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AI-DRIVEN DECISION SUPPORT SYSTEMS IN STRATEGIC BUSINESS MANAGEMENT: A CASE-BASED ANALYSIS

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Purpose: The purpose of this paper is to examine the role of Artificial Intelligence (AI) in decision support systems (DSS) and its strategic impact on organizational performance. It explores how AI technologies enhance decision quality, speed, and adaptability, and proposes a conceptual framework for their integration into strategic management.
Design/methodology/approach: The study adopts a qualitative case study methodology, analyzing three multinational corporations—Amazon, IBM, and Salesforce—that have applied AI-enabled DSS to supply chain management, human resources, and customer relationship management. The analysis integrates machine learning, natural language processing, predictive analytics, and reinforcement learning into a unified "Data–Intelligence–Action" model.
Findings: The research demonstrates that AI-DSS significantly improve forecasting accuracy, efficiency, and adaptability. Case results highlight measurable improvements in KPIs: optimized supply chain management at Amazon, reduced staff turnover and enhanced recruitment quality at IBM, and increased conversion and customer satisfaction at Salesforce. The "Data–Intelligence–Action" model emphasizes feedback loops as a driver of continuous improvement and strategic agility.
Research limitations/implications: The study focuses on large enterprises, which may limit generalization to small and medium-sized firms. Future research should explore diverse industries, different organizational scales, and ethical aspects of human–AI collaboration in decision-making.
Practical implications: For practitioners, the study provides guidance on piloting and scaling AI solutions, integrating them into existing DSS, and evaluating results through KPIs. The findings point to strong commercial benefits, including cost optimization, improved customer retention, and enhanced competitiveness.
Social implications: The paper highlights the importance of ethical AI adoption, trust-building, and responsible innovation. AI-DSS can strengthen organizational resilience, support digital transformation, and inform public and industry policy on human–AI interaction.

Originality/value: The originality of the paper lies in combining empirical case evidence with a novel conceptual model ("Data–Intelligence–Action"), which generalizes the strategic role of AI across industries. It adds value to both scholars and practitioners by linking theoretical insights with actionable frameworks for digital strategy.
Keywords: AI-driven decision support, strategic management, machine learning, predictive analytics, KPI optimization, case study.
Category of the paper: research paper.

1. Introduction

In today's business environment, characterized by high levels of uncertainty, rapid market dynamics, and large amounts of data, strategic management requires new approaches to decision-making. Classical methods based on intuition, experience, or manual analysis often prove insufficiently effective in complex and multifactorial tasks.

In this context, the role of decision support systems (DSS) is growing, which allow structuring information and providing managers with relevant data for informed choices. The current stage of DSS development is associated with the introduction of artificial intelligence (AI) technologies, which significantly expand the functionality of such systems - from forecasting to automated recommendations.

The application of AI approaches in strategic management is particularly promising, where decisions have long-term consequences and require high accuracy, adaptability, and speed of response. Based on the analysis of real cases of companies that have implemented AI-oriented DSS, this article examines the impact of such decisions on management efficiency, key performance indicators (KPIs), and overall business development dynamics.

The purpose of this article is to:

- analyze approaches to implementing AI in DSS,
- assess the effectiveness of such systems using specific business cases,
- identify the opportunities and limitations of using AI in strategic decision-making.

2. Presentation of the main material

Decision Support Systems: Evolution and Modern Context

Decision support systems (DSS) emerged in response to the need to provide managers with relevant information for decision-making in complex situations. Classic DSSs were based on a combination of databases, analysis models, and user interfaces. The main functions of such systems were data storage and processing, scenario modeling, and support for choosing among alternatives.

During the 1990s and 2000s, DSSs evolved towards integration with Business Intelligence, allowing companies to perform deeper analysis of internal and external factors. However, the increasing complexity of data and the need for forecasting led to the need to improve DSSs by incorporating the latest technologies.

Artificial Intelligence in Management: New Horizons for DSS

The integration of artificial intelligence into decision support systems has become a qualitative breakthrough. Modern AI solutions allow not only to analyze data, but also to learn from historical information, form forecasts, generate recommendations, and sometimes even independently initiate decisions within given parameters.

