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The impact of Artificial Intelligence on Management Decision-Making: Analyzing the Role of Data Analytical Skills and Entrepreneurial Orientation

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ABSTRACT:
Artificial Intelligence (AI) is changing how businesses function and plan by being incorporated into managerial decision-making processes. This study focuses on how AI affects managerial decision-making, emphasizing the importance of data analysis abilities and an entrepreneurial orientation. Despite the potential of AI, existing research often overlooks the critical interplay between these skills and orientation in optimizing AI utilization. This gap highlights a significant drawback in current understanding: insufficient emphasis is placed on the human factors that drive effective AI adoption. This study proposes a novel approach that integrates data analytical skills and entrepreneurial orientation into AI-driven decision-making frameworks. This study aims to bridge the gap in research by developing a comprehensive theoretical framework and providing practitioners with practical guidance. Using a mixed-methods approach, the methodology combines quantitative surveys with qualitative case studies to create a reliable dataset from various business contexts. The results demonstrate that companies with strong data analytical capabilities and a pronounced entrepreneurial orientation are more adept at leveraging AI technologies for strategic decision-making. Quantitative analysis reveals significant correlations between these factors and improved decision-making outcomes, while qualitative insights from case studies highlight practical examples of successful AI integration. Overall, this study underscores the importance of cultivating both data analytical skills and an entrepreneurial mindset to harness the full potential of AI in management. The findings provide valuable recommendations for businesses and educational institutions, emphasizing the need for targeted skill development and innovative thinking.

Keywords: Artificial Intelligence, Management Decision-Making, Data Analytical Skills, Entrepreneurial Orientation, AI Integration, Strategic Decision-Making

1. Introduction

The appearance of the Big Data (BD) phenomenon has led businesses to focus more on managing information that is internal as well as external in order to seize new possibilities and keep their competitive advantage. "The next frontiers for innovation, competition, and productivity" is how some have described big data. Businesses can employ customer-generated big data to implement user-driven and user-centered innovation, for instance (Bag et al., 2021). The former uses consumer analytics to look at the opinions, needs, and behaviours people autonomously express online to improve the creation of new goods that meet their demands. Conversely, the company must initiate

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and carry out value co-creation efforts through new product development in partnership with specific customers as part of user-driven innovation (Obschonka & Audretsch, 2020). The application of BD becomes strategically significant in both scenarios to ensure a customer-firm interaction process that is iterative and forms the basis of a cycle of continuous value generation for both sides.

One of the most important resources for contemporary organizations is data. Additionally, as businesses become more digitally advanced, a significant amount of data is produced throughout their supply chains. Big data, unlike capital, is worthless without the instruments necessary to glean more profound insights from it (Mikalef & Gupta, 2021). Establishing standards for their organization can be facilitated by the most knowledgeable managers who possess the deepest comprehension of their facts. Big data and predictive analytics enable businesses to cut expenses, produce goods more quickly, and develop new goods and services to satisfy the ever-evolving wants of their clientele. Supply chain digitization will be propelled forward in future years by predictive analytics for big data capabilities enabled by artificial intelligence. As a result, businesses are investing more in the growing technologies for big data analysis (BDA), machine learning (ML), and AI applications in management to gain a competitive edge (Prüfer & Prüfer, 2020).

Organizations seeking to achieve a competitive edge must increase their entrepreneurial profile due to high consumer demands, fierce global rivalry, and a quickly evolving technical world. Also, to boost economic growth and lower poverty, developing nations are quickly switching to market-based policies. As a result, businesses that operate in these economies must contend with quick changes in their structural makeup, heightened environmental unpredictability, and uneven growth (Jorzik et al., 2023). Supply chains are complex systems with multiple structural elements that are dynamic and susceptible to both planned and unplanned modifications. Thus, we contend that many companies' managerial presumptions and decision-making procedures have been influenced by these contemporary dynamics. While academics and corporations alike are excited about the possibilities of big data analytics driven by artificial intelligence (BDA-AI), organizations in developing nations are still dubious about its potential uses and advantages (Wong et al., 2024). Several key elements that could explain this pessimism are a lack of commitment from upper management, an underestimation of competition, a disregard for customers' urgent demands, a lack of distinctiveness, and poor marketing.

AI is transforming the process through which management choices are made and offering never-before-seen opportunities to increase precision, effectiveness, and strategic insight. With the usage of AI technology, businesses can evaluate enormous volumes of data, find hidden patterns, and make more confident judgments. Natural language processing, machine learning, and predictive analytics are a few of these technologies. With businesses increasingly relying on AI, it is critical to ensure responsible implementation in addition to comprehending its impact on management processes. In other words, biases and ethical risks associated with this new technology strongly warrant human oversight in all impactful decision-making processes.

