# AI ADOPTION IN MANAGEMENT DECISION-MAKING AND FIRM PERFORMANCE: EVIDENCE FROM A ROMANIAN AUTOMOTIVE COMPANY

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**Abstract**

*This study examines the relationship between artificial intelligence (AI) adoption, managerial decision-making, and firm performance, focusing on a large Romanian automotive company. The main objective is to assess how data-driven decision-support mechanisms can address inefficiencies in organizational performance. The research employs a longitudinal case study based on financial data extracted from the Romanian Ministry of Finance for the period 2020–2024, using key performance indicators such as turnover, profit margin, and labor productivity. The empirical results reveal a significant divergence between revenue growth and declining profitability, indicating structural inefficiencies in cost management and decision-making processes. These findings suggest that traditional managerial approaches may be insufficient in complex industrial environments characterized by operational volatility and increasing cost pressures. The analysis is contextualized within the European automotive sector, where the adoption of AI-based solutions for forecasting, production planning, and supply chain management has accelerated in recent years. Compared to these trends, Romanian firms exhibit a slower pace of digital integration, which may limit their competitiveness. The study contributes to the literature by providing empirical evidence from an underexplored regional context and by linking financial performance dynamics with AI-driven decision-making frameworks. It also offers practical implications for managers in manufacturing industries, highlighting the role of artificial intelligence in improving decision quality, operational efficiency, and long-term performance.*

**Key words:** *artificial intelligence, managerial decision-making, automotive industry, digital transformation, Romania.*

**JEL Classification:** *C23, D83, L62, M15, O33*

## INTRODUCTION

The rapid expansion of artificial intelligence (AI) technologies has fundamentally transformed managerial decision-making processes, particularly in data-intensive industries such as manufacturing. AI systems enable firms to process large volumes of structured and unstructured data, improving forecasting accuracy, operational efficiency, and strategic responsiveness. In this context, AI is increasingly regarded as a critical driver of organizational performance and competitive advantage (Davenport et al., 2020; Agrawal et al., 2022).

Recent empirical studies demonstrate that AI capabilities enhance decision-making performance, particularly by increasing decision speed and improving analytical accuracy, provided that firms possess adequate digital infrastructure and strategic alignment (Brynjolfsson et al., 2021). At the same time, the literature highlights that AI adoption is uneven across firms and regions, particularly in emerging economies (Cirera et al., 2022;

Nicolescu, 2020). This heterogeneity raises important questions regarding the actual impact of AI on firm performance in different economic contexts.

In management research, AI is no longer viewed solely as a technological tool but as a core component of digital transformation strategies, influencing organizational structures, managerial cognition, and decision-making mechanisms (Verhoef et al., 2021). Bibliometric analyses indicate a strong increase in research on AI in management between 2021 and 2025, with a growing focus on its role in decision support, innovation, and performance outcomes. These developments reflect a broader shift toward data-driven management models, where traditional intuition-based decisions are increasingly complemented or replaced by algorithmic insights.

## II.LITERATURE REVIEW

The relationship between artificial intelligence (AI) and managerial decision-making has gained significant attention in recent years, particularly in the context of digital transformation and organizational performance. AI is increasingly conceptualized as a decision-support mechanism that enhances managerial capabilities by providing predictive and prescriptive insights derived from large datasets (Davenport et al., 2020; Agrawal et al., 2022). However, despite the growing interest in artificial intelligence, its adoption and impact on managerial decision-making remain uneven across countries and industries, particularly in emerging economies where digital capabilities are still developing (Cirera et al., 2022).

A growing body of research emphasizes the role of AI in improving decision quality and organizational performance. Empirical studies show that AI-driven decision-making systems contribute to increased efficiency, reduced uncertainty, and enhanced strategic alignment, particularly in complex and dynamic environments (Brynjolfsson et al., 2021; Raisch & Krakowski, 2021). These findings are further supported by evidence indicating that firms leveraging AI capabilities achieve superior performance in terms of decision speed and analytical accuracy (Jarrahi, 2018; Wamba-Taguimdje et al., 2020).

Recent contributions highlight the multidimensional nature of AI adoption in organizations. AI integration extends beyond operational improvements, influencing strategic planning, innovation processes, and inter-organizational collaboration (Verhoef et al., 2021; Cockburn et al., 2020). These studies underline that AI adoption represents not merely a technological upgrade but a transformation of managerial logic and organizational routines.

From a theoretical perspective, AI adoption is closely linked to the concept of dynamic capabilities, which enable firms to adapt to rapidly changing environments. Research shows that AI enhances firms' ability to identify opportunities, manage risks, and optimize resource allocation, thereby improving performance outcomes (Teece, 2018; Mikalef et al., 2021). This perspective aligns with the view that AI acts as a strategic resource that complements human decision-making rather than replacing it.

In addition, studies focusing on organizational behavior emphasize the importance of human–AI interaction in decision-making processes. The effectiveness of AI depends on managerial trust, cognitive adaptation, and the integration of human judgment with algorithmic recommendations (Dellermann et al., 2019; Jarrahi, 2018). This hybrid approach is increasingly recognized as essential for achieving sustainable performance improvements. In the context of Central and Eastern Europe, these challenges are further amplified by institutional and economic constraints, which limit the ability of firms to effectively integrate AI into managerial processes (Ionescu, 2022).

Another important stream of literature examines the determinants of AI adoption at the firm level. Evidence suggests that technological readiness, data availability, and workforce skills are critical factors influencing the successful implementation of AI systems (OECD, 2023; Cirera et al., 2022). These constraints are particularly relevant in emerging economies; including Romania, where digital transformation remains uneven and firms face structural barriers in adopting advanced technologies (Ionescu, 2022; Popescu, 2021). Moreover, sector-specific characteristics play a significant role, with industries such as automotive and manufacturing demonstrating higher potential for AI integration due to their reliance on data-driven processes and automation (Choi et al., 2020).

Despite the growing interest in AI adoption, several studies highlight persistent challenges, including high implementation costs, data quality issues, and resistance to organizational change (Bessen, 2022; Fountaine et al., 2019). These barriers are particularly relevant for firms operating in emerging economies, where digital infrastructure and managerial capabilities may be less developed.

Overall, the literature indicates that while AI has the potential to significantly enhance managerial decision-making and firm performance, its impact depends on a combination of technological, organizational, and contextual factors. However, empirical evidence remains limited in the context of emerging economies, particularly in the automotive sector. This gap is especially relevant for countries such as Romania, where firms face structural constraints in adopting advanced digital technologies. Therefore, further empirical research is needed to examine how AI-driven decision-making can influence firm performance in real-world industrial environments.

## III.RESEARCH HYPOTHESES

Based on the existing literature on artificial intelligence and managerial decision-making, as well as the identified research gap in the context of emerging economies, the following research hypotheses are proposed:

H1: Inefficiencies in managerial decision-making are associated with declining firm profitability, even in the presence of stable or increasing revenues.

H2: The adoption of artificial intelligence-based decision-support systems has the potential to improve firm performance by enhancing forecasting accuracy, resource allocation, and operational efficiency.

H3: Firms operating in emerging economies, such as Romania, exhibit lower levels of AI adoption, which may negatively, influence their performance compared to firms in more digitally advanced environments.

## IV.CONCEPTUAL FRAMEWORK

Figure 1 illustrates the conceptual framework underlying this study. The model highlights the relationship between artificial intelligence (AI) adoption, managerial decision-making, and firm performance within the context of a manufacturing company operating in an emerging economy.

AI-based decision-support systems are conceptualized as a key enabler of improved managerial decision-making by enhancing forecasting accuracy, data processing capabilities, and resource allocation efficiency. In turn, the quality of managerial decision-making directly influences firm performance, particularly in terms of profitability, operational efficiency, and financial stability.

In addition, the model incorporates complementary factors such as customer preferences, industry benchmarks, and employee involvement, which may influence managerial decision-making by providing additional contextual and operational inputs.

At the same time, the model incorporates contextual factors specific to emerging economies, such as limited digital infrastructure, organizational constraints, and lower levels of AI adoption. These factors may moderate the relationship between AI adoption and firm performance, potentially explaining performance gaps between firms operating in different economic environments.

Thus, the conceptual framework assumes a causal chain in which AI adoption influences managerial decision-making, which subsequently affects firm performance, while contextual factors shape the strength and direction of these relationships.

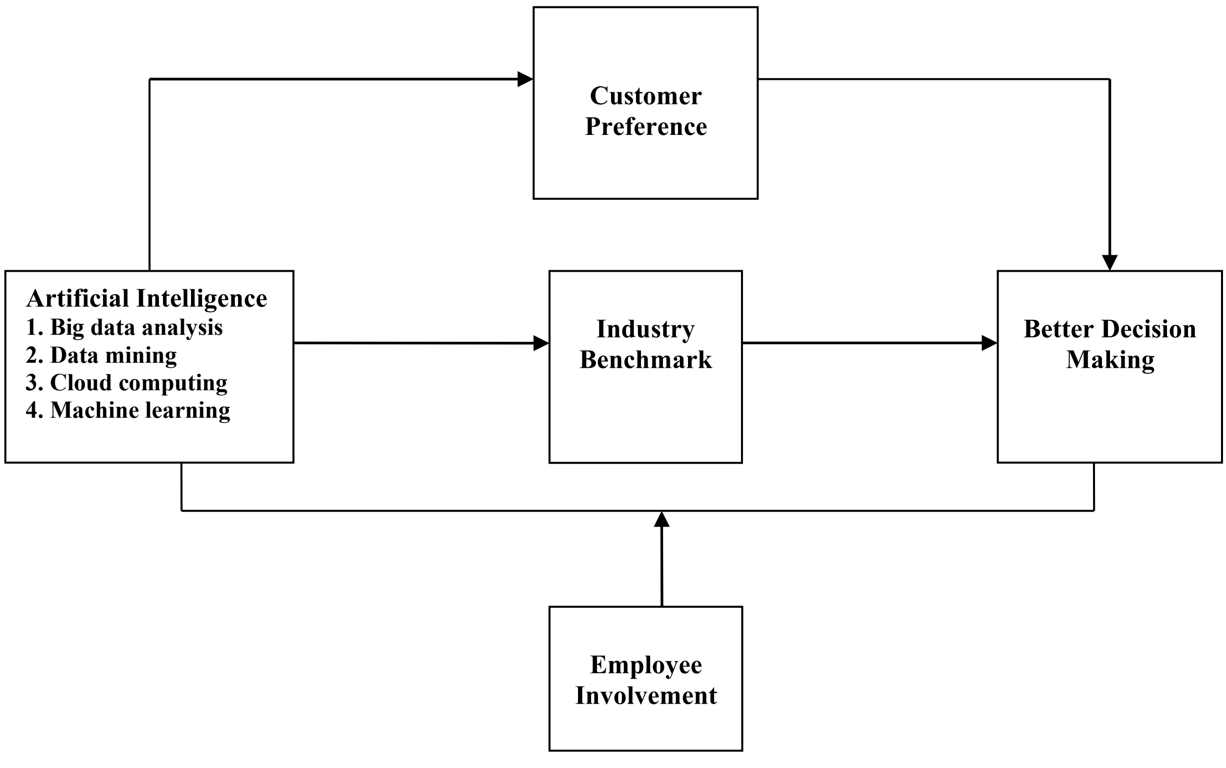


**Figure 1 - Conceptual framework of artificial intelligence adoption and managerial decision-making in the automotive industry**

**Source:** Author's elaboration based on Davenport et al. (2020), Brynjolfsson et al. (2021), and Raisch & Krakowski (2021)

The proposed conceptual model provides the theoretical foundation for the research hypotheses, linking AI adoption to managerial decision-making (H2), managerial decision-making to firm performance (H1), and contextual differences between emerging and developed economies to variations in AI adoption and performance outcomes (H3).

## V.METHODOLOGY

This study employs a quantitative case study approach to investigate the relationship between managerial decision-making, firm performance, and the potential role of artificial intelligence (AI) within a large Romanian automotive company (hereafter referred to as Company A). Case study methodology is widely used in management research to analyze complex organizational phenomena in real-world contexts (Yin, 2018). The selected company operates as part of a German multinational group and is classified as a large taxpayer, with an average workforce of approximately 650–750 employees during the analyzed period.

The empirical analysis is based on publicly available financial data extracted from the Romanian Ministry of Finance for the period 2020–2024 (Romanian Ministry of Finance, 2024). The selected timeframe allows for a longitudinal assessment of firm performance, capturing both growth and decline phases in the company's financial evolution. Longitudinal financial analysis is commonly used to identify structural trends and performance dynamics within firms (Penman, 2013).

The research design integrates descriptive and analytical methods. First, key financial indicators are examined to identify trends in performance dynamics. Second, these trends are interpreted in relation to managerial decision-making processes and contextualized within the broader framework of digital transformation and AI adoption.

To assess firm performance, the study uses the following indicators, which are standard measures in financial and managerial analysis (Palepu et al., 2020; Damodaran, 2021):

- Turnover (Total Revenue) – reflecting the scale of business operations;
- Net Profit – indicating overall financial performance;
- Profit Margin (Net Profit/Turnover) – measuring profitability efficiency;
- Productivity per Employee (Turnover/Number of Employees) – evaluating operational efficiency;
- Debt Level – capturing financial structure and potential risk exposure.

The indicators are calculated annually to identify structural changes in the company's financial performance.

Particular attention is given to the divergence between revenue growth and profitability decline, which may signal inefficiencies in cost management or strategic decision-making.

The methodological framework also includes a comparative component, positioning the findings within the context of the European automotive industry. Secondary data from Eurostat and OECD reports are used to provide benchmark insights regarding AI adoption and digital transformation trends at the European level.

Given the lack of direct data on AI implementation within Company A, the study adopts an inferential approach. Specifically, it analyzes performance inefficiencies and evaluates the potential contribution of AI-based decision-support systems in addressing these issues. This approach is consistent with prior research that examines the impact of digital technologies on firm performance through indirect indicators (Brynjolfsson et al., 2021; Raisch & Krakowski, 2021).

The limitations of the study are acknowledged. As a single-case analysis, the results cannot be generalized across all firms or industries. However, the detailed examination of a large manufacturing company provides valuable insights into the interaction between managerial decision-making and performance dynamics in a real-world context.

Overall, the methodology combines empirical financial analysis with a conceptual evaluation of AI-driven management, offering a robust framework for understanding how advanced technologies can enhance decision-making processes and organizational performance.

## VI.RESULTS

The empirical analysis of Company A is based on financial data for the period 2020–2024, extracted from official reports published by the Romanian Ministry of Finance. To ensure analytical consistency, key performance indicators were calculated and synthesized in Table 1, following established methodologies in financial analysis (Penman, 2013; Palepu et al., 2020).

**Table 1. Financial performance indicators of Company A (2020–2024)**

| Indicator | 2020 | 2021 | 2022 | 2023 | 2024 |
|---|---|---|---|---|---|
| Turnover (RON) | 365,425,433 | 410,726,477 | 445,483,270 | 421,642,246 | 430,196,390 |
| Net Profit (RON) | 17,951,994 | 14,704,576 | -9,374,443 | -54,690 | -3,188,051 |
| Profit Margin (%) | 4.91 | 3.58 | -2.10 | -0.01 | -0.74 |
| Employees | 756 | 677 | 731 | 666 | 668 |

| | | | | | |
|---|---|---|---|---|---|
| Productivity (RON/employee) | 483,000 | 607,000 | 609,000 | 633,000 | 644,000 |

**Source:** authors' calculations based on data from the Romanian Ministry of Finance

The data presented in Table 1 indicate a clear divergence between turnover dynamics and profitability outcomes. Turnover increased steadily from 365 million RON in 2020 to a peak of 445 million RON in 2022, followed by a decline and stabilization at approximately 430 million RON in 2024. Such divergence between revenue growth and profitability is frequently associated with cost inefficiencies and suboptimal resource allocation, as highlighted in strategic management literature (Porter, 1985; Kaplan & Norton, 2008).

In contrast, net profit exhibits a pronounced downward trend. The company recorded a net profit of approximately 18 million RON in 2020, which decreased to 14.7 million RON in 2021 and shifted to a significant loss of over 9 million RON in 2022. Although financial performance approached break-even in 2023, losses resumed in 2024. This deterioration is reflected in the evolution of the profit margin, which declined from 4.91% in 2020 to negative values after 2022. Profit margin is widely regarded as a key indicator of managerial efficiency in transforming revenues into financial results (Damodaran, 2021).