According to a study by Power et al. (2021), modern DSS have evolved towards the concept of "intelligent decision support", where machine learning, big data analytics, and pattern recognition play a key role. Shollo & Galliers (2015) analyze the use of analytics in strategic management and emphasize the role of data-driven reasoning in decision-making. Delen & Demirkan (2013) propose an integration model of business intelligence & analytics (BI&A), which underlies AI solutions in corporate management.

KPIs as indicators of the strategic impact of AI solutions

Implementing AI into decision-making processes allows organizations to assess their effectiveness in a new way. The most commonly used key performance indicators (KPIs) that reflect the impact of AI-enabled DSS include:

- prompt decision-making,
- accuracy of forecasts,
- profitability,
- customer satisfaction,
- cost optimization.

Kiron et al. (2014) in a report in the MIT Sloan Management Review note that companies that actively use analytics and AI have higher strategic indicators — in particular, more accurate demand forecasts and more effective marketing campaigns.

Ghasemaghaei (2019) emphasizes that data analytics capabilities are positively correlated with decision quality and financial results in a dynamic environment.

3. Case analysis in management: the importance of empirical approaches

The case method as an approach to the study of management practices allows us to reveal the deep processes of technology adaptation in a specific organizational context. It is of particular value in the study of technological innovations, where not only the “what” is important, but also the “how” - that is, how exactly solutions are implemented, who are the drivers of change, what obstacles arise.

According to Yin (2018), case studies are effective in situations where the phenomenon is not yet fully understood or has multiple contexts. Therefore, the chosen approach allows for a deeper analysis of the impact of AI-DSS on strategic management through real-world examples.

This study uses a qualitative case study approach to explore the application of AI-based decision support systems in a specific business context. This approach is particularly appropriate when investigating a complex, multifactorial, and evolving phenomenon, such as the integration of AI into strategic management.

Yin's (2018) approach to constructing case studies, which includes a multi-level analysis structure: description of the environment, diagnosis of the problem, analysis of technology implementation, and evaluation of results.

Three case studies of companies with open access to data were selected for the study, which demonstrated the successful implementation of AI platforms in the field of management decision-making. The main selection criteria were:

- the presence of strategic management elements in the focus of activities,
- use of AI technologies in analytical processes or DSS,
- availability of documented results (reports, studies, articles).

1. Amazon — applying predictive analytics to supply chain management.
2. IBM Watson is a solution for HR analytics and strategic workforce planning.
3. Salesforce Einstein is an AI module to support sales and marketing strategies.

These examples not only illustrate the multi-disciplinary application of AI-DSS, but also allow us to compare the effects of implementation in different functional areas.

The chosen approach allows us to gain a deep understanding of the mechanisms of AI's impact on management decisions and to form the basis for future quantitative research.

Amazon is one of the most well- known examples of large-scale implementation of artificial intelligence in strategic decision-making. In the field of logistics and supply chain management, Amazon uses demand forecasting analytics, route optimization, and automated inventory management based on machine learning algorithms.

Since 2012, Amazon has been actively investing in AI analytics to manage inventory and predict consumer behavior. One of the key tools has been the Forecasting AI platform, which allows:

- forecast demand for goods with an accuracy of up to 90%,
- adaptively distribute stocks between regional warehouses,
- optimize the supply chain according to seasonality and market changes.

Such solutions work in integration with Amazon Web Services (AWS), where machine learning models analyze historical data about orders, weather conditions, traffic situations, and even social trends.

According to analytical reports (Deloitte, 2021), the use of AI has allowed Amazon to:

- reduce delivery time by 15-20%,
- reduce storage costs by 30%,
- improve the accuracy of order forecasts by 25%.

This, in turn, increased the overall customer satisfaction score and allowed us to respond more quickly to changing demand during a crisis (for example, during COVID-19).

The introduction of AI into supply chains has allowed Amazon to move to a "reactive-predictive" management model. Instead of traditionally reacting to shortages, the company acts proactively — building up inventory before a product becomes popular. This approach is an example of a new generation of strategic planning, where artificial intelligence acts as a key partner in decision-making.

IBM Watson is one of the most well-known AI platforms, widely used in the field of HR analytics. Its tools allow you to:

- predict the risk of employee dismissal,
- to form personalized career tracks,
- optimize personnel selection processes,
- to identify hidden patterns in performance assessments.

