [Internet]. Stanford Institute for Human-Centered Artificial Intelligence (HAI); 2026 [cited 2026 May 26]. Available from: <https://hai.stanford.edu/ai-index/2026-ai-index-report>
23. Stanford University. *AI Index 2026 dataset* [Internet]. 2026 [cited 2026 May 26]. Available from: <https://drive.google.com/drive/folders/1zJTOg0iR0j5SijCwFutwWvDt143lW277>
24. Gélinas D, Sadreddin A, Vahidov R. Artificial intelligence in human resources management: A review and research agenda. *Pacific Asia Journal of the Association for Information Systems*. 2022;14(6):1–42. doi:10.17705/1pais.14601
25. Afzal MNI, Shohan AHN, Siddiqui S, Tasnim N. Application of AI on Human Resource Management: A Review. *Journal of HRM*. 2023;26(1):1–11. doi:10.46287/FHEV4889
26. Madanchian M, Taherdoost H, Mohamed N. AI-based human resource management tools and techniques; a systematic literature review. *Procedia Computer Science*. 2023;229:367–377. doi:10.1016/j.procs.2023.12.039
27. Nawaz N, Arunachalam H, Pathi BK, Gajenderan V. The adoption of artificial intelligence in human resources management practices. *International journal of information management data insights*. 2024;4(1):100208. doi:10.1016/j.jjime.2023.100208
28. Simon HA. A behavioral model of rational choice. *The quarterly journal of economics*. 1955;69(1):99–118. doi:10.2307/1884852

29. Galbraith JR. Organization design: An information processing view. *Interfaces*. 1974;4(3):28-36. doi:10.1287/inte.4.3.28
30. Lawrence PR. Lorsch JW. Differentiation and integration in complex organizations. *Administrative science quarterly*. 1967;12(1):1–47. doi:10.2307/2391211
31. Artomova A. (2025). Digital transformation of enterprise innovation systems: Mechanisms of change, cost reduction, and competitiveness enhancement. *Social Development: Economic and Legal Issues*. 2025;2:1–8. doi:10.70651/3083-6018/2025.2.01

Appendix A

Table 1A. Pairwise comparisons.

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig. ^a
Financial services -Consumer goods and retail	0.273	0.921	0.296	0.767	1.000
Financial services -Business, legal and professional services	0.364	0.921	0.395	0.693	1.000
Financial services -Health care, pharma and medical products	-0.818	0.921	-0.888	0.374	1.000
Financial services -Energy and materials	1.000	0.921	1.086	0.278	1.000
Financial services -Media and telecom	-1.409	0.921	-1.530	0.126	1.000
Financial services -Technology	-2.818	0.921	-3.059	0.002	0.047
Consumer goods and retail -Business, legal and professional services	0.091	0.921	0.099	0.921	1.000
Consumer goods and retail -Health care, pharma and medical products	-0.545	0.921	-0.592	0.554	1.000
Consumer goods and retail -Energy and materials	-0.727	0.921	-0.790	0.430	1.000
Consumer goods and retail -Media and telecom	-1.136	0.921	-1.234	0.217	1.000
Consumer goods and retail -Technology	-2.545	0.921	-2.763	0.006	0.120
Business, legal and professional services -Health care, pharma and medical products	-0.455	0.921	-0.493	0.622	1.000
Business, legal and professional services -Energy and materials	-0.636	0.921	-0.691	0.490	1.000
Business, legal and professional services -Media and telecom	-1.045	0.921	-1.135	0.256	1.000
Business, legal and professional services -Technology	-2.455	0.921	-2.665	0.008	0.162
Health care, pharma and medical products -Energy and materials	0.182	0.921	0.197	0.844	1.000
Health care, pharma and medical products -Media and telecom	-0.591	0.921	-0.642	0.521	1.000
Health care, pharma and medical products -Technology	-2.000	0.921	-2.171	0.030	0.628
Energy and materials -Media and telecom	-0.409	0.921	-0.444	0.657	1.000
Energy and materials -Technology	-1.818	0.921	-1.974	0.048	1.000
Media and telecom -Technology	-1.409	0.921	-1.530	0.126	1.000

Source: calculated by authors based on Stanford University [23].

