Artificial Intelligence Adoption and Its Impact on Global Strategic Decision-Making in Multinational Corporations

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to successfully incorporate AI in their operations and achieve significant benefits of its usage (Jöhnk et al., 2021).

Abstract
The relationship between artificial intelligence (AI) introduction and the organizational performance in the firms existing in more than one country and industry. The researcher in the study applies quantitative approach, which is founded on such extensive data as 100,000 firm-level observations, to investigate the patterns of AI adoption and their impact on productivity, organizational change. Descriptive, correlation and regression analysis was conducted to evaluate the effect of the variables of AI adoption, year of adoption, training hours, workforce impact, and role creation. The findings indicate that the direct effect of the variables of AI adoption on productivity is not critical. However, the workforce-related factors, such as the number of workers impacted and the creation of new jobs are highly correlated with organizational change. This means that AI indirectly impacts firms in terms of the structural and process level changes, but not directly impacting on performance. The study contributes to the body of knowledge by providing empirical evidence on the impact of AI on shaping organizational processes and reiterating the need to connect the implementation of AI to organizational and process capabilities of an organization. The findings suggest that businesses ought to be concerned with adopting AI strategically to achieve considerable outcomes.

Keywords: Artificial Intelligence Adoption, Organizational Transformation, Productivity, Strategic Proxy, Global Firms

1. Introduction

AI has become a potential game-changer that is changing how organizations operate, make decisions, and compete in various industries. The growing involvement of AI technologies in business activities is indicative of a more general trend away toward information-driven and automated systems that are more efficient and more innovative. Companies are increasingly using AI to streamline their processes, enhance their productivity, and aid in the difficult process of decision-making. With companies embracing more sophisticated AI applications, especially generative AI systems, AI applications in operations are expanding into strategic areas. This development shows the increased significance of learning about the role of AI adoption in business results and decision-making mechanisms in modern business settings. The organizations to implement AI technologies is a key factor that defines the success of implementation. The technological infrastructure, managerial skills, and organizational culture are the key factors that determine the outcome of AI preparedness and adoption. Better-prepared firms have more chances

The application of AI is becoming closely linked to organizational change, specifically, restructuring of the workforce, productivity, and process optimization. When AI technologies are integrated, job positions are frequently modified, new jobs are created, and tasks are distributed among humans and machines. These changes indicate the overall influence of AI on organizational settings and emphasize the role of AI as a change agent. Although AI has the potential benefits, implementing AI is not without challenges. Companies are often faced with the hurdles of automation, change resistance, and the fear that automation displace human decisions. Such obstacles have the potential to impede successful implementation and restrict the achievement of benefit of AI (Booyse and Scheepers, 2024). In its turn, to understand the impact of AI on the work of organizations, it is important to understand the opportunities and restrictions of its implementation. The strategic use of AI is an increasingly popular topic in the past few years and businesses have realized that it can enhance their competitiveness and innovation. Using AI to improve the operational efficiency is also utilized, not to mention the strategic effort, which enables organizations to respond more efficiently to the dynamic environment of the market (Borges et al., 2021).

The use of AI in organizational decision-making has proliferated, and the interest in its application in strategic cases increased. Using AI systems, one can process large volumes of data and offer insights that can be used by managers in their decision making. This has led to the growing interest in the use of AI as a decision-support system in an organization. However, the question of whether AI can be relied upon in decision-making or not remains debatable. Even though AI can enhance the accuracy and efficiency of the decisions, there is a worry of the reliability, transparency, and biases. The managers will need to weigh the benefits of AI and the need to make complicated strategic decisions using human judgment (Brink et al., 2024). The moral element and the regulation of AI use are another concern of the principle of responsible AI. Institutions are being called upon to ensure that AI systems are applied transparently and accountably, especially when they determine important decisions (Dennehy et al., 2023). Recent progress in generative AI has increased the scope of AI in assessing strategic decisions. Such technologies can allow organizations to simulate, evaluate risk, and create alternative strategies, which improves decision-making potentials (Doshi et al., 2025).