One of the key solutions is Watson Career Coach, a system that uses NLP (natural language processing) to analyze resumes, performance reports, employee satisfaction surveys, social activity, and other factors.

According to IBM data and independent research (Chui et al., 2018; Bersin, 2020), the use of AI in HR has led to:

- reducing staff turnover by 25-30% due to risk forecasting,
- reduction of recruitment costs by 20%,
- increasing the accuracy of candidate matching up to 85%.

This has a direct impact on strategic human capital management, allowing HR to be moved from an operational to a strategic management level.

Table 1.
The impact of AI solutions on HR-KPIs in IBM Watson

Indicator	Before the implementation of AI	After the implementation of AI	Change (%)
Average rental period (days)	45	32	-29%
Staff turnover	18%	13%	-28%
Candidate suitability (quality)	65%	85%	+31%
Recruitment costs (in $ thousand)	250	200	-20%

Sources: IBM Workforce Report (2021), Deloitte Human Capital Trends (2020).

The model of a strategic HR solution with the participation of AI can be presented as an adapted "Sense–Analyze–Act" process, where:

1. Sense — data collection from various sources: assessments, surveys, digital activity.
2. Analyze — using ML/NLP algorithms for analysis and prediction.
3. Act — management decision: promotion, dismissal, retraining, adaptation.

This forms a closed loop of self-learning for the organization, where every decision is based on data and adjusted by AI models in real time.

AI in HR allows you to move from reactive to proactive HR management, reducing risks, improving staff loyalty and forming long-term HR policies. In a strategic dimension, this allows you to align human capital development with the organization's business goals, which is critically important in turbulent times.

Salesforce Einstein is a built-in artificial intelligence module in the Salesforce CRM platform that provides real-time analytics, prediction, and automated recommendations. Its main function is to improve the efficiency of customer relationship management (CRM) through machine learning algorithms, behavioral clustering, and personalized suggestions.

Einstein analyzes customer communication history, website behavior patterns, emails, content interactions, and even the emotional tone of the message. Based on this, it:

- predicts the probability of concluding a deal,
- ranks potential customers by value (lead scoring),
- offers personalized marketing steps.

KPI-results of implementation

According to data from Salesforce (2021) and Accenture Digital (2020), companies that implemented Einstein observed:

- 20-25% increase in conversion rate,
- increase customer retention by 15-18%,
- reducing the time to close a deal by 20%,
- 30% increase in customer satisfaction.

These effects significantly impact strategic customer base management, allowing for more precise targeting and increased customer lifetime value (CLV).

Table 2.
Comparison of results before/after implementing Salesforce Einstein

Indicator	**Before the implementation of AI**	**After the implementation of AI**	**Change (%)**
Lead conversion	18%	23%	+27%
Average time to deal (days)	35	28	-20%
Customer retention rate	62%	73%	+17%
Customer Satisfaction Score (CSAT)	78	89	+14%

Sources: Salesforce Annual Report (2021), Accenture AI in CRM Survey (2020).

AI-based decision-making model in sales

Salesforce's AI module uses a hybrid decision-making model that combines:

- supervised learning (for predictions of deal success),
- clustering (to identify customer segments),
- reinforcement learning (to optimize marketing actions over time).

The result is an automated system for prioritizing manager actions, which prompts:

- who to call first,
- which customer to offer a discount to,
- which communication channel will be the most effective.

This allows you to move operational sales management to a strategic level, focusing not only on “deals”, but on the customer lifecycle and long-term interaction.

Einstein integration in sales enables a closed data-driven management loop — from the first contact to the post-sales support. This approach transforms the classic Sales Funnel model into an "AI-enabled Customer Journey" where decisions are made not only by the manager, but also by a recommendation system that takes into account thousands of parameters in real time.

An analysis of three cases (Amazon, IBM, Salesforce) demonstrates that regardless of the field of application, AI platforms as part of decision support systems perform universal strategic functions:

- Forecasting future events or scenarios (demand forecasting, staff turnover, deal success rate).
- Prioritizing decisions based on large amounts of historical data.
- Automation of routine analytical processes, which reduces the burden on managers.
- Optimization of KPIs, such as efficiency, accuracy, speed, customer or employee satisfaction.

All companies are also demonstrating a shift to proactive management, where AI not only prompts but also initiates actions, which is crucial for strategic thinking in a VUCA (Volatility, Uncertainty, Complexity, Ambiguity) environment.

AI components of DSS change not only the tools, but also the philosophy of management decisions. In the traditional model of strategic management, decisions are made based on intuition, experience or limited data. AI allows you to move to a data-driven strategy, where:

- analytics not only confirms hypotheses, but also reveals patterns that managers may not have noticed,
- decisions are based on empirical data, not subjective judgments,
- the reaction time to changes is significantly reduced,
- personalization of solutions becomes possible at the level of each client or employee.

This is especially important in the era of digital transformation, when companies are forced to be flexible, adaptive, and technologically savvy.

Despite the obvious benefits, implementing AI in DSS is not without its challenges. Key challenges include:

- Ethical issues: algorithm bias, decision transparency, impact on privacy.
- Human factor: distrust of AI, resistance to change, need for staff training.
- Implementation cost: for small and medium-sized enterprises, the investment may be too large.
- Interpreting results: AI can be a "black box", and not all decisions can be explained to management or regulators.

These challenges require a new approach to management culture, with an emphasis on learning, ethics, and human-machine interaction.

Based on the analysis, a number of practical recommendations can be formulated for companies planning to implement AI-DSS:

- start with local pilot projects focused on one process or KPI,
- ensure the integration of AI solutions into existing systems, rather than creating a parallel infrastructure,
- involve multidisciplinary teams - analysts, managers, IT specialists,
- develop ethical protocols for data use,
- conduct regular evaluation of the effectiveness of AI solutions through specific strategic metrics.

It is also advisable to intensify academic research, in particular in the following areas:

- interaction of AI solutions and human decision-making,
- comparing the effectiveness of different types of AI algorithms in DSS,
- cultural differences in the acceptance of AI as a management partner.

Based on the three studied cases, it can be concluded that the use of AI platforms in DSS is not unified - each organization adapts them according to its industry specifics, strategic priorities and organizational structure. However, there are common features that allow us to identify typical approaches to implementation.

The table below summarizes the key characteristics of AI-DSS implementation in three organizations.

Table 3.
Comparison of AI-DSS effects in three cases

Company	Implementation function	AI tools	Key KPI changes
Amazon	Logistics and supply	ML for prediction, AWS AI tools	↓ warehousing costs, ↑ demand accuracy
IBM	Personnel management	NLP, predictive analytics	↓ staff turnover, ↑ recruiting quality
Salesforce	Sales and Marketing	Lead scoring, reinforcement learning	↑ conversion, ↑ CSAT, ↓ deal time
Company	**Implementation function**	**AI tools**	**Key KPI changes**

This comparative analysis allows us to identify three strategic principles that are formed when using AI-DSS:

1. Focus on prediction and adaptation — in all cases, AI is used to model future events.
2. Targeted optimization of business functions - the implementation of AI is associated with increasing the efficiency of a specific functional area (logistics, HR, marketing).
3. Systemic decision support — AI does not replace a manager, but provides informed decision options in real time.

So, while industries vary, the role of AI as a strategic tool is universal.

Based on the analysis, the author proposes a generalizing model that demonstrates the logic of AI-DSS functioning as part of the strategic management cycle. It is based on three key stages — "Data – Intelligence – Action" — and is supplemented by feedback that ensures the adaptability of the system.

Model description:

1. Data – input data from various sources:
   - internal business data (financial indicators, HR reports, CRM),
   - external (market trends, customer behavior, social networks),
   - unstructured data (reviews, text, emotions).
2. Intelligence – data processing using AI algorithms:
   - machine learning (ML) to detect patterns,
   - natural language processing (NLP) for text analysis,
   - scenario modeling for strategic forecasting,
   - reinforcement learning to optimize actions.
3. Action – decision making:
   - AI generates recommendations (the level of automation depends on the context),
   - the manager makes the final decision or confirms the automatic action,
   - The results of decisions are recorded in the system for further analysis.
4. Feedback loop – data on the results of actions is fed back into the system, improving the accuracy of future predictions. A cycle in which the results of decisions are recorded, analyzed, and reused to train models. This ensures the system's adaptability to new conditions, increases the accuracy of forecasts, and develops organizational intelligence.

The “Data – Intelligence – Action” model proposed within the framework of this study is a logical generalization of the impact of artificial intelligence on the process of strategic management in the context of digital transformation. It reflects a modern vision of the functioning of decision support systems, in which data, intellectual processing and actions form a single dynamic cycle. The model demonstrates that the source of management decisions is not only structured indicators of the enterprise’s activity, but also diverse external and unstructured data - customer behavior, market signals, feedback, emotional reaction of users, etc. It is this wealth of information that becomes the basis for the next stage - processing, where artificial intelligence identifies patterns, predicts and generates management alternatives.

Unlike traditional DSS models, the proposed concept provides not only decision support, but also partial autonomy in the formation and initiation of management actions. Thanks to the use of machine learning algorithms, natural language processing and reinforcement learning elements, such systems do not simply respond to user requests, but actively model future scenarios and suggest optimal steps based on accumulated experience. In the final phase, the proposed solution is implemented or verified - directly by the manager or automatically, depending on the level of trust, complexity of the situation and organizational policy.

A key element of the model is the built-in feedback loop, a mechanism that allows the system to analyze the results of its own decisions and use this information for further learning. Thus, a closed loop of continuous improvement is created, which is based on the interaction between data, intelligence and actions. This approach corresponds to the paradigm of adaptive strategic management, where the organization does not just react to changes, but constantly improves its own approaches to planning and management.

The concept of “Data – Intelligence – Action” is universal and can be scaled to different industries and levels of management. Its flexibility allows you to adapt the model to the needs of logistics systems, personnel management, marketing strategies, customer service and other areas. It also provides for the coexistence of human and machine intelligence in one management space, which is one of the defining vectors of management development in the era of artificial intelligence.

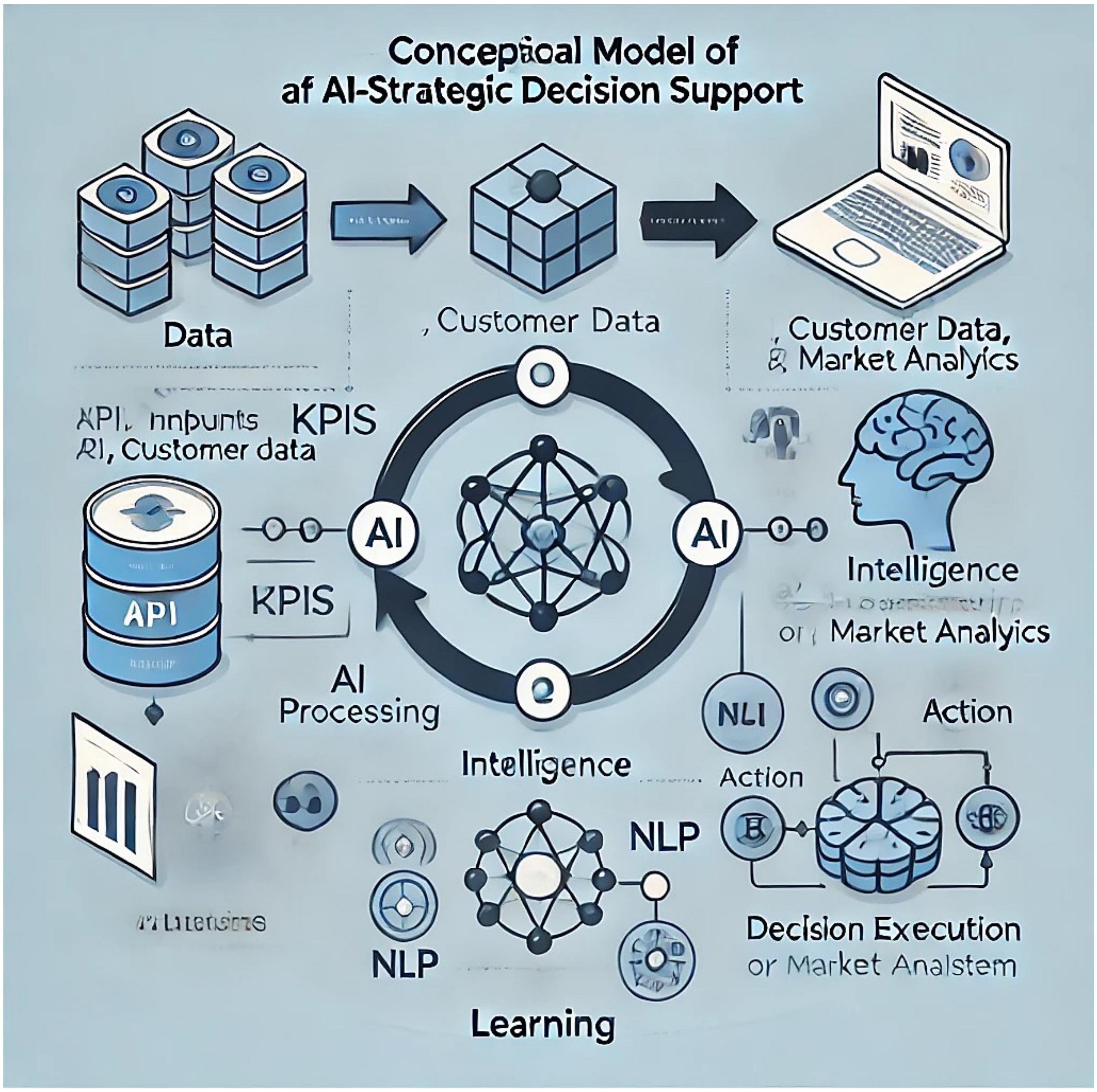

Figure 1. Conceptual model of AI-enabled strategic decision support.

The model corresponds to the concept of dynamic strategic management, where AI does not simply serve processes, but becomes an integrated element of the management cycle. The "Data – Intelligence – Action" model is not a rigid scheme, but acts as a flexible framework that can adapt to different functional areas: logistics, HR, finance, marketing. It combines the advantages of classic DSS (structure and choice support) with the capabilities of modern AI (forecasting, adaptation, learning), which makes it an effective tool for strategic management in conditions of uncertainty. In addition, the model takes into account the human factor, i.e., it involves the participation of the manager in the decision-making cycle, which reduces the risks of automation failures and helps to increase trust in AI.

4. Conclusions

This study demonstrates that the integration of artificial intelligence into decision support systems (AI-DSS) has a transformative impact on strategic management practices. Through the analysis of three case studies in logistics, human resources, and customer relationship management, the research highlights the cross-industry applicability of AI-driven solutions. In each case, AI technologies contributed to optimizing key performance indicators, accelerating decision-making, and enhancing adaptability to dynamic market conditions.

Theoretical contributions include the development of the "Data–Intelligence–Action" conceptual model, which captures the cyclical, adaptive nature of AI-enhanced decision-making. This model extends current understanding of strategic thinking by illustrating how empirical, data-driven insights increasingly complement or even replace intuition-based approaches. Practically, the findings suggest that AI-DSS can serve not only as tools for operational improvement but as catalysts for strategic renewal. They offer organizations a roadmap for informed digital transformation, enabling higher precision and responsiveness in decision-making.

However, the study is not without limitations. The case selection focuses on large, resource-rich enterprises, which may not reflect the challenges faced by small and medium-sized businesses. Additionally, while technological benefits are evident, the successful deployment of AI-DSS also hinges on organizational readiness, leadership openness, and cultural alignment—factors not exhaustively explored in this research.

Despite these limitations, the study offers several lessons. First, AI can redefine the boundaries of strategic decision-making by embedding continuous learning and feedback into core management processes. Second, trust in AI systems must be actively cultivated through transparent processes, ethical oversight, and regulatory alignment. These insights open avenues for further investigation into the social, ethical, and institutional dimensions of AI adoption.

In sum, AI-DSS hold the potential to reshape strategic management, not merely by enhancing efficiency, but by redefining how organizations conceptualize and execute strategic choices. Future research should extend the empirical base, particularly in less digitized sectors, and deepen exploration of the human-AI interface in decision-making. The knowledge generated through this study contributes to a broader understanding of data-driven strategy and provides a foundation for responsibly integrating AI into strategic governance.

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