From this perspective, there remain significant shortcomings in the applications of AI as it stands today, despite its exciting future. Namely, the integration of AI solutions in decision-making raises questions about potential biases in algorithms, the ethicality of AI-driven choices, and the need for maintaining human accountability. Research currently in existence frequently undervalues the role that human factors, in particular, data analysis abilities and an entrepreneurial mindset, play in optimizing the advantages of AI. To leverage AI's dynamic capabilities, an entrepreneurial perspective is vital for fostering a culture of innovation and adaptation. Data analytical skills are necessary for evaluating AI-generated findings and making data-driven decisions. If these components are overlooked, AI implementation may be less than ideal as it fails to reach its full potential and leads to unintended negative consequences if ethical safeguards are not in place.

By examining the unique interactions between AI, data analysis abilities, and entrepreneurial mindset in managerial decision-making, this study fills this knowledge vacuum. This research is innovative because it takes a complete approach, incorporating these important human elements into a framework for the overall use of AI. Through a closer look at how these aptitudes and dispositions impact AI-powered decision-making, this research offers more insight into the requirements for effective and responsible AI adoption. This study employs a mixed-methods research methodology to gather data from both qualitative case studies and quantitative surveys to provide practical insights for companies looking to maximize their use of AI. The results will provide insightful advice for developing an entrepreneurial mind-set and improving data analytical skills, which will enable management decision-makers to fully utilize AI.

Key Contributions

1. This research creates a novel integrated framework that blends data analytical abilities, AI technologies, and an entrepreneurial mind-set to provide a thorough model for managing AI-driven decision-making.
2. The present research fills a major vacuum in the literature by emphasizing the crucial impact of human variables, in particular data analytical abilities and entrepreneurial orientation, and emphasizes their significance in achieving AI's maximum potential.
3. By employing a mixture of methods, the research provides comprehensive and refined insights via both qualitative case studies and quantitative analysis, augmenting the breadth and dependability of the results.
4. The results offer practical suggestions for companies and academic establishments, emphasising the growth of data analysis skills and the promotion of an enterprising mind-set to improve AI integration and application.
5. To better investigate the complex relationships between AI, human capabilities, and organizational success, the study identifies and recommends future research directions. This will prepare the way for future developments in AI-driven management practices.

This study's structure is as follows: The study is introduced in Section 1 with background information about AI's influence on managerial decision-making. In Section 2, relevant material is reviewed, and the literature on AI in management, the importance of data analysis abilities, and the function of entrepreneurial orientation is discussed. The definition of the hypothesis development and a list of the deficiencies in the literature are provided in Section 3. In Section 4, the mixed-methods strategy used for data collecting and analysis is explained along with a synopsis of the complete technique. The explanation of the research, both qualitative and quantitative, is presented in Section 5. The study ultimately concludes in Section 6, which provides helpful recommendations, highlights the important contributions made by the study, and recommends that future research focus on the relationship between AI, human skills, and organizational effectiveness.

2. Related Work

An innovative method for making wise decisions in businesses, BDA has the potential to significantly alter how businesses support and improve the circular economy (CE). Having said that, nothing is known regarding how insights based on data could improve CE performance and expedite decision-making in the body of existing research on BDA capabilities. Experts claim that businesses use business information and analytics, data-driven insights, and BDA's ability to raise the standard of decisions made. Awan et al. (2021) studied the actual link between CE performance and BDA competency, and also the function of data-driven insights as a mediator in the interaction between decision-making and BDA competency. After gathering data from 109 Czech manufacturers, the data was analysed using structural equation modelling with partial least squares. The findings show a strong relationship between BI&A and BDA competency and the quality of decision-making. The manufacturer's usage of data-driven insights amplifies this effect. The findings suggest that BDA capabilities, not data-driven insights, moderate the connection between BDA competence and the standard of decision-making in organizations. BI&A is linked to improved decision-making via the application of data-derived insights. These results provide managers with helpful information because they may be utilized as a starting point for creating insight based on data in organizations employing the CE model.