Note: Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is 0.05.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Appendix B

Table 1B. Pairwise Comparisons

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig. ^a
Manufacturing-Supply chain/ inventory management	-1.000	1.658	-0.603	0.546	1.000
Manufacturing-Strategy and corporate finance	-1.062	1.658	-0.641	0.522	1.000
Manufacturing-Risk, legal, and compliance	-1.187	1.658	-0.716	0.474	1.000
Manufacturing-Human resources	2.750	1.658	1.658	0.097	1.000
Manufacturing-Software engineering	-4.187	1.658	-2.525	0.012	0.636
Manufacturing-Product and/or service development	-5.062	1.658	-3.053	0.002	0.125
Manufacturing-Service operations	-5.625	1.658	-3.392	0.001	0.038
Manufacturing-IT	6.688	1.658	4.033	0.000	0.003
Manufacturing-Knowledge management	6.688	1.658	4.033	0.000	0.003
Manufacturing-Marketing and sales	-7.000	1.658	-4.221	0.000	0.001
Supply chain/ inventory management-Strategy and corporate finance	0.063	1.658	0.038	0.970	1.000
Supply chain/ inventory management-Risk, legal, and compliance	0.188	1.658	0.113	0.910	1.000
Supply chain/ inventory management-Human resources	1.750	1.658	1.055	0.291	1.000
Supply chain/ inventory management-Software engineering	3.188	1.658	1.922	0.055	1.000
Supply chain/ inventory management-Product and/or service development	4.063	1.658	2.450	0.014	0.786
Supply chain/ inventory management-Service operations	4.625	1.658	2.789	0.005	0.291
Supply chain/ inventory management-IT	5.688	1.658	3.430	0.001	0.033
Supply chain/ inventory management-Knowledge management	5.688	1.658	3.430	0.001	0.033
Supply chain/ inventory management-Marketing and sales	6.000	1.658	3.618	0.000	0.016
Strategy and corporate finance-Risk, legal, and compliance	0.125	1.658	0.075	0.940	1.000
Strategy and corporate finance-Human resources	1.688	1.658	1.018	0.309	1.000
Strategy and corporate finance-Software engineering	3.125	1.658	1.884	0.060	1.000
Strategy and corporate finance-Product and/or service development	4.000	1.658	2.412	0.016	0.872

Continuation Table:

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig. ^a
Strategy and corporate finance-Service operations	4.563	1.658	2.751	0.006	0.326
Strategy and corporate finance-IT	5.625	1.658	3.392	0.001	0.038
Strategy and corporate finance-Knowledge management	5.625	1.658	3.392	0.001	0.038
Strategy and corporate finance-Marketing and sales	5.938	1.658	3.580	0.000	0.019
Risk, legal, and compliance-Human resources	1.563	1.658	0.942	0.346	1.000
Risk, legal, and compliance-Software engineering	-3.000	1.658	-1.809	0.070	1.000
Risk, legal, and compliance-Product and/or service development	3.875	1.658	2.337	0.019	1.000
Risk, legal, and compliance-Service operations	-4.437	1.658	-2.676	0.007	0.410
Risk, legal, and compliance-IT	5.500	1.658	3.317	0.001	0.050
Risk, legal, and compliance-Knowledge management	5.500	1.658	3.317	0.001	0.050
Risk, legal, and compliance-Marketing and sales	5.813	1.658	3.505	0.000	0.025
Human resources-Software engineering	-1.437	1.658	-0.867	0.386	1.000
Human resources-Product and/or service development	-2.312	1.658	-1.394	0.163	1.000
Human resources-Service operations	-2.875	1.658	-1.734	0.083	1.000
Human resources-IT	-3.937	1.658	-2.374	0.018	0.967
Human resources-Knowledge management	-3.937	1.658	-2.374	0.018	0.967
Human resources-Marketing and sales	-4.250	1.658	-2.563	0.010	0.571
Software engineering-Product and/or service development	0.875	1.658	0.528	0.598	1.000
Software engineering-Service operations	1.438	1.658	0.867	0.386	1.000
Software engineering-Knowledge management	2.500	1.658	1.508	0.132	1.000
Software engineering-IT	2.500	1.658	1.508	0.132	1.000
Software engineering-Marketing and sales	2.813	1.658	1.696	0.090	1.000
Product and/or service development-Service operations	-0.562	1.658	-0.339	0.734	1.000
Product and/or service development-IT	1.625	1.658	0.980	0.327	1.000
Product and/or service development-Knowledge management	1.625	1.658	0.980	0.327	1.000

Continuation Table:

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig. ^a
Product and/or service development-Marketing and sales	1.938	1.658	1.168	0.243	1.000
Service operations-IT	1.063	1.658	0.641	0.522	1.000
Service operations-Knowledge management	1.063	1.658	0.641	0.522	1.000
Service operations-Marketing and sales	1.375	1.658	0.829	0.407	1.000
IT-Knowledge management	0,000	1.658	0.000	1.000	1.000
IT-Marketing and sales	-0.312	1.658	-0.188	0.851	1.000
Knowledge management-Marketing and sales	-0.312	1.658	-0.188	0.851	1.000

Source: calculated by authors based on Stanford University [23].

Note: Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is 0.05.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.