AI implementation and business value have been a popular topic in the literature, with researchers observing that it may enhance the performance and competitive edge of firms. The AI features allow organizations to gain insights on the data, optimize, and improve decision making, which leads to value creation (Enholm et al., 2022). Nevertheless, the benefits are determined by a number of factors like the acceptance of AI technologies by the managers. Managerial trust and use of AI systems is also a significant determinant of how much AI can affect organizational performance (Gieselmann et al., 2025). Another application of AI is in innovation management to aid in the creation of new products, services, and business models. AI promotes innovation and can improve strategic planning because it allows organizations to understand trends and anticipate the future (Haefner et al., 2021). The use of AI is becoming more applicable to international business as companies are forced to work under different and complicated conditions. Effective use of AI can make nations globally more competitive and assist them in making decisions at multinational levels (Holtbrügge et al., 2025).

The contribution of this study to the literature is that it demonstrates through a large-scale and diverse database the empirical relationship between the adoption of AI and organizational outcomes. The study offers an in-depth understanding of how the adoption of AI influences organization change through the integration of descriptive, correlational, and regression studies. The findings show the role of AI in organizational forms and the importance of the factors related to workforce in mediating its impact. Moreover, the research is also relevant to the general discourse on the topic of human-AI collaboration in decision-making, the interaction of technological potentials with organizational work (Jarrahi, 2018). The main aim of the study is to analyze the trends in adoption of artificial intelligence in companies in various countries and industries, as well as assess the connection between AI and organizational performance. In particular, the study examine how the features of AI adoption affect productivity and workforce transformation, and how much the changes are based on overall organizational and strategic changes.

2. Methodology

2.1 Research Design

The given study is based on a quantitative research design determining the existing connection between the adoption of artificial intelligence (AI) and organizational performance among companies that function in various geographic and industrial settings. The cross-sectional analytical method was employed, and it allowed exploring the differences in the level of AI adoption at the firm level and how they related to productivity and the overall organizational change. The study design will be created in such a manner that it will be able to address the descriptive trends of the data first, then proceed to inferential statistical tests to determine the relationships among the variables and the importance of the AI adoption indicators in describing the organizational performance.

2.2 Data Source and Sample

The study relies on secondary data of 100,000 firm-level observations that is available in a publicly accessible repository (Rishi, 2025). The sample covers 14 industries and 14 countries, thus offering a wide geographic and industry base. All observations reflect a single firm and provide the data regarding the features of AI adoption, influence on the workforce, and performance of the organization. The huge sample boosts the statistical integrity of the analysis and facilitates sound cross-sectional comparisons on a country-industry basis.

2.3 Variable Definition and Operationalization

To investigate the relationship between AI adoption and organizational outcomes, the study involves independent and dependent variables. Variables that captured AI adoption included variables of the nature of implementation such as the year of adoption, number of hours spent on training, number of employees affected, and number of new jobs created. The main dependent variable was productivity change, which are firm-level performance outcomes. Furthermore, a composite strategic proxy index was created to capture greater organizational change where strategic decision-making was not directly measured. It was an index calculated by normalizing and adding productivity change, the number of workers affected, and new jobs, by using a z-score to normalize and means to balance across scales.

2.4 Descriptive Analysis

To investigate the distribution of firms in countries, industries, and AI tools, descriptive statistical analysis was used. The representativeness of the dataset in geographic and sectoral was evaluated through frequency distributions. Also, the temporal patterns of AI adoption were examined to assess how AI was distributed over the years. It also calculated country-level mean values of variables of significant interest such as productivity change, training hours, and roles created to determine variation in organizational outcomes across geographic contexts.

2.5 Correlation Analysis

Pearson correlation analysis was carried out to assess the relationships between numerical variables. It is a method that quantifies the strength and direction of the linear relationships of pairs of variables and acts as a precursor before regression modeling. The correlation matrix assessed the possible relationships between AI adoption variables and organizational outcomes and determined the likelihood of multicollinearity. Another visual representation created to help comprehend the outcomes was a heatmap visualization.

2.6 Regression Analysis

Two regular least squares (OLS) regressions were estimated to investigate the effect of AI adoption on organizational outcomes. The first model evaluated the direct correlation between AI adoption variables and productivity, where productivity is taken as the dependent variable. The latter model studied how variables of AI adoption relate to the composite strategic proxy index to enable indirect evaluation of wider organizational change. Independent variables in both models were adoption year, training hours, number of employees affected, and new roles created. Regression analysis allowed simultaneous comparison of several predictors and estimated their statistical significance and relative impact.

3. Results

3.1 Distribution of Firms Across Countries and Industries

To create a complete view of the dataset, and to achieve the applicability of the data to the global analysis, the distribution of the companies per country, per industry was analyzed. It is a significant process of identifying the extent to which the dataset is representative of geographic and sectoral diversity that is critical in studies involving multinational environments. Considering the rate of observations in different countries and industries, it is possible to see whether the data sample is biased towards a specific region or industry, or it is the actual reflection of AI adoption patterns within the global business context. The global and sectoral coverage of the dataset was obtained with the help of the spread of firms by country and industry. This provides an image of the representativeness of AI adoption in other geographic and industrial contexts. The distribution of firms in the country is presented in table 1.

Table 1. Distribution of Firms by Country

Country	Number of Firms
Brazil	7322
Australia	7255
Canada	7238
South Korea	7233
UAE	7179
France	7169
Germany	7152
Singapore	7142
Switzerland	7117
South Africa	7109
USA	7057
India	7021
UK	7013
Japan	6993

As shown in Table 1, the data set is balanced well in 14 countries with minor variations in the firms. Brazil (n = 7,322) and Australia (n = 7,255) are slightly higher and Japan (n = 6,993) is least represented. The distribution is relatively homogenous, which indicates that no country dominates the data and, therefore, serves to demonstrate global equalization of AI adoption. The concentration of firms is presented in Table 2, which is industry-wise.

Table 2. Distribution of Firms by Industry

Industry	Number of Firms
Healthcare	7281
Advertising	7220
Entertainment	7198
Education	7195
Utilities	7187
Manufacturing	7153
Defense	7149
Finance	7128
Hospitality	7113
Retail	7109
Legal Services	7099
Telecom	7087
Transportation	7079
Technology	7002

According to Table 2, the balance of 14 industries is equal. Healthcare (n = 7,281) and Advertising (n = 7,220) are slightly higher and Technology (n = 7,002) is the least. The close distribution means that AI is not embraced within specific industries but incursively across industries.

3.2 Patterns of Generative AI Tool Adoption

To dig deeper into the essence of AI adoption on the firm level, the distribution of generative AI tools applied to organisations was examined. The analysis can help understand the preference to technologies and the relative popularity of various AI platforms in enterprise settings. The adoption patterns of tools are significant in determining either convergence towards a few prevailing technologies, or an effect on diversification between a wide range of platforms, which can indicate a variance in strategic focus, compatibility with technology, or an exploration of new AI applications. The adoption of generative AI tools in organizations was examined to determine the firm-level preference of technology. Table 3 shows the frequency of GenAI tool usage.

Table 3. Distribution of GenAI Tool Adoption

GenAI Tool	Frequency
Gemini	16885
Groq	16748
LLaMA	16676
Mixtral	16667
ChatGPT	16663
Claude	16361

As Table 3 depicts, the use of AI tools is fairly spread across six platforms. Gemini (n = 16,885) enjoys the largest amount of usage with Groq and LLaMA coming second and last with Claude (n = 16,361). The low difference between tools shows that there is no leading platform and that organizations are testing numerous AI technologies. Figure 1 depicts the temporal pattern of adoption of AI.

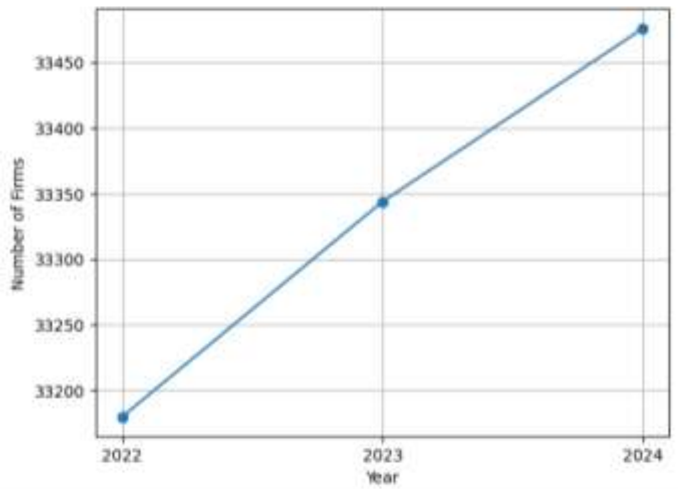

Figure 1. Distribution of AI Adoption by Year

The years of adoption have a distribution of 33,180 firms using AI in 2022, 33,344 in 2023 and 33,476 in 2024. The differences between years are small and it entails that there is no shift in the temporal distribution of adoption but is relatively constant. It means that the usage of AI in the dataset is equalized in the last years.

3.3 Country-Level Variation in Organizational Outcomes

To examine the hypothesis of the various impacts of AI adoption based on geographic area, the mean of the key organizational outcome variables in nations was considered. The analysis will focus on identifying trends in productivity change, workforce change as well as training intensity cross-country. These differences are essential to assessing whether the effects of AI adoption can be regional, i.e., can be subject to economic conditions, technological maturity or institutional environment, or it is universal in other country settings. To test geographic differences in organizational outputs, country specific means of productivity change, hours of training, and new positions made were tested. Table 4 contains the results.

Table 4. Country-wise Mean Values of Key Variables

Country	Productivity Change (%)	Training Hours Provided	New Roles Created
Australia	18.413329	12772.483529	15.461061
Brazil	18.484567	12820.736957	15.462852
Canada	18.374924	12612.774385	15.414894
France	18.627089	12613.825499	15.388897
Germany	18.248476	12714.161214	15.554390
India	18.255049	12761.015952	15.440393
Japan	18.512598	12681.051623	15.468468
Singapore	18.549986	12794.932792	15.384626
South Africa	18.396089	12645.049515	15.570826
South Korea	18.491511	12708.690032	15.643163

Switzerland	18.553126	12806.192356	15.507377
UAE	18.654562	12882.672517	15.497144
UK	18.425282	12646.618851	15.573221
USA	18.585816	12933.209863	15.666856

Table 4 shows that there is very little difference by country in all key variables. The change in productivity is close to a range of values (between 18.25 and 18.65), and so does the training hours and new positions produced. This implies that the organizational effect of AI adoption is quite similar across geographic regions in the dataset.

3.4 Correlation Analysis

The Pearson correlation analysis was performed on all numerical variables in the dataset to evaluate the relationships between AI adoption variables and organizational outcome. This is done as a pre-statistical test to establish possible linear relationships amongst the variables before regression modeling. The strengths and directions of pairwise correlations can be used to determine that changes in AI adoption traits are either related to fluctuations in productivity, workforce restructuring, or training intensity, thus giving preliminary information about the underlying data structure. A Pearson correlation analysis was used to test the relationships between variables. Table 5 gives the correlation matrix.

Table 5. Correlation Matrix

Variable	**Adoption Year**	**Employees Impacted**	**New Roles Created**	**Training Hours**	**Productivity Change**
Adoption Year	1.0000	0.0005	-0.0012	-0.0049	-0.0032
Employees Impacted	0.0005	1.0000	0.0028	0.0025	0.0029
New Roles Created	-0.0012	0.0028	1.0000	-0.0002	0.0033
Training Hours	-0.0049	0.0025	-0.0002	1.0000	-0.0004
Productivity Change	-0.0032	0.0029	0.0033	-0.0004	1.0000

Table 5 reveals that all the correlation coefficients are very near to zero, which indicates no meaningful linear dependencies between variables. Specifically, change in productivity exhibits insignificant correlation with AI adoption variables, which does not imply that the simple linear associations can capture productivity outcomes in this dataset.

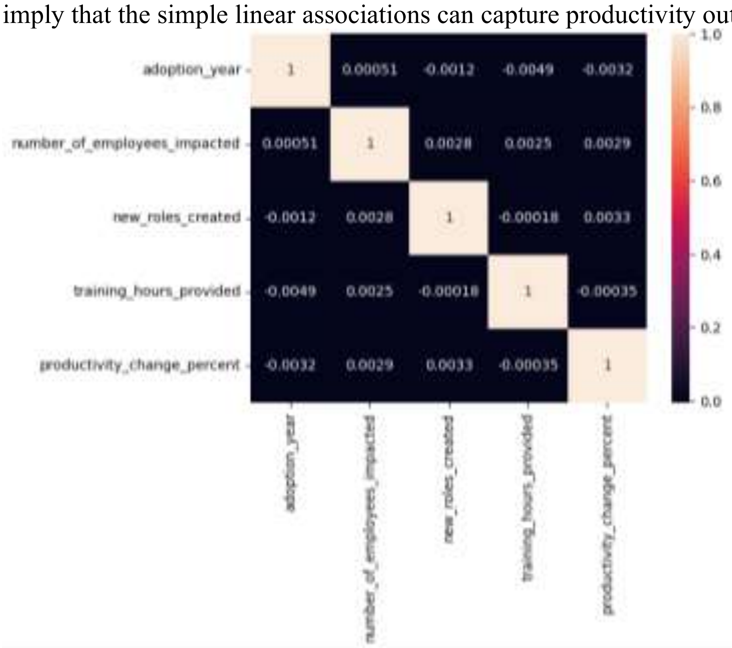

Figure 2. Correlation Matrix Heatmap of AI Adoption and Organizational Variables

Figure 2 visualization also confirms the findings of correlation matrix, as the intensity of the relationships between the variables is always low. There are no noticeable clusters or strong associations among the variables, and hence no meaningful patterns can be observed. Such visual data support the statistical results and prove no significant linear correlation in the dataset.

3.5 Regression Analysis: AI Adoption and Productivity

An ordinary least squares (OLS) regression equation was estimated to test the direct impact of AI usage on the change in firm-level productivity as the dependent variable. The objective of this analysis is to test the hypothesis that the timeline of AI adoption, the effects it has on workforce, the establishment of new roles, and the level of training have a significant effect on productivity performance. Regression modeling enables the concomitant analysis of multiple predictors, thus giving a stronger indication of the relationship between AI adoption and productivity than a straightforward descriptive/correlational analysis. An OLS regression was estimated to determine the impact of AI adoption on productivity. Table 6 shows the results.

Table 6. Regression Results (Dependent Variable: Productivity Change)

Variable	**Coefficient**	**p-value**

Adoption Year	-0.0375	0.310
Employees Impacted	0.0000047	0.366
New Roles Created	0.0036	0.298
Training Hours	-0.0000005	0.906

Model Statistics: $R^2 = 0.000$, $F = 0.7371$, $p = 0.567$

Table 6 indicates that the regression model lacks explanatory power and is not significant. None of the independent variables show significant impacts on productivity change. According to these findings, the variables of AI adoption do not directly affect productivity outcomes in the dataset.

3.6 Regression Analysis: Strategic Proxy Index

Since the dataset did not directly measure strategic decision-making, a composite strategic proxy index was created to allow more comprehensive organizational change related to AI adoption. This index combines several outcome variables such as change in productivity, workforce, and creation of roles and therefore, gives a more elaborate measure of organizational change. A regression model based on OLS was then estimated to test the level to which variables of AI adoption can affect this composite measure, which can indirectly evaluate the relationship between AI adoption and strategic transformation. A composite strategic proxy index was built to describe wider organizational change. Table 7 shows the regression findings.

Table 7. Regression Results (Dependent Variable: Strategic Proxy Index)

Variable	**Coefficient**	**p-value**
Adoption Year	-0.0013	0.310
Training Hours	-0.00000002	0.906
Employees Impacted	0.00005807	<0.001
New Roles Created	0.0387	<0.001

Model Statistics: $R^2 = 0.669$, $F = 50450$, $p < 0.001$

The model has a high power of explanations as indicated in Table 7. The variables that are workforce-related, such as the number of affected employees and the number of new jobs created, have a great importance as predictors of strategic proxy index. On the contrary, AI adoption variables are not significant statistically. These results demonstrate that organizational restructuring process and not just characteristics of adoption are more significantly linked to the outcome of strategic transformation.

4. Discussion

The results of this research give valuable information on how artificial intelligence (AI) implementation impacts organisational performance of companies. The findings reveal that variables of AI adoption such as adoption year and training intensity are not significantly directly related to productivity outcomes. This implies that the adoption of AI technologies alone might not necessarily help to improve performance. Rather, the influence of AI seems to be more multifaceted and moderated by the internal factors in the organization. This finding conforms to the general concept that AI should be formalized in organizations in a strategic way that can create value. The interaction of AI and strategic management highlights the fact that technology cannot work without proper alignment with organizational objectives and competencies (Keding, 2021).

One of the important research results is that there are high associations between the workforce-related variables and the composite strategic proxy index. The number of workers affected and new positions generated was identified to be important predictors of organizational change suggesting that AI implementation affects companies more through structural adjustments than direct performance implications. This confirms the argument that AI can improve decision making by facilitating improved knowledge management and use of information in organizations. Knowledge systems driven by AI transformation of the organizational process are vital in determining decision outcomes (Leoni et al., 2024). Additionally, the findings indicate that AI adoption is a factor in organizational change that can adopt augmented decision-making instead of complete automation. AI is also applied to assist managerial decisions and not to make them in international business contexts, emphasizing the need to collaborate between humans and AI (Lindner et al., 2025).

Though the research never measures the strategic decision-making, the results give the indirect evidence based on the constructed strategic proxy index. The lack of direct correlation between the AI adoption variables and this index indicates that adoption characteristics (timing and training) do not predict strategic transformation exclusively. Rather, the findings suggest the effect of AI integration on strategic decision-making depends on its implementation in organizational processes. It can be driven by AI technologies rather than determined by them, and the latter can assist managers to examine options and make superior decisions. It reinforces the idea that the appearance of AI should be proceeded by organizational maneuvering so that the strategic potential might be realised (Loureiro et al., 2021). Another important observation is that the development of AI in companies is also necessary. The skill to use AI to their advantage can enable companies to be more innovative and more successful, and that is why the capacity to build capabilities is revealed to become one of the most important factors that can turn the implementation of AI usage into a significant result (Mikalef and Gupta, 2021).

The impact of AI in innovation and organizational change is also justified by the results of workforce restructuring. The invention of new jobs and relocation of responsibilities reflect that AI embracement is tightly associated with innovation activities in companies. AI technologies allow organizations to process data to a greater extent and see the possibilities of innovation, which improves their adaptability to evolving conditions. This is consistent with the current studies that

emphasize AI in strategic development and innovation management (Haefner et al., 2021). Furthermore, decision-making structures are changing as the organizational structures transform. AI is becoming part of decision processes, which results in new decision-making structures that merge human judgment and algorithmic insights (Shrestha et al., 2019).
This study has various implications on managers and practitioners. To begin with, organizations must understand that AI will not produce performance gains on its own. Rather, one should focus on the ways of incorporating AI into the procedures and decision-making frameworks of organizations. Managers need to balance the use of AI capabilities and control over strategic decisions. To use AI effectively, human skills and AI-generated knowledge must be used collaboratively, i.e., they should complement each other (Tabesh, 2022). Moreover, organizations will need to work on creating a data-oriented culture that enables the utilization of AI technologies. Data-utilization skills are key to improving the performance of firms and making AI initiatives a success (Fosso Wamba et al., 2024). The extent of AI adoption is also industry-specific because organizations are not equally ready and capable of implementing AI technologies. The efficacy of AI implementation may be affected by industry-specific factors, and specific implementation strategies are necessary (Yang et al., 2024).
This study has a number of limitations which must be noted despite its contributions. First, the data lacks direct strategic decision-making measures and the use of a composite proxy index might cause issues in the interpretation of the findings. Also, there is the risk of endogeneity due to the inclusion of variables in both dependent and independent constructs, and it should be taken into account when interpreting the findings. Future studies need to engage primary data or longitudinal data in their studies to represent the dynamic relationship between use of AI and strategic decision-making. Industry/region-specific differences in AI adoption may also be studied further to reveal more information about contextual factors.

5. Conclusion

The connection between the implementation of artificial intelligence (AI) and organizational performance in companies that work in different geographic and industrial settings. The results indicate that the variables of AI adoption, including the time of adoption and the levels of training, do not have direct and significant effect on the productivity. Rather, the findings bring up the importance of organizational change, specifically workforce redesign and role generation, as more instrumental in defining the outcomes predetermined by AI implementation. The paper also illustrates that AI has an indirect impact on organizations by facilitating the change of organizational structures and processes as opposed to directly contributing to the increase of performance. It implies that the prosperity of AI is not only in its implementation but also in its implementation inside the organization systems and alignment with the strategic goals. A composite strategic proxy index is further insightful to the wider organizational transformation, but it also highlights the fact that strategic decision-making is challenging to measure using secondary data. On the whole, the research adds to the expanding literature on AI adoption by stating the significance of organizational readiness and competence building. Further studies are necessary by adding direct measures of strategic decision-making and longitudinal studies to understand the long-term effects of AI on organizational performance.

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