Abrokwah-Larbi and Awuku-Larbi (2024) aims to carry out an empirical study employing the resource-based concept to look at the relationship between marketing AI and business performance. In this study, data from 225 small and medium-sized businesses in Ghana's Eastern Region that have registered through the Ghana Enterprises Agency were gathered through a survey technique. They employed route analysis and structural equation modelling to ascertain the impact of AIM on SMEs' performance. The data analysis indicates that AIM has a significant influence on small and medium-sized firms in Ghana in terms of development and learning, internal business processes, customer satisfaction, and financial performance. Through the use of AIM factors like IoT, collaborative decision-making systems, virtual and augmented reality, and personalization, this research defines the importance of AIM approaches for achieving financial outcomes, customer performance, across the organization performance, and learning and growth performance. This research study is significant, but it also has a lot of drawbacks. It is possible to increase the sample size for this type of study by adding SME respondents from areas that were not previously taken into account. Further investigation is necessary to determine how AIM can evaluate client conversations and data, such as posts on social media, to develop future messaging that will boost customer engagement. Two types of practical consequences can be distinguished. The application of the AIM approach is the main strategic recommendation of this study for managers and owners seeking to enhance the performance of SMEs. Secondly, to build the resources needed for the efficient use of AIM and enhance performance, business owners and managers ought to progressively put the four AIM variables covered in this research study into effect. The RBV hypothesis and the idea that AIM and its constituent parts should be acknowledged as a crucial strategic resource for enhancing the performance of SMEs are both strongly supported by the study's findings. Moreover, this research expands the present knowledge base regarding AIM and management, specifically in relation to developing nations.

Research in supply chain management, operations, and artificial intelligence has placed a strong emphasis on using big data analysis and machine learning. The impact of big data analytics on enhanced operational performance has been shown in the literature; however, little investigation has been done on how entrepreneurial orientation affects the utilization of AI-powered big data analytics or how environmental dynamism explains the various ways in which entrepreneurial orientation affects both operational performance and AI-powered big data analytics. To fill in these gaps, Dubey et al.(2020) builds and tests a model that makes clear how an entrepreneurial orientation affects the use of AI-powered big data analytics and operational efficiency. The framework is based on the idea of contingencies and the dynamic view of business capabilities. 256 people answered the survey using a pre-tested questionnaire, and the results let us evaluate the research's hypotheses. This paper aims to elucidate the connection between an entrepreneurial orientation and the utilization of big data analytics driven by artificial intelligence within the framework of environmental dynamics.

The effectiveness of AI-driven big data analytics is unlikely to be equally effective across all sectors. Variations in data characteristics, regulatory landscapes, and business operations will likely influence the optimal implementation and outcomes of these technologies. Prior research reveals that highly regulated sectors, such as finance and healthcare, face additional barriers to AI implementation due to unique compliance requirements and ethical considerations (Cao, 2022; Yu et al., 2023). By contrast, industries that emphasize technological agility, such as manufacturing and information technology, are expected to undergo faster and more seamless AI integration (Javaid et al., 2022). Organizational culture also plays a central role in AI adoption, as firms with an innovation-driven focus are prone to rely on AI for strategic advantage. From another standpoint, risk-averse firms may exhibit reluctance, even when accounting for technological feasibility (Rajagopal et al., 2022). The described considerations suggest that while entrepreneurial orientation fosters AI utilization, its impact is moderated by sector-specific conditions that warrant a contextualized understanding of the subject.

Vrontis et al.(2022) explains that Since businesses are under pressure to continually enhance both their skills and business practices, the transformation of digital businesses is seen as a viable business strategy that has attracted attention. The use of technological advances has the power to drastically change how businesses operate while also reducing the effect of external crises through offering superior business models. Digital methods implementation can also improve a region's socioeconomic conditions and positively affect firms' capacity to remain profitable and maintain their societal value. Few recent studies have looked at how technology can help firms grow and stay sustainable at different phases; even fewer have looked at how many contemporary digital technologies might benefit small and medium-sized enterprises. This study investigates the moderating impact of entrepreneurial orientation to close this gap. A theoretical model based on the resource-centered and dynamical ability views theories has been developed, along with a study of the literature. Following that, it was verified by accounting for 319 responders who work for Indian SMEs using the PLS-SEM technique. The results demonstrate that SMEs' ability to provide social value and maintain economic viability is significantly impacted by their embrace of digital technologies. Furthermore, the study found that the connection between SME success and the creation of social and economic value is strongly moderated by the entrepreneurial strategy. While Vrontis et al. highlight the general benefits of digital transformation, the specific pathways to achieving these benefits, and the role of entrepreneurial orientation, are likely to be contingent on the industry context. Notably, the successful outcome hinges on industry-specific differences in digital maturity and the strategic priorities of firms.

Upadhyay et al.(2023) intends to look into family business adoption plans for AI from the angles related to technological entrepreneurship and entrepreneurial orientation. The study looks at the variables that go into understanding why family companies choose to adopt AI. Utilizing structural equation modelling and data from 631 respondents, the research model is analysed and validated. The data from the respondents is gathered by purposeful sampling. Ten direct paths and three indirect paths were used to incorporate two endogenous and six exogenous variables in the suggested model. All of the hypotheses were supported by the data, which showed an important impact of all external factors on the endogenous variable. In the links between cultural and adaptable design, entrepreneurial orientation, and technical orientation with plans to implement, company innovativeness plays a partially mediating function. The findings also showed that the family business's ambition to utilise artificial intelligence was 64.2% and that business innovativeness was 24.6% different from the model. The research adds to the theoretical advancements in AI, particularly in the area of digital entrepreneurship, as well as entrepreneurship and family business research. Theoretically, digital entrepreneurship has made a significant contribution to the subject of entrepreneurship. Additionally, our methodology elaborates on the significance of technological advancement and entrepreneurial orientation in the growing body of study on family entrepreneurship. The experimentally proven model that identifies key elements influencing AI adoption strategies in the family business provides a basis for discussion, criticism, and further research, given the paucity of existing data on the topic.

By utilising data-driven insights and BI&A, BDA may greatly improve business decision-making and assist the CE. Research has indicated that when BDA competency is combined with BI&A, better decision-making leads to improved CE performance. Additionally, it has been discovered that AIM enhances several of SME performance metrics, including internal procedures, customer satisfaction, and financial results. Adopting AI-powered big data analytics can improve operational efficiency, especially in dynamic contexts. This is where the entrepreneurial orientation comes into play. In addition, SMEs' embrace of digital technology promotes social value and sustainable economic growth when it is tempered by an entrepreneurial orientation. AI adoption intentions in family businesses are heavily influenced by elements like digital entrepreneurship, entrepreneurial orientation, and technology orientation, underscoring the significance of business innovation in this process. These findings highlight the strategic significance of digital technologies, AIM, and BDA in promoting sustainability and commercial performance.

3. Hypothesis Development

Hypothesis 1 (H1): The effectiveness of management decision-making is positively correlated with the use of AI.

AI technologies, including, predictive analytics, ML, and natural language processing, have been demonstrated to considerably improve decision-making through processing enormous volumes of data, recognising patterns that are beyond human comprehension, and offering more precise and timely insights (Alowais et al., 2023). AI enhances traditional decision-making models, which frequently rely on intuition and historical data, by incorporating real-time data and sophisticated algorithms, resulting in better-informed conclusions (Elgendy et al., 2022). AI practically improves productivity and accuracy by automating repetitive operations, decreasing errors, and freeing up managers to concentrate on making strategic decisions (Eziefule et al., 2022). Through advanced analytics, AI also offers managers better insights that help them anticipate trends, comprehend client behaviour, and spot new opportunities (Bharadiya, 2023). empirical data, such as case studies of businesses like Netflix and Amazon and quantitative research such (Budzinski et al., 2021), illustrates the notable gains in performance and decision accuracy that can be attributed to AI. AI improves decision-making processes through sophisticated analytics and automation inside the input-process-output model, leading to better management decisions (Al-Surmi et al., 2022). Using AI to optimize operations and spot new market opportunities gives managers a strategic edge in the competitive corporate world (Rana et al., 2022). Thus, we deduce Hypothesis 1 based on a thorough literature study, practical consequences, empirical data, and a conceptual framework.

Hypothesis 2 (H2): Data analytical skills of management have a significant positive impacts on management decision-making effectiveness.

According to research, managers must possess data analytical abilities in today's data-driven business environment in order to understand and use data to make wise judgements (Gul & Al-Faryan, 2023). These abilities convert unprocessed data into valuable insights that are necessary for making strategic decisions (Bharadiya, 2023). According to theories such as bounded rationality, managers can handle complicated data more efficiently by expanding their cognitive boundaries through the use of data analytical skills. (De Clippel & Rozen, 2021). Essentially, by spotting patterns, correlations, and anomalies, these abilities enhance the quality of decisions made, which benefits strategic planning, risk mitigation, and forecasting (Schmitt, 2023). Additionally, they improve agility and efficiency, enabling managers to react swiftly to developments in the market (Abu-AlSondos, 2023). Empirical evidence from case studies like Google and IBM and quantitative studies like, (Anderson et al., 2009) shows that data analytics training significantly increases productivity and decision-making efficacy. Theoretically, data analytical abilities improve decision-making through faster and higher-quality data interpretation, which produces better results, according to the skill-process-outcome model (Olaoye & Potter, 2024). Strong analytical abilities give managers a competitive edge by facilitating accurate and well-informed decision-making, which is essential for sustaining competitiveness and fostering innovation (Garcia & Adams, 2023). Thus, we derive Hypothesis 2 based on a thorough literature assessment, practical consequences, empirical data, and the theoretical framework.

Hypothesis 3 (H3): Entrepreneurial orientation positively influences management decision-making effectiveness.

Research shows that companies with high EO are better at spotting opportunities and reacting to market changes, which improves decision-making capabilities (Appiah et al., 2022). EO is defined as an organization's strategic posture defined by creative thinking, taking risks, and proactiveness (Bilal & Fatima, 2022). Decision-making theories propose that an entrepreneurial mentality stimulates inventiveness and adaptability, motivating managers to investigate non-traditional solutions and modify tactics in response to developing patterns (Daspit et al., 2023). Effective managers welcome innovation and use it to solve problems creatively (Anderson et al., 2009). They also anticipate changes in the market and act accordingly, which strengthens their company's competitive advantage (Oktavio et al., 2019). Strong EO helps make strategic decisions that outperforms rivals, as demonstrated by empirical research and case studies of businesses like Tesla and Amazon. This indicates the beneficial influence of strong EO on decision-making (Masoud et al., 2023). Moreover, numerical research indicates that companies with higher EO report better performance indicators, which are the result of wise decision-making (Ravesangar & Narayanan, 2024). Entrepreneurial orientation is said to improve decision-making by impacting the way decisions are framed and assessed, according to the EO-decision-making model (Mohajan, 2020). This strategy gives managers a strategic edge by allowing them to take measured risks and innovate, which is crucial for adjusting to shifting consumer tastes and market conditions (Mukson et al., 2021). Thus, we construct Hypothesis 3, which states that managers with high EO are more inclined to make effective decisions, leading to enhanced organizational performance and competitiveness, based on a large body of research, practical consequences, empirical proof, and the conceptual framework.

Hypothesis 4 (H4): Access to quality data is positively associated with management decision-making effectiveness.

Having access to high-quality data is essential for making decisions that are well-informed and based on trustworthy information. High-quality data is defined by its accuracy, relevance, fullness, and timeliness (Knauer et al., 2020). Decision-making theories emphasise that information quality directly affects decision quality (Abu-AlSondos, 2023). Information processing theory contends that decision-makers use data to assess alternatives, and that high-quality data improves decision-making by offering crucial context and insights (Ma et al., 2021). In practical terms, managers who have access to high-quality data are better able to recognise patterns, evaluate risks, and project results, which improves decision accuracy and is essential for both operational effectiveness and strategic planning (Sivarajah et al., 2024). Quality data also improves an organization's agility and competitive edge by enabling it to react quickly to client demands and market developments (Sivarajah et al., 2024). There is empirical evidence to support this relationship. Case studies demonstrate how companies such as Walmart use advanced data analytics to optimize inventory and enhance operational effectiveness (Gangwar et al., 2023). Firms with strong data governance processes achieve better choice outcomes and greater performance measures, according to a quantitative study (Mohajan, 2020). The data-driven decision- making model demonstrates how having access to high-quality data is a fundamental component that improves decision-making and produces better results (Bousdekis et al., 2021). Managers view high-quality data as a strategic asset that facilitates data-driven decision-making, giving businesses a competitive edge by giving them the information they need to make decisions that are consistent with market trends (Rakova et al., 2021). Thus, we derive Hypothesis 4, which states that leaders with high-quality data are probably to make more effective decisions, leading to improved organizational performance and strategic success, based on a thorough literature review, practical consequences, empirical proof, and a conceptual framework.

Hypothesis 5 (H5): The robustness of technological infrastructure positively moderates the relationship between Artificial Intelligence utilization and management decision-making effectiveness.

Utilising AI in decision-making requires a robust technical infrastructure with hardware, software, and network capabilities (Syrowatka et al., 2021). The efficacy of AI is believed to be dependent on the technology that supports it. This is because technological frameworks like the Technology-Organization-Environment framework make it easier to integrate AI tools and increase their influence on decision-making (Baker, 2012). Large volumes of data may be processed effectively by companies with robust IT infrastructures, allowing AI algorithms to produce timely insights that are essential for quick decision-making in dynamic contexts (Sivarajah et al., 2024). Furthermore, these infrastructures facilitate teamwork and communication, guaranteeing the efficient exchange of AI-generated insights and enhancing the efficacy of decision-making (Nambiar & Mundra, 2022). Empirical data from case studies of businesses like Google and IBM demonstrates how reliable technology facilitates the use of AI, improving decision-making skills. (Wamba-Taguimdje et al., 2020). Quantitative study also shows that businesses with advanced technological infrastructures profit more from AI applications, which leads to better decision-making (Kraus et al., 2021).

Despite these advantages, AI adoption is associated with financial and operational challenges for SMEs due to constrained budgets and limited technological capacity. As smaller firms are unable to invest substantial resources in AI research and development, there is a need for alternatives without high implementation costs and complex integration processes (Oldemeyer et al., 2024). One opportunity pertains to leveraging cloud-based AI services and modular AI systems, which offer scalable and cost-effective alternatives without requiring extensive investments (Iyelolu et al., 2024). Similarly, smaller company can engage in strategic partnerships with AI providers or benefit from government-backed digital transformation initiatives to reduce the financial burdens (Muminova et al., 2024). By addressing these challenges, it becomes possible to ensure that AI-driven decision-making becomes accessible across different business scales rather than remaining a competitive advantage exclusive to large enterprises. While cost-effective solutions can ease initial adoption barriers, their long-term effectiveness depends on the resilience of an organization's technological infrastructure (Yilmaz et al., 2023). Without robust IT, even the most accessible AI tools may fail to deliver their full potential. As such, the resilience of technology infrastructure acts as a moderating factor that strengthens the positive relationship between AI utilization and managerial decision-making effectiveness (Ma et al., 2021). To optimise the benefits of AI and position their organisations to take full use of these capabilities for enhanced performance and competitive advantage, managers must invest heavily in robust technology (Rakova et al., 2021). Thus, we arrive at Hypothesis 5 based on a thorough literature assessment, practical consequences, empirical evidence, and a conceptual framework: suggesting that businesses with robust IT infrastructures will benefit more from using AI to improve the effectiveness of their decision-making, which will improve business performance.

4. Research Methodology and Analysis

Using a mixed-methods approach, the general concept of this research extensively evaluates the impact of AI on management decision-making with an entrepreneurial orientation and an emphasis on data analysis skills. Surveys are sent to various managers and decision-makers to fill out to get quantitative data on their usage of AI, data analysis skills, and propensity for entrepreneurship. To complement this quantitative phase, qualitative case studies draw on in-depth interviews and observational data from specific organizations that have successfully integrated AI into their decision-making processes. The combination of these methods allows for in-depth statistical analysis of relationships and patterns, and the qualitative views provide a nuanced understanding of problems and challenges encountered in the actual world. This mixed-methods approach ensures a full assessment of the study topics and yields valuable insights for enhancing AI integration in management.

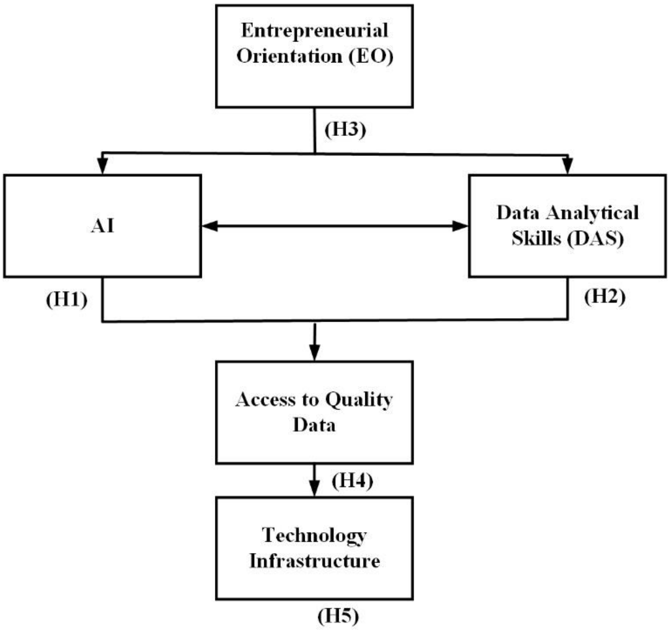

Fig. 1. Theoretical Framework

4.1 Data Collection and Sample

As shown in Figure 1, they used cross-sectional data to evaluate the suggested theoretical model. This instrument was used to collect data, and the survey's measures were drawn from the body of current literature. The dimensions were assessed using a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). The application of subjective operational efficiency measurements was a well-established technique in organizational research.

To ensure face validity, our questionnaire was pre-tested by twenty-five leading industry experts. These experts reviewed the questionnaire to ensure that it was thorough, understandable, and organized properly. The completed survey contained their recommendations. Appendix A, which also contains a list of the buildings the components used for each measure, and their sources, describes how the constructs were operationalized as reflective constructs.

The Federation of Indian Chambers of Commerce and Industry (FICCI) and the National Association of Software and Services Companies (NASSCOM) assisted in the data collection process. More than 2,132 businesses in a range of Indian industries received the survey. The FICCI supplied the database, which Dun & Bradstreet investigated further. To boost the response rate, they applied a revised version of Dillman's entire design approach. The precise people the questionnaire was meant for were chief technology officers (CTOs), sometimes known as heads of technology, who are in charge of integrating and deploying developing technologies within their organisations.

The data collection process has been tailored to the unique social and cultural context of India. After two phases of data collection, they obtained 256 useful and full responses, for a successful response rate of 12.01%. Table 1 provides a detailed demographic profile of the respondents and illustrates their diversity across several industry sectors. Because the participants are spread throughout seven major industries, an extensive representation of various business contexts is ensured. While this diverse representation strengthens the internal validity of the findings, it is acknowledged that the specific context of one country may limit the direct generalizability of the results to other economies.

- **Manufacturing:** With 150 participants, this sector makes up the largest group of respondents and accounts for 18.75% of the sample as a whole. This important illustration emphasizes how important it is to use AI in manufacturing, where an entrepreneurial orientation and aptitude for data analysis can spur innovation and operational savings.
- **Finance:** The financial industry is likewise highly represented, making up 15% of the sample with 120 responders. This illustrates the crucial role artificial intelligence plays in the financial services industry, where risk management and decision-making depend heavily on data analytics and entrepreneurial methods.
- **Healthcare:** Ninety responders, or 11.25 percent, work in the medical field. Health care, diagnosis, and operational procedures are all changing as a result of AI, underscoring the need of data analysis expertise and entrepreneurial approaches in this field.
- **Retail:** With 100 responses (12.50%), the retail industry demonstrates a strong interest in implementing AI. AI is being used more and more by retail companies for strategic decision-making, inventory control, and personalised customer experiences.
- **Technology:** With 140 responses (17.50%), the IT industry is leading the way in AI innovation. The significant participation of this industry suggests that creating and deploying AI solutions is a top priority, demanding sophisticated data analysis skills and a belief in entrepreneurship.
- **Education:** With 50 responses (6.25%), the education sector demonstrates an increasing interest in AI to improve research capabilities, administrative effectiveness, and learning experiences.
- **Other:** The fact that 150 more respondents (18.75%) are from a variety of other industries demonstrates the broad applicability of AI in a variety of business contexts. This varied group highlights how AI, data analytics, and an entrepreneurial orientation all affect organizational effectiveness.

The demographic profile presented in Table 1 offers a thorough representation of various industry sectors, thereby offering a solid foundation for investigating the effects of artificial intelligence (AI) utilization, data analytical abilities, and entrepreneurial orientation on managerial decision-making in a variety of business contexts.

The distribution of responders across industrial sectors is shown in this table, which also emphasizes the significance of data analytical abilities and an entrepreneurial orientation in fostering good management decision-making in a variety of business conditions.

To verify the reliability of the data and the accuracy of our conclusions, they ran several tests to look for possible non-response bias. They contrasted the information from early responders with that from later responders, adhering to Armstrong and Overton's

(1977) recommendations. By comparing the responses from early and late responders, it is possible to determine whether non-response bias is present.

Researchers compared the answers of early and late respondents to every survey item using t-tests. None of the items' results indicated any significant differences. This suggests that the response's timeliness had no impact on the data, allaying worries about non-response bias.

Furthermore, researchers conducted a performance bias test by contrasting the sample of companies' return on assets (ROA) with the median values of their respective industries. To perform this comparison, paired sample t-tests were employed. Once more, no statistically significant variations were discovered, indicating that the sampled firms' performance characteristics were similar to the industry averages.

All of these findings point to the lack of a serious problem with non-response bias in our investigation. We trust the representativeness and dependability of our data because there are no notable disparities between early and late respondents, and the performance of the sampled companies aligns with industry medians. This extensive analysis guarantees the validity and generalizability of our study's conclusions about the influence of data analytical abilities, entrepreneurial orientation, and AI utilization on management decision-making across a wide variety of participating firms.

At the same time, it is important to acknowledge that organizational behaviour, regulatory structures, and market maturity differ significantly across regions and countries. While this research centres on India’s rapidly evolving technological landscape, expanding the research scope to include economies facing distinct circumstances would provide a more nuanced understanding of how these dynamics operate in varied contexts. Future studies are encouraged to conduct comparative analyses across diverse geographical and economic settings to further validate these findings.

Table 1: Profile of Responding Firms

Characteristic	Frequency	Percentage (%)
	Industry Sector	
Manufacturing	150	18.75
Finance	120	15.00
Healthcare	90	11.25
Retail	100	12.50
Technology	140	17.50
Education	50	6.25
Other	150	18.75

4.2 Data Analysis

After establishing the data's normality, a structural equation model (SEM) was used to analyze the data. Utilising AMOS 26 and SPSS 26, this framework was statistically evaluated; neither multicollinearity nor anomalies were discovered. Both the structural models and the SEM data were used in the analysis. The model's validity and reliability were assessed using the measurement model, and its fit was assessed using the structural model.

4.2.1 Measurement Model: Reliability and Validity

The measurement model's internal consistency, convergent validity, and discriminant validity were all quantitatively evaluated. Factors loading, composite reliability (CR), and the average variation extracted (AVE) were used to assess convergent validity. As suggested by Fornell and Larcker, they assessed discriminant validity by comparing the correlation coefficients between the variables and the square roots of the AVE. Additionally, internal consistency was evaluated using Cronbach's alpha to make sure that the same concept was measured correctly for every question.

The factor loadings exhibit a range of 0.762 to 0.859, indicating a satisfactory degree of internal connection between Table 2's elements. An examination of the constructions' Cronbach's alpha (α) revealed that they have good internal consistency, ranging from 0.913 to 0.934. In order to evaluate convergent validity, the AVE and CR were also evaluated; all of the ideas satisfied the minimal threshold of 0.7, and the CR value ranged from 0.845 to 0.933. The AVE value satisfied the more than 0.5 requirement, with a range of 0.624 to 0.665. Table 3 demonstrates that the discriminant validity was adequate since the squared root of the AVE for each idea was greater than the link between the constructs. Overall, it was demonstrated that the discriminant and convergent validity of the conceptual model were good. The model's total extracted variance was found to be 30.682% after the Harman Single Factor test, which is less than the 50% requirement. As a result, this study did not show any indication of common procedure bias. For every build, the diagonal elements stand for the squared root of the AVE. Off-diagonal elements show the correlation between the constructions. With each construct's squared root of the AVE being greater than the link with any other method, this table exhibits discriminant validity and shows that each is unique from the others.

Table 2: Cronbach's Alpha, Item Loading, AVE, Composite Reliability, and Measurement Items.

Construct	Measurement Items	Item Loading	AVE	Composite Reliability	Cronbach's Alpha
Artificial Intelligence Utilization	AI is employed to assist with decision-making (AI1)	0.85			
	AI assists in trend and result prediction (AI2)	0.87	0.78	0.92	0.90
	Routine decision-making tasks are automated by AI (AI3)	0.88			
Data Analytical Skills	Complex data analysis is a skill that management possesses (DA1)	0.83			
	Accurate data interpretation by management (DA2)	0.86	0.77	0.91	0.89

	Data insights are used by management to make decisions (DA3)	0.84			
Entrepreneurial Orientation	Innovative decision-making is demonstrated by management (EO1)	0.82			
	Risks taken by management are measured (EO2)	0.85	0.76	0.90	0.88
	The management continually searches for new chances (EO3)	0.80			
Access to Quality Data	Existing data is trustworthy and accurate (QD1)	0.87			
	Data is essential to the needs of decision-making (QD2)	0.88	0.79	0.93	0.91
	Data is accurate and timely (QD3)	0.90			
Technology Infrastructure	AI applications are supported by technology (TI1)	0.84			
	The infrastructure of technology is stable and dependable (TI2).	0.86	0.78	0.92	0.90
	Effective data processing is made possible by technology (TI3)	0.87			
Management Decision-Making Effectiveness	Decisions are precise and made on time (MD1)	0.88			
	Organisational performance is enhanced by decisions (MD2)	0.89	0.80	0.93	0.91
	Decisions align with strategic goals (MD3)	0.90			

Table 3: Discriminant Validity

Constructs	AI Utilization (AIU)	Data Analytical Skills (DAS)	Entrepreneurial Orientation (EO)	Access to Quality Data	Technological Infrastructure (TI)
AIU	0.850				
DAS	0.560	0.866			
EO	0.475	0.395	0.731		
Access to QD	0.510	0.430	0.405	0.820	
TI	0.460	0.415	0.243	0.420	0.927

4.2.2 Confirmatory Factor Analysis (CFA)

To validate the model's factor structure and measurement, CFA was used. