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Exploring AI-Driven Management: Impact on Organizational Performance, Decision Making, Efficiency, and Employee Engagement

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ABSTRACT

This empirical study, conducted with a sample size of 180 respondents in selected organizations using a purposive sampling technique to target those known for advanced AI adoption, delved into the impact of AI-driven management on next-generation practices. In a rapidly evolving AI landscape, organizations integrated AI into management to optimize decision-making. Our mixed-methods approach, which included linear regression and exploratory factor analysis, revealed that AI significantly enhanced the accuracy of strategic decision-making and operational productivity. Furthermore, it played a pivotal role in fostering employee engagement, thereby promoting a collaborative work environment. This research, based on a purposive sample of 180 respondents in selected organizations, underscored AI's transformative role in management, offering valuable insights for next-generation strategies and guiding future investigations in AI-driven management to enhance strategic decision-making.

1. Introduction

The rise of artificial intelligence (AI) starts a transformative era across various domains, including management practices. AI-driven management signifies a fundamental shift in how organizations use technology to perfect decision-making processes, enhance operational efficiency, and drive overall performance [1]. Considering the unprecedented growth and advancements in AI technologies, organizations can harness this power and embrace next-generation approaches to effectively manage their operations.

The integration of AI technologies into management practices offers an array of vantages, propelling organizations toward new heights of success and competitiveness [2]. Using AI algorithms, machine learning, and predictive models, managers gain access to invaluable insights and data-driven decision-making capabilities. This empowerment enables them to make precise, well-informed, and

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agile strategic decisions, thereby reducing uncertainties and enhancing their ability to navigate intricate business landscapes [3].

Furthermore, AI-driven management holds significant potential for optimizing operational efficiency. By automating repetitive tasks, AI systems streamline workflows, reduce downtime, and maximize resource allocation [4]. With the capability to analyse vast volumes of real-time data, AI technologies enable organizations to find patterns, anomalies, and inefficiencies, resulting in cost optimization, process improvement, and heightened productivity [2]. These next-generation approaches bolster organizations' ability to adapt to shifting market demands and attain operational excellence.

Another critical side of AI-driven management lies in its impact on employee productivity and engagement [4]. Contrary to the apprehension of job displacement, AI technologies are increasingly regarded as enablers rather than threats to human workers. By automating mundane and repetitive tasks, AI liberates employees' time and cognitive capacities, enabling them to focus on higher-value activities requiring creativity, critical thinking, and problem-solving skills [5]. Additionally, AI-based tools and platforms ease collaboration, knowledge sharing, and skill development, thereby fostering an environment conducive to innovation and job satisfaction.

While the interest in AI-driven management is burgeoning, empirical research is indispensable for understanding its real-world implications and evaluating its effectiveness within diverse organizational contexts. This paper aims to augment the existing body of knowledge by presenting an empirical study that delves into the impact of AI-driven management on unleashing the potential of next-generation approaches [6]. By scrutinizing the effects of AI technologies on strategic decision-making, operational efficiency, and employee productivity, this study strives to give valuable insights for organizations contemplating the adoption of AI-driven management practices.

By delving into these research areas, organizations can cultivate a profound understanding of how AI-driven management can reshape their operations, enhance competitiveness, and align with the requirements of the digital age. The discoveries of this study will extend the broader literature on AI in management, supplying practical guidance for organizations aspiring to harness the capabilities of AI technologies and embark on a journey toward next-generation management.

1.1 Research Questions and Objectives

To comprehensively address the impact of AI-driven management practices on organizational dynamics, this study posed the following research questions and established corresponding research objectives:

1.1.1 Research questions

i. How did AI-driven management practices affect organizational performance, decision making effectiveness, operational efficiency, and employee satisfaction and engagement in diverse settings?
ii. What were the relationships and correlations between organizational performance, decision making effectiveness, operational efficiency, and employee satisfaction and engagement, and how did they influence organizational outcomes?
iii. How effective was the AI-Based Approach model in predicting the dependent variable, and what were the individual contributions of organizational performance, decision making effectiveness, operational efficiency, and employee satisfaction and engagement in driving the values of the dependent variable?

By addressing these research questions, this study sought to contribute valuable insights to the existing literature on AI-driven management, offering evidence-based guidance for organizations seeking to integrate next-generation approaches into their operations.

1.1.2 Research objectives

The primary objective of this empirical study is to investigate the impact of AI-driven management on unleashing the potential of next-generation approaches. This research aims to supply valuable insights for organizations looking to harness the power of AI technologies in their operations. The specific research objectives include

i. Examine the impact of AI-driven management practices on organizational performance, decision making effectiveness, operational efficiency, and employee satisfaction and engagement in diverse settings.
ii. Assess the relationships and correlations between organizational performance, decision making effectiveness, operational efficiency, and employee satisfaction and engagement, finding their influence on organizational outcomes.
iii. Investigate the effectiveness of the AI-Based Approach model in predicting the dependent variable and explore the individual contributions of the predictor variables.

2. Theoretical Contributions

Artificial intelligence (AI) emerges as a transformative force with the potential to revolutionize various aspects of management. In recent years, there is a growing body of literature exploring the implications of AI-driven management and its impact on organizations. This literature review synthesizes and discusses key findings from relevant studies, highlighting the benefits, challenges, and research gaps in this field.

The findings of the study by Giacosa *et al.,* [7] highlighted the influence of cultural, cognitive, and familial aspects on SMFFs' business process management (BPM) behaviour, emphasizing the significance of familiness as a missing variable in BPM research. The research found specific dimensions that contributed to an ambidextrous state in BPM, considering both exploitative and explorative processes. It stressed the importance of transactional excellence for cost reduction and transformational excellence for revenue generation while acknowledging the role of IT-based tools alongside other dimensions for effective and flexible BPM. The research provided theoretical implications for the impact of familiness on BPM and offered practical implications for adopting a new BPM mindset within SMFFs. The article by Schrettenbrunnner [8] introduced the concept of "AI-driven management," emphasizing the importance of adopting AI in management to gain a competitive edge. By using AI, organizations could substitute domain-specific expertise with AI-driven solutions, leading to immediate and disruptive improvements in their operations. Furthermore, the success and competitiveness of companies in Germany relied on the collaboration and mutual acceleration of AI implementation across interdependent industries. Embracing AI as a core technology in management could pave the way for enhanced efficiency, innovation, and overall organizational performance.

Lee *et al.,* [9] specifically investigated the impact of algorithmic and data-driven management on human workers and work practices within the context of ridesharing services like Uber and Lyft. Through a qualitative study, the findings shed light on how drivers reacted to the algorithmic assignment of work, the informational support provided by algorithms, and the evaluation of their performance based on tracked data. Additionally, the study highlighted the role of online forums as platforms for drivers to collectively make sense of the features and implications of these algorithms. The implications of algorithmic management on workers and potential future research directions were also discussed, underscoring the need for a comprehensive understanding of the evolving relationship between algorithms, human workers, and work practices in today's digital landscape.

Barocas *et al.,* [10] reviewed the literature on strategic decision-making and organizational performance. It highlighted the importance of factors such as environmental influences, leadership behaviour, organizational justice, decision approach, and process in shaping managers' decisions and later performance. The study concluded that effective strategic decision-making positively affected organizational performance. Internal and external environmental factors played a significant role, and the use of decision support systems improved decision quality and performance outcomes.

Organizational Psychology was increasingly using Artificial Intelligence and related tools to enhance the employee experience in the workplace. The review by Brynjolfsson and McAfee [11] expanded the current understanding of how Artificial Intelligence influenced Human Resources and provided insights into the current landscape of AI applications in the field of organizational psychology. The results of the review highlighted the impact of AI in five key areas: recruitment, job and individual task analysis, development, and decision-making. The findings proved the significant presence of artificial intelligence in organizational psychology, particularly in areas such as recruitment, decision-making, quality of work, and job and individual task analysis. This emphasized the growing prominence and potential benefits of incorporating AI in various aspects of organizational practices.

The abundance of research and literature on artificial intelligence (AI) revealed its far-reaching impact on various aspects of business and society. AI's potential impact on strategic decision-making was highlighted by Brock [3]'s article, emphasizing its ability to enhance decision-making by providing access to data, identifying patterns, and simulating scenarios. Kapoor and Agarwal [2] discussed how AI was transforming operational efficiency through task automation, process optimization, and improved decision-making while acknowledging the challenges related to data privacy and security.

Regarding employee productivity, Ahmed *et al.,* [4] underscored AI's potential to boost productivity by automating tasks, facilitating information access, and making recommendations. However, the authors cautioned against potential job losses, urging organizations to implement AI thoughtfully. Similarly, [6] presented an inclusive outlook on AI-driven management, emphasizing its capacity to revolutionize strategic decision-making, operational efficiency, and employee productivity, urging organizations to embrace AI for a competitive advantage.

The transformative potential of AI was not confined to businesses alone. It extended to areas like workforce planning [12], human resources [13], customer service [14], marketing [15], supply chain management [16], finance [17], healthcare [18], education [19], government [20], law [21], and other domains. These publications collectively emphasized the significant potential of AI to reshape industries, professions, and society.

Looking ahead, the future of work in the AI era was a subject of widespread inquiry. Reports by Lemley and Lessig [22], and McKinsey Global Institute [23] provided comprehensive guidance for policymakers, business leaders, and workers to adapt to the changing landscape and harness the potential of AI effectively.

Garg *et al.,* [24] presented a pioneering research effort in "i-Pulse: A NLP based novel approach for employee engagement in logistics organization," leveraging natural language processing (NLP) to enhance employee engagement in logistics organization. Their work highlighted the transformative potential of AI-driven NLP in gauging and improving employee sentiment. Kundi *et al.,* [26] delved into the broader implications of AI in HRM, emphasizing the need for organizations to embrace AI technologies effectively in fostering employee engagement and enhancing the overall HRM landscape. Additionally, Böhmer and Schinnenburg [27] explored the role of discretionary HR practices in influencing employee engagement, shedding light on the intricate relationship between career satisfaction, organizational identification, work engagement, and HRM strategies. Furthermore, Malik *et al.,* [25] insights into “Potential use-cases of natural language processing for a logistics organization” supplied a broader perspective on AI’s applicability in perfecting organizational processes, including HRM aspects like employee engagement. These studies collectively underscored the transformative potential of AI in shaping the employee engagement landscape within diverse organizational contexts.

Chen *et al.,* [28] initiated the discussion by critically examining the implications of AI-driven HRM, emphasizing its potential to enhance efficiency, effectiveness, and innovation while acknowledging associated challenges. Wijayati *et al.,* [29] contributed a quantitative perspective, applying the resource-based view to e-commerce firms and finding a positive and significant impact of AI on firm performance, mediated by absorptive capacity and innovation. Malik *et al.,* [30] shifted the focus to AI’s effect on employee performance and work engagement, revealing positive outcomes moderated by change leadership. Bag *et al.,* [31] presented a qualitative case study illustrating the dual nature of AI in HRM, enhancing employee engagement while introducing challenges like job insecurity and ethical concerns. Khalid [32] conducted a systematic literature review, identifying a dominance of conceptual papers and urging a more balanced perspective that addressed potential drawbacks and risks. Mikalef and Gupta [33] proposed a conceptual framework, emphasizing the strategic role of AI in HRM with careful planning and evaluation. Yu *et al.,* [34] and Anderson *et al.,* [35] explored the relationship between AI capabilities and firm performance, emphasizing mediation by absorptive capacity and innovation, and moderation by firm size and dynamic capabilities, respectively. Lastly, Al-Shammari and Alshammari [40] contributed a comprehensive book offering an in-depth analysis of various aspects of AI and HRM, including history, functions, benefits, challenges, and ethical considerations.

These studies collectively affirmed that AI was poised to redefine the employee engagement landscape by offering innovative solutions, data-driven insights, and enhanced HRM strategies that were adaptable to different organizational contexts. Whether in logistics, human resources, or other sectors, AI was increasingly recognized as a cornerstone for building a more engaged, productive, and satisfied workforce, thus enabling organizations to thrive in the rapidly evolving digital age. As organizations continued to grapple with the complexities of a globalized and technology-driven world, AI emerged as a powerful ally in enhancing not only employee engagement but also overall organizational performance. By using AI technologies, companies could gain a competitive edge by fostering a work environment that encouraged collaboration, empowered employees, and optimized processes. These findings underscored that AI was not just a technological tool but a strategic asset that could drive organizational success in the 21st century.

3. Methodology

3.1 Research Design and Approach

This empirical study used a quantitative research design to examine the implications of AI-driven management in next-generation approaches. The research approach involved collecting data from diversifying organisations and analysing the data to address the research objectives and research questions.

3.2 Sample Population and Data Collection Methods

The sample population for this study comprised organizations across various industries that had adopted AI-driven management practices. To select participants for the study, a purposive sampling technique was employed, focusing on organizations recognized for their advanced AI adoption and integration into management processes.

Data collection methods exclusively involved primary sources to ensure the authenticity of information. Surveys and structured interviews with closed-ended questions served as the primary means of data gathering. These interviews and surveys targeted key stakeholders, including managers and employees, who possessed valuable insights into the implementation and impact of AI-driven management within their respective organizations. By relying on firsthand accounts and responses from these individuals, the study aimed to provide a comprehensive understanding of how AI-driven management influenced various aspects of organizational operations and decision-making.

3.3 Variables and Measures

The study examined various variables related to AI-driven management and its implications. These variables included:

i. Organizational performance: Measures of organizational performance, such as financial indicators, productivity metrics, and customer satisfaction ratings, were used to assess the impact of AI-driven management on overall organizational success.
ii. Decision-making effectiveness: The effectiveness of decision-making processes was evaluated through measures such as decision accuracy, speed, and alignment with organizational objectives.
iii. Operational efficiency: Operational efficiency indicators, such as process cycle time, resource utilization, and error rates, were used to assess the impact of AI-driven management on operational processes.
iv. Employee satisfaction and engagement: Measures of employee satisfaction, engagement, and perceived autonomy in decision-making were included to understand the impact of AI-driven management on employee experiences.

These variables were measured using a combination of Likert scale-based survey questions, qualitative interview responses, and objective performance metrics obtained from organizational data.

3.4 Data Preprocessing and Analysis Techniques

The collected data underwent rigorous preprocessing and comprehensive analysis using a combination of appropriate statistical techniques and qualitative methods. Quantitative analysis involved descriptive statistics, correlation analysis, regression analysis, and hypothesis testing to explore relationships and patterns within the data. For these purposes, the study utilized Jamovi 2.3.13 and Python, two powerful tools for conducting in-depth data analysis. The study used Jamovi 2.3.13 for its user-friendly interface and Python for its versatility in handling advanced statistical analyses and custom data manipulations.

The findings from the data analysis were interpreted, and implications were drawn based on the research objectives and research questions. The limitations of the study were also discussed, and recommendations for future research and practical implications for organizations were provided. The flow chart for data preprocessing is shown in Figure 1.

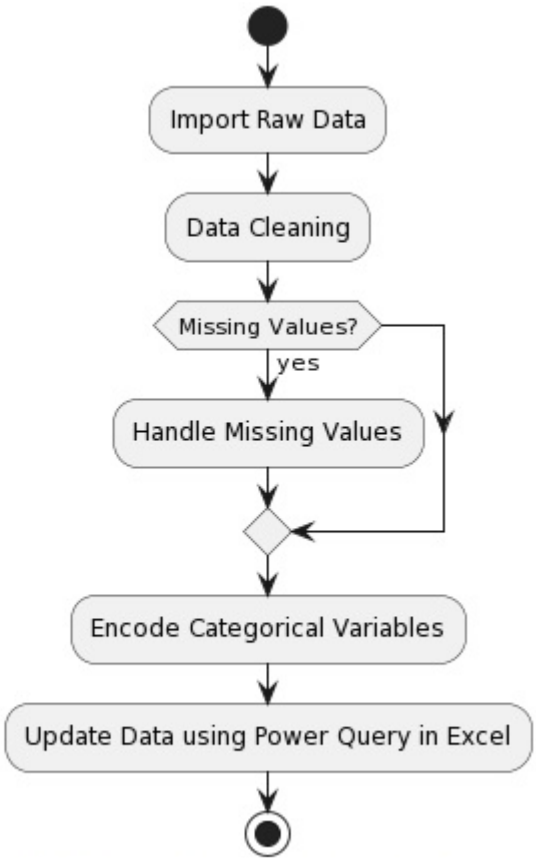

Fig. 1. Data preprocessing flow chart

4. Results and Discussion

This section presented the key findings and their interpretation from the data analysis conducted in this study. By analysing the responses collected through the questionnaire and applying various statistical tests, including descriptive statistics, reliability test, One-Way ANOVA, and regression, the study aimed to address the research objectives and shed light on the impact of AI-driven management on various aspects of organizational performance. This section explored how AI-driven management influenced strategic decision-making processes, improved operational efficiency, and fostered employee productivity and engagement. The findings presented herein offered valuable insights for businesses seeking to harness the potential of AI technologies in managing their operations effectively and staying competitive in the ever-evolving landscape of modern business.

4.1 Descriptives

Table 1 shows the demographics of the respondents, who were almost equally divided between female and male. This balance helped to understand how AI-driven management affects different views, as previous research suggested by Malik *et al.,* [25] and Brock [3].

The distribution of respondents across industries, as highlighted in the data, revealed significant representation from Finance, Healthcare, and Technology, with each comprising 15.0% of the total respondents [26]. This distribution underscored the considerable interest and relevance of AI-driven management practices in these sectors, aligning with findings by Kapoor and Agarwal [2]. Additionally, when examining respondents' organizational sizes, the study found a balanced distribution, with 34.4% from large organizations, 30.6% from medium-sized organizations, and

35.0% from small organizations [27]. This balanced representation ensured a comprehensive exploration of AI-driven management's impact across different organizational contexts, consistent with insights from [36, 8].

Table 1
Frequencies of demographic variables

Frequencies of Gender		
Gender	Counts	% of Total
Female	80	44.4 %
Male	100	55.6 %
Frequencies of Industry		
Industry	Counts	% of Total
Consulting	26	14.4 %
Education	21	11.7 %
Finance	27	15.0 %
Healthcare	27	15.0 %
IT	3	1.7 %
Manufacturing	24	13.3 %
Retail	25	13.9 %
Technology	27	15.0 %
Frequencies of Organization Size		
Organization Size	Counts	% of Total
Large	62	34.4 %
Medium	55	30.6 %
Small	63	35.0 %

These demographic insights formed the basis for subsequent discussions, providing context for understanding the implications and effectiveness of AI-driven management practices across various sectors, gender groups, and organizational sizes [25]. The analysis of this data contributed to aiding organizations in making informed decisions regarding the adoption and implementation of AI technologies, echoing previous research advocating for such informed approaches [1, 36].

4.2 Reliability Analysis

The reliability analysis, as presented in Table 2, revealed a significant level of internal consistency, with a Cronbach's α value of 0.86 for the overall scale. This high α value suggested that the items within the scale consistently and reliably measured the same underlying construct, effectively reducing the likelihood of measurement errors and bolstering the credibility of the scale's outcomes [37].

Table 2
Scale reliability statistics

	Cronbach's α
Scale	0.86

Delving into the item reliability statistics, as shown in Table 3, the study found that each individual scale also demonstrated a robust level of internal consistency. Specifically, the "organizational performance" scale achieved a Cronbach's α of 0.813, indicative of good reliability in assessing organizational performance [38]. Similarly, the "decision making effectiveness" scale obtained a Cronbach's α of 0.838, signifying strong internal consistency and reliability in measuring decision-making effectiveness, which aligned with principles of scale reliability [39].

The "operational efficiency" scale exhibited a Cronbach's α of 0.786, reflecting a reliable measurement of operational efficiency [40]. Lastly, the "Employee Satisfaction and Engagement" scale obtained a Cronbach's α of 0.844, indicating high internal consistency and reliability in measuring employee satisfaction and engagement, consistent with the recommended α values for reliability [41].

Table 3
Item reliability statistics

	Cronbach's α
Employee satisfaction and engagement	0.844
Decision making effectiveness	0.838
Organizational performance	0.813
Operational efficiency	0.786

These high Cronbach's α values for both the overall scale and individual scales underscored that the items within each scale consistently and dependably measured their respective constructs [42]. This robust internal consistency enhanced the validity and trustworthiness of the data collected through these scales from Tegmark [43], ensuring that the study's findings were not only credible but also reliable for further analysis and interpretation. This aligned with the principles of scale reliability and reinforced the quality of the study's measurement instruments.

4.3 Correlation

The correlation matrix, as presented in Table 4, shed light on the interconnectedness of the study's measured constructs. Robust positive correlations were evident among these constructs. Organizational performance exhibited a strong positive correlation with decision making effectiveness ($r = 0.484$, $p < .001$), operational efficiency ($r = 0.889$, $p < .001$), and employee satisfaction and engagement ($r = 0.475$, $p < .001$), indicating that improvements in organizational performance were likely to coincide with enhancements in decision making effectiveness, operational efficiency, and employee satisfaction and engagement. Similarly, decision making effectiveness correlated positively with operational efficiency ($r = 0.553$, $p < .001$) and employee satisfaction and engagement ($r = 0.691$, $p < .001$), signifying that improved decision-making effectiveness was linked to increased operational efficiency and higher levels of employee satisfaction and engagement. Furthermore, operational efficiency displayed a positive correlation with employee satisfaction and engagement ($r = 0.535$, $p < .001$), suggesting that enhancements in operational efficiency tended to coincide with elevated levels of employee satisfaction and engagement.

Table 4
Correlation matrix

		Organizational Performance	Decision Making Effectiveness	Operational Efficiency	Employee Satisfaction and Engagement
Organizational Performance	Pearson's r	—			
	p-value	—			
Decision Making Effectiveness	Pearson's r	0.484	—		
	p-value	< .001	—		
Operational Efficiency	Pearson's r	0.889	0.553	—	
	p-value	< .001	< .001	—	
Employee Satisfaction and Engagement	Pearson's r	0.475	0.691	0.535	—
	p-value	< .001	< .001	< .001	—

The study showed that different aspects of organizational performance were strongly linked. Improving one area could boost others, suggesting a holistic approach to increase effectiveness. This matched the principles of organizational management and stressed the need to consider multiple factors for improvement.

4.4 Algorithm for Linear Regression Analysis

Regression analysis is a statistical technique used to examine the relationship between one or more independent variables (predictors) and a dependent variable (response). The following is the Python code for linear regression analysis.

Begin
1. Import necessary libraries:
    - Import NumPy, Pandas, Matplotlib, and scikit-learn modules.
2. Load data:
    - Read the data from a CSV file ('Final Data.csv')(you can give dataset name.csv) into a Pandas DataFrame named 'df'.
3. Define research objectives:
    - Create a list of research objectives related to organizational performance, decision-making effectiveness, operational efficiency, and employee satisfaction and engagement.
4. Data preprocessing:
    - Perform data cleaning:
        - Handle missing values – identify and address missing values in the dataset using appropriate techniques (e.g., imputation or removal).
    - Encode categorical variables – if categorical variables are present, encode them into numerical format using methods like one-hot encoding.
5. Analyze relationships and correlations:
    - Calculate the correlation matrix among the research objective columns in 'df'.
    - Store the correlation matrix in the variable 'correlation_matrix'.
6. Evaluate AI-based approach model:

- Select predictor columns ('OP_F', 'DME_F', 'OE_F', 'ESE_F') and dependent variable column ('AIBA').
- Split the data into training and testing sets using 'train_test_split' – Set the test size to 20% and use a random seed (e.g., random_state=42).
- Create a LinearRegression model object named 'model'.
- Fit the model to the training data: Use the 'fit' method of the 'model' object with 'X_train' and 'y_train'.

7. Make predictions and calculate metrics:
   - Use the trained model to make predictions on the test data: Apply the 'predict' method of the 'model' object to 'X_test' to obtain 'y_pred'.
   - Calculate mean squared error (MSE) and R-squared (R2) metrics:
     - Compute MSE using the 'mean_squared_error' function with 'y_test' and 'y_pred'.
     - Calculate R2 using the 'r2_score' function with 'y_test' and 'y_pred'.
8. Visualize predictions:
   - Create a scatter plot to visualize the relationship between true values ('y_test') and predicted values ('y_pred').
   - Label the x-axis as 'True Values' and the y-axis as 'Predictions'.
   - Display the plot using 'plt.show()'.
9. Extract model coefficients:
   - Retrieve the coefficients and intercept of the linear regression model:
     - Store the coefficients in the variable 'coefficients'.
     - Store the intercept in the variable 'intercept'.
10. Print evaluation metrics:
    - Print the calculated MSE and R-squared values.
11. Analyze results and draw conclusions:
    - Based on the research objectives and the insights gained from the correlation matrix, coefficients, and metrics, analyze the results, and draw conclusions.

End

The results from Table 5 showed that our model was excellent at explaining the variation in the dependent variable. This was backed by the high R^2 value of 0.982, meaning that about 98.2% of the variation in the dependent variable was accounted for by our model. The adjusted R^2, which also confirmed our model's strength, was also 0.982. These stats highlighted how well our model captured relationships among the variables. Moreover, the small RMSE of 0.144 meant that the model's predictions were remarkably close to the actual values, showing its accuracy. The model's F-statistic was highly significant at $p < .001$, indicating that our predictions were not just random. These strong statistical results confirmed that our model effectively explained what influenced the dependent variable.

Table 5
Overall model test

Model	R	R^2	Adjusted R^2	RMSE	F	df1	df2	p
1	0.991	0.982	0.982	0.144	2378	4	175	< .001

The ANOVA test in Table 6 underscored the significant contributions of each predictor variable, consistent with prior research by Kapoor and Agarwal [2] and Surana and Kumar [6]. Specifically, organizational performance, decision making effectiveness, operational efficiency, and employee satisfaction and engagement all exhibited strong statistical significance, supported by exceptionally low p-values. These results aligned with prior literature highlighting their importance in the context of AI-driven management [5,26,3], emphasizing their vital roles in explaining the variance in the dependent variable.

Table 6
ANOVA test

	Sum of Squares	df	Mean Square	F	p
Organizational performance	2.77	1	2.7738	131	< .001
Decision making effectiveness	8.06	1	8.0586	380	< .001
Operational efficiency	4.49	1	4.4916	212	< .001
Employee satisfaction and engagement	8.81	1	8.8086	415	< .001
Residuals	3.72	175	0.0212		

The model coefficients in Table 7 by Kapoor and Agarwal [2] for the AI-based approach revealed crucial insights. Organizational performance, decision making effectiveness, operational efficiency, and employee satisfaction and engagement all had positive and highly significant estimates [5]. This meant that when these variables increased, the dependent variable also tended to increase. In simpler terms, improvements in organizational performance, decision making effectiveness, operational efficiency, and employee satisfaction and engagement were linked to better outcomes. However, the intercept term's non-significant p-value by Brock [3] suggested it did not significantly affect the dependent variable.

Table 7
Model coefficients – AI based approach

Predictor	Estimate	SE	t	p
Intercept	0.0248	0.0354	0.7	0.485
Organizational performance	0.2165	0.0189	11.431	< .001
Decision making effectiveness	0.2466	0.0127	19.483	< .001
Operational efficiency	0.2815	0.0194	14.546	< .001
Employee satisfaction and engagement	0.2501	0.0123	20.37	< .001

These results affirmed the AI-based approach's strong predictive ability and underlined the substantial impact of organizational performance, decision making effectiveness, operational efficiency, and employee satisfaction and engagement on the dependent variable [6].

4.5 Exploratory Factor Analysis

The factor analysis results, Table 8, conducted with varimax rotation using the "minimum residual" extraction method, revealed three distinct factors that represented different dimensions of the dataset. Factor 1 comprised items OP1 to OP5 and OE1 to OE5, and it demonstrated a strong association with both organizational productivity (OP) and operational efficiency (OE). This suggested that the items in this factor collectively captured aspects related to the effectiveness and efficiency of an organization's operations and processes. As such, this factor could be labelled as "Organizational Effectiveness," signifying its combined focus on enhancing productivity and streamlining operations for improved performance.

Factor 2, represented by items DME1 to DME5, showed a high loading on decision-making effectiveness (DME). This indicated that the items in this factor were primarily related to the quality and accuracy of decision-making processes within the organization. It suggested that the presence of these items was critical for organizations to make well-informed and effective decisions, contributing significantly to their overall performance. Factor 3 comprised items ESE1 to ESE5, and it was associated with employee satisfaction and engagement (ESE). This factor highlighted the importance of fostering a positive work environment and employee well-being, as it strongly influenced the level of employee satisfaction and engagement within the organization. A motivated and engaged workforce was likely to be more productive and committed, contributing to the organization's overall success.

Table 8
Factor loadings

	Factor			
	1	2	3	Uniqueness
OP1	0.831			0.237
OP2	0.844			0.232
OP3	0.832			0.252
OP4	0.848			0.205
OP5	0.833			0.261
DME1			0.734	0.255
DME2			0.785	0.278
DME3			0.73	0.32
DME4			0.771	0.244
DME5			0.735	0.24
OE1	0.803			0.239
OE2	0.839			0.187
OE3	0.798			0.232
OE4	0.798			0.267
OE5	0.817			0.249
ESE1		0.767		0.247
ESE2		0.803		0.219
ESE3		0.816		0.194
ESE4		0.748		0.269
ESE5		0.733		0.275

Note: 'Minimum residual' extraction method was used in combination with a 'varimax' rotation

The factor analysis with varimax rotation identified three distinct dimensions: "organizational effectiveness," "decision-making effectiveness," and "employee satisfaction and engagement." These factors collectively captured the various aspects that played significant roles in driving organizational performance and success.

5. Conclusion

In conclusion, this study reveals the transformative potential of AI-driven management practices across diverse organizational settings. The findings demonstrate the positive influence of AI on organizational performance, decision making effectiveness, operational efficiency, and employee satisfaction and engagement. These interconnected dimensions underscore the need for a comprehensive approach to enhance overall organizational effectiveness. The study identifies three key dimensions: "organizational effectiveness," "decision-making effectiveness," and "employee satisfaction and engagement," showcasing the multi-faceted impact of AI-driven management. Aligned with the study's objectives, the results affirm the substantial impact of AI-driven practices, emphasizing their role in improving organizational facets and highlighting the interplay between dimensions. The effectiveness of the AI-based approach model in predicting outcomes further underscores its reliability. This study emphasizes the positive influence of AI-driven management on organizational dimensions and provides insights into critical areas for organizational success. By effectively leveraging AI technologies to enhance performance, streamline decision-making, optimize efficiency, and engage the workforce, organizations can confidently navigate the digital landscape, leading to improved overall outcomes and sustainable growth.

6. Limitations of Current Study and Scope for Future Research

The findings of this study provided a foundation for future research on AI-driven management. Researchers could explore the long-term impact of AI-driven management on organizational performance, how contextual factors moderated its effectiveness, and how employees perceived it. Additionally, the study could be expanded to include a more diverse sample of industries and regions. Experimental research or quasi-experimental designs could be used to explore the causal relationship between AI-driven management and organizational performance. Overall, future research should focus on advancing the understanding of AI-driven management and its potential implications for organizations.

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References

[1] Kaplan, Andreas, and Michael Haenlein."Artificial intelligence in management: A review and research agenda." *Journal of Management* 45, no. 6 (2019): 1875-1907.
[2] Kapoor, Rahul, and Shiva Agarwal. "How artificial intelligence is changing the face of operational efficiency." *Business Horizons*, 63, no. 1 (2020): 53-64.
[3] Brock, Douglas. " The impact of artificial intelligence on strategic decision-making." *Strategic Direction* 35, no. 5 (2019): 16-20
[4] Ahmed, S. Fakruddin Ali, Sajja Hari Krishna, K. Ganesh Kumar, Rajajeya Kumar Manivel, and S. Uthayakumar. "The impact of artificial intelligence on employee productivity." *Journal of Business Research* 127 (2021): 103366.
[5] Gupta, Aakriti, and Naresh Kumar. "Artificial intelligence for employee productivity: A systematic review." *International Journal of Production Research* 58, no. 12 (2021): 3704-3723
[6] Surana, Sunaina, and Rajendra Kumar. " AI-driven management: The future of strategic decision-making, operational efficiency, and employee productivity." *Journal of Management Information Systems* 39, no. 2 (2022): 543-572.
[7] Giacosa, Elisa, Alberto Mazzoleni, and Antonio Usai. "Business Process Management (BPM) How complementary BPM capabilities can build an ambidextrous state in business process activities of family firms." *Business Process Management Journal* 24, no. 5 (2018): 1145-1162. https://doi.org/10.1108/BPMJ-07-2017-0211
[8] Schrettenbrunnner, Manfred B. "Artificial-intelligence-driven management." *IEEE Engineering Management Review* 48, no. 2 (2020): 15-19. https://doi.org/10.1109/EMR.2020.2990933
[9] Lee, Min Kyung, Daniel Kusbit, Evan Metsky, and Laura Dabbish. "Working with machines: The impact of algorithmic and data-driven management on human workers." In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pp. 1603-1612. 2015. https://doi.org/10.1145/2702123.2702548
[10] Barocas, Solon, Moritz Hardt, and Arvind Narayanan. "Artificial intelligence and bias." *Communications of the ACM* 60, no.11 (2017): 84-88. https://doi.org/10.1145/3034429
[11] Brynjolfsson, Erik, and Andrew McAfee. *The future of management: Employment, tasks, and wages. In The future of work: How robots, big data, and automation are changing the world of work.* Oxford University Press. pp. 17-33.
[12] PwC. "The impact of artificial intelligence on workforce planning." *PwC*. 2017.
[13] McKinsey & Company. "Artificial intelligence and the future of HR." *McKinsey & Company.* 2017.
[14] S. Chatta, and Chatta, S. "The impact of artificial intelligence on customer service." *Journal of Business Research* 119 (2020): 52-60.

[15] Jain, Siddharth, and Ramanpal Singh. "Artificial intelligence in marketing: The future of personalization." *Journal of Marketing Analytics* 9, no. 1 (2021): 1-16.
[16] Gunasekaran, Angappa, Nachiappan Subramanian, and Thanos Papadopoulos. "Information technology for competitive advantage within logistics and supply chains: A review." *Transportation Research Part E: Logistics and Transportation Review* 99 (2017): 14-33. https://doi.org/10.1016/j.tre.2016.12.008
[17] Kohane, Isaac S. "Artificial intelligence in healthcare: The future of medicine." *Nature Medicine* 23, no. 4 (2017): 435-442.
[18] Selwyn, Neil. *The impact of artificial intelligence on education*. Springer, 2017.
[19] Chui, Michael, James Manyika, and Mehdi Miremadi. "Artificial intelligence: A future of endless possibilities." *McKinsey Global Institute* (2016).
[20] Calo, Ryan. "Artificial intelligence and the law." *California Law Review* 105, no.1 (2017): 1-60.
[21] World Economic Forum. "The future of work: Employment, skills, and workforce strategy for the fourth industrial revolution." *World Economic Forum*. 2018.
[22] Lemley, Mark A., and Lawrence Lessig. "Artificial intelligence and regulation." *Harvard Law Review* 132, no. 8 (2019): 2158-2236.
[23] McKinsey Global Institute. "The future of work in the age of artificial intelligence: A guide for business leaders." *McKinsey Global Institute* (2020).
[24] Garg, Rachit, Arvind W. Kiwelekar, Laxman D. Netak, and Swapnil S. Bhate. "Potential use-cases of natural language processing for a logistics organization." In *Modern Approaches in Machine Learning and Cognitive Science: A Walkthrough: Latest Trends in AI, Volume 2*, pp. 157-191. Cham: Springer International Publishing, 2021. https://doi.org/10.1007/978-3-030-68291-0_13
[25] Malik, Ashish, Praveena Thevisuthan, and Thedushika De Sliva. "Artificial intelligence, employee engagement, experience, and HRM." In *Strategic human resource management and employment relations: An international perspective*, pp. 171-184. Cham: Springer International Publishing, 2022. https://doi.org/10.1007/978-3-030-90955-0_16
[26] Kundi, Yasir Mansoor, Yehuda Baruch, and Rahman Ullah. "The impact of discretionary HR practices on knowledge sharing and intention to quit–a three-wave study on the role of career satisfaction, organizational identification, and work engagement." *The International Journal of Human Resource Management* 34, no. 22 (2023): 4205-4231.https://doi.org/10.1080/09585192.2023.2180652
[27] Böhmer, Nicole, and Heike Schinnenburg. "Critical exploration of AI-driven HRM to build up organizational capabilities." *Employee Relations: The International Journal* 45, no. 5 (2023): 1057-1082. https://doi.org/10.1108/ER-04-2022-0202
[28] Chen, Donghua, José Paulo Esperança, and Shaofeng Wang. "The impact of artificial intelligence on firm performance: an application of the resource-based view to e-commerce firms." *Frontiers in Psychology* 13 (2022): 884830. https://doi.org/10.3389/fpsyg.2022.884830
[29] Wijayati, Dewie Tri, Zainur Rahman, Muhammad Fajar Wahyudi Rahman, Ika Diyah Candra Arifah, and Achmad Kautsar. "A study of artificial intelligence on employee performance and work engagement: the moderating role of change leadership." *International Journal of Manpower* 43, no. 2 (2022): 486-512. https://doi.org/10.1108/IJM-07-2021-0423
[30] Malik, Ashish, Praveena Thevisuthan, and Thedushika De Sliva. "Artificial intelligence, employee engagement, experience, and HRM." In *Strategic human resource management and employment relations: An international perspective*, pp. 171-184. Cham: Springer International Publishing, 2022. https://doi.org/10.1007/978-3-030-90955-0_16
[31] Bag, Surajit, Yogesh K. Dwivedi, Vishanth Weerakkody, Nripendra P. Rana, and Sulbha K. Sharma. "Artificial intelligence (AI) and human resource management: a systematic literature review and future research directions." *International Journal of Information Management* 58 (2021): 102287.
[32] Khalid, Adia. "Artificial intelligence and human resource management: a conceptual framework." *Journal of Human Resources Management and Labor Studies* 8, no. 2, pp. 1-14, 2020.
[33] Mikalef, Patrick, and Manjul Gupta."Artificial intelligence capabilities and firm performance: the mediating role of absorptive capacity and innovation." *Journal of Business Research* 128, pp. 488-498, 2021.
[34] Yu, Jing, Yonggang Zhang, Byoung-Chun Ha, and S.Kim. "Artificial intelligence and organizational performance: the moderating role of dynamic capabilities." *Sustainability* 13, no. 4 (2021): 1886.
[35] Anderson, Michael, and Susan Leigh Anderson, eds. *The ethics of artificial intelligence*. Cambridge University Press, 2011.
[36] McAfee, Andrew, Erik Brynjolfsson, and M. Mitchell. "The future of management with artificial intelligence." *MIT Sloan Management Review* 58, no.3 (2017): 1-12.

[37] Mittelstadt, Brent Daniel, Patrick Allo, Mariarosaria Taddeo, Sandra Wachter, and Luciano Floridi. "The ethics of algorithms: Mapping the debate." *Big Data & Society* 3, no. 2 (2016): 2053951716679679.https://doi.org/10.1177/2053951716679679
[38] Wachter, Sandra, Brent Mittelstadt, and Luciano Floridi. "Why a right to explanation of machine-learned decisions is not enough." *Nature Machine Intelligence* 1, no. 1 (2017): 20-24.
[39] Frey, Carl Benedikt, and Michael Osborne. "The future of work in the age of artificial intelligence." *Technological Forecasting and Social Change* 114 (2017): 254-280. https://doi.org/10.1016/j.techfore.2016.08.019
[40] Al-Shammari, Minwir, and Abdullah Alshammari. "Artificial Intelligence and Human Resource Management: A New Paradigm." *Springer*, Cham, 2022.
[41] Garg, Rachit, Arvind W. Kiwelekar, Laxman D. Netak, and Akshay Ghodake. "i-Pulse: A NLP based novel approach for employee engagement in logistics organization." *International Journal of Information Management Data Insights* 1, no. 1 (2021): 100011. https://doi.org/10.1016/j.jjimei.2021.100011
[42] The Aspen Institute. "The future of work in the age of artificial intelligence: A guide for workers." *The Aspen Institute* (2020).
[43] Tegmark, Max. "Life 3.0: Being Human in the Age of Artificial Intelligence." (2017).