To assess operational efficiency, labor productivity was calculated as turnover per employee. The results show a substantial increase between 2020 and 2021, from approximately 483,000 RON to over 600,000 RON per employee, followed by relative stabilization at higher levels in subsequent years. This pattern suggests that the company improved its output efficiency despite declining profitability. Similar phenomena have been documented in the literature, where productivity gains do not necessarily translate into financial performance improvements due to rising costs or inefficiencies in decision-making (Syverson, 2011; Brynjolfsson et al., 2021).

The evolution of workforce size further reflects managerial adjustments. The number of employees decreased from 756 in 2020 to 677 in 2021, increased again in 2022, and declined in the following years. These fluctuations indicate attempts to optimize labor resources and respond to changing production demands. However, the persistence of declining profitability suggests that workforce optimization alone was insufficient to restore financial performance, confirming that cost control requires a broader strategic approach (Porter & Heppelmann, 2014).

To provide additional insights into financial structure and operational pressures, selected balance sheet indicators are presented in Table 2.

**Table 2. Selected financial structure indicators (LEI)**

| Indicator | 2020 | 2021 | 2022 | 2023 | 2024 |
|---|---|---|---|---|---|
| Total Assets (approx.) | 160 mil. | 194 mil. | 187 mil. | 197 mil. | 240 mil. |
| Total Liabilities | 68,611,299 | 76,082,000 | 65,395,025 | 72,538,410 | 119,646,141 |
| Current Assets | 128,777,645 | 136,608,403 | 133,143,932 | 151,757,290 | 193,815,292 |

**Source:** authors' calculations based on data from the Romanian Ministry of Finance

The data in Table 2 reveal a substantial increase in total liabilities, particularly in 2024, when liabilities approached 120 million RON. This upward trend indicates growing financial pressure and increased reliance on external financing. According to corporate finance theory, rising leverage levels may amplify financial risk, especially when profitability is declining (Brealey et al., 2020).

At the same time, current assets increased significantly, driven primarily by higher receivables and inventories. The sharp increase in receivables suggests potential inefficiencies in cash flow management or changes in customer payment behavior. Similarly, fluctuations in inventory levels indicate challenges in demand forecasting and production planning. These issues are particularly critical in the automotive industry, where supply chain complexity requires accurate and timely decision-making (Choi et al., 2020; Wamba-Taguimdje et al., 2020).

Taken together, the results highlight a structural imbalance between operational performance and financial outcomes. While the company maintained production capacity and revenue levels, it faced increasing difficulties in controlling costs and managing financial resources effectively. This imbalance is reflected in declining profit margins, rising liabilities, and increasing working capital requirements.

From a managerial perspective, these findings suggest that traditional decision-making approaches may not be sufficient to address the complexity of modern industrial operations. The observed inefficiencies point to the need for more advanced decision-support systems capable of integrating large volumes of data and providing real-time insights. In this context, artificial intelligence (AI) emerges as a relevant strategic tool. AI-based systems have been shown to improve forecasting accuracy, optimize inventory management, and support cost control decisions (Agrawal et al., 2022; Davenport et al., 2020).

Although direct evidence of AI adoption within Company A is not available, the identified performance gaps indicate a significant potential for improvement through digital transformation. When compared to broader trends in the European automotive industry, where AI adoption has accelerated in recent years, the performance trajectory of Company A suggests a relative lag in digital integration.

Overall, the empirical results provide strong evidence of declining financial efficiency and highlight the importance of improving managerial decision-making processes. They also establish a solid foundation for analyzing the potential role of AI in enhancing performance in complex industrial environments.

## VII.DISCUSSION

The empirical findings reveal a structural divergence between turnover growth and declining profitability, which raises important questions regarding the effectiveness of managerial decision-making processes within Company A. This pattern is consistent with recent literature emphasizing that revenue expansion does not necessarily translate into improved financial performance in the absence of efficient decision-support mechanisms and cost optimization strategies.

From a theoretical perspective, the observed results can be interpreted through the lens of AI-driven decision-making frameworks. Studies by Brynjolfsson, Rock, and Syverson (2021) demonstrate that the productivity gains associated with digital technologies, including artificial intelligence, are often delayed due to organizational frictions and the need for complementary managerial capabilities. This "productivity paradox" is particularly relevant in the context of Company A, where increased operational output has not been matched by proportional profitability gains.

Similarly, research by Raisch and Krakowski (2021) highlights that the integration of AI into managerial decision-making processes requires a reconfiguration of organizational routines and decision structures. In the absence of such transformation, firms may experience inefficiencies despite access to advanced technologies.

The declining profit margins observed in Company A suggest that decision-making processes may not be sufficiently optimized to manage increasing operational complexity.

The findings also align with empirical studies examining the role of AI in enhancing decision quality. According to Jarrahi (2018) and Davenport, Guha, Grewal, and Bressgott (2020), AI systems improve managerial decision-making by augmenting human judgment with data-driven insights, particularly in environments characterized by uncertainty and large datasets. In the automotive sector, where supply chain disruptions and demand volatility are common, such capabilities are critical for maintaining efficiency and competitiveness.

Furthermore, the increase in receivables and inventories identified in the empirical analysis reflects potential inefficiencies in demand forecasting and inventory management. These challenges have been widely documented in the literature, with studies by Wamba-Taguimdje et al. (2020) and Choi, Wallace, and Wang (2020) demonstrating that AI-based predictive analytics can significantly improve supply chain performance by reducing forecasting errors and optimizing inventory levels.

In addition, the rising level of liabilities observed in Company A indicates growing financial pressure, which may be associated with suboptimal financial decision-making. Research by Cockburn, Henderson, and Stern (2020) suggests that AI technologies can enhance financial planning and risk management by providing more accurate predictive models and real-time data analysis. The absence of such tools may contribute to the financial imbalances identified in the case study.

From an organizational perspective, the fluctuating number of employees reflects attempts to adjust workforce size in response to changing operational conditions. However, as noted by Verhoef et al. (2021), digital transformation is not limited to workforce optimization but involves a broader reconfiguration of business processes and decision-making structures. The limited impact of workforce adjustments on profitability in Company A supports this argument, indicating that deeper structural changes are required.

The comparison with the European automotive industry further reinforces these conclusions. According to OECD (2023) reports and Eurostat data, AI adoption in manufacturing sectors has increased significantly across EU countries, particularly in areas such as predictive maintenance, quality control, and supply chain optimization. Studies by Bessen (2022) and Babina et al. (2024) show that firms adopting AI technologies tend to achieve higher productivity and improved financial performance, provided that these technologies are effectively integrated into managerial processes.

In contrast, firms in emerging economies, including Romania, often face barriers to AI adoption, such as limited digital infrastructure, skill shortages, and organizational resistance to change. Research by Cirera, Comin, and Cruz (2022) highlights that these constraints can delay the benefits of digital transformation, resulting in performance gaps compared to more advanced economies. The case of Company A appears to reflect such a scenario, where operational scale is maintained but efficiency gains are limited.

Another important aspect highlighted by the literature is the role of managerial capabilities in mediating the impact of AI on performance. According to Fountaine, McCarthy, and Saleh (2019), successful AI adoption depends on the ability of managers to integrate technological tools into decision-making processes and align them with organizational strategy. The performance challenges observed in Company A may therefore be linked not only to technological factors but also to managerial practices and decision-making frameworks.

Moreover, recent studies emphasize the importance of human–AI collaboration in achieving optimal decision outcomes. Dellermann, Ebel, Söllner, and Leimeister (2019) argue that hybrid intelligence systems, which combine human expertise with AI capabilities, offer superior performance compared to purely human or purely automated decision-making. This perspective suggests that the potential benefits of AI in Company A would depend on the effective integration of human and algorithmic decision processes.

In the context of cost management, the literature provides strong evidence that AI can contribute to improved efficiency. Studies by Agrawal, Gans, and Goldfarb (2022) demonstrate that AI reduces the cost of prediction, enabling more accurate and timely decisions across various business functions. This is particularly relevant for Company A, where rising costs have eroded profitability despite stable revenues.

Overall, the discussion highlights that the performance dynamics observed in Company A are consistent with broader patterns identified in the literature on AI and managerial decision-making. The findings suggest that the company's challenges are not unique but reflect systemic issues related to the adoption and integration of digital technologies in complex industrial environments.

The analysis also underscores the importance of moving beyond traditional decision-making approaches toward data-driven and AI-supported models. By leveraging advanced analytics and predictive tools, firms can improve decision quality, optimize resource allocation, and enhance overall performance. In this sense, the case of Company A illustrates both the risks of insufficient digital integration and the opportunities associated with AI-driven transformation.

Finally, the study contributes to the existing literature by providing empirical evidence from a real-world case in the Romanian automotive sector, highlighting the need for further research on AI adoption in emerging economies. The findings support the argument that AI has the potential to significantly enhance managerial decision-making and firm performance, but its impact depends on a complex interplay of technological, organizational, and contextual factors.

## VIII.CONCLUSIONS

This study examined the relationship between managerial decision-making, firm performance, and the potential role of artificial intelligence (AI), based on a longitudinal case analysis of a large Romanian automotive company over the period 2020–2024. The empirical findings revealed a significant divergence between turnover dynamics and profitability outcomes, indicating structural inefficiencies in the company's financial performance despite relatively stable operational activity.

More specifically, while the company maintained a consistent level of revenue generation, profitability deteriorated over time, with profit margins declining from positive values in 2020–2021 to negative levels in subsequent years. This pattern suggests that managerial decision-making processes may not have been sufficiently effective in adapting to increasing operational complexity, cost pressures, and market volatility. The observed increase in liabilities, alongside rising receivables and inventory levels, further supports the conclusion that financial and operational decisions require optimization.

From a theoretical perspective, the findings are consistent with recent literature emphasizing that the impact of digital technologies, including AI, on firm performance depends not only on technological adoption but also on the quality of managerial decision-making and organizational capabilities (Brynjolfsson et al., 2021; Raisch & Krakowski, 2021). The results confirm that in the absence of advanced decision-support systems, firms may struggle to translate operational scale into financial efficiency.

The study contributes to the existing body of knowledge in several ways. First, it provides empirical evidence from a real-world case in the Romanian automotive sector, a context that remains underexplored in the literature on AI and management. Second, it demonstrates how financial performance indicators can be used to identify decision-making inefficiencies and assess the potential role of AI in addressing these challenges. Third, it bridges the gap between theoretical frameworks on AI-driven decision-making and practical performance outcomes in a complex industrial environment.

From a managerial perspective, the findings highlight the importance of adopting data-driven decision-making approaches. The integration of AI-based systems could enhance forecasting accuracy, improve resource allocation, and support cost optimization, thereby contributing to improved financial performance. In particular, the use of predictive analytics in demand forecasting and inventory management could reduce operational inefficiencies and enhance responsiveness to market changes. Similarly, AI-driven financial planning tools could support more effective risk management and budgeting decisions.

At the policy level, the study underscores the need for increased support for digital transformation in emerging economies such as Romania. Compared to firms in more advanced European economies, Romanian companies may face structural barriers to AI adoption, including limited digital infrastructure, skill shortages, and organizational resistance to change. Addressing these challenges requires coordinated efforts involving government policies, industry initiatives, and educational programs aimed at developing digital competencies.

Despite its contributions, the study has several limitations. First, the analysis is based on a single case study, which limits the generalizability of the findings. Although the selected company is representative of large manufacturing firms, the results may not fully capture the diversity of experiences across different industries or firm sizes. Second, the study relies on publicly available financial data, which does not provide direct information on the extent of AI adoption within the company. As a result, the role of AI is inferred rather than empirically measured.

Future research should address these limitations by extending the analysis to multiple firms and incorporating direct measures of AI adoption. Survey-based studies or interviews with managers could provide deeper insights into how AI is integrated into decision-making processes and how it influences performance outcomes. Additionally, comparative studies across countries or industries could help identify contextual factors that shape the effectiveness of AI-driven management.

Another promising direction for future research is the exploration of human–AI collaboration in decision-making. Understanding how managers interact with AI systems and how this interaction affects decision quality could provide valuable insights for both theory and practice. Furthermore, longitudinal studies examining the long-term impact of AI adoption on firm performance would contribute to a more comprehensive understanding of digital transformation processes.

In conclusion, this study demonstrates that improving managerial decision-making is essential for achieving sustainable firm performance, particularly in complex industrial environments. While AI offers significant potential to enhance decision processes, its effectiveness depends on the ability of organizations to integrate technological capabilities with managerial practices. The findings highlight both the challenges and opportunities associated with AI-driven transformation, providing a foundation for future research and practical implementation in the field of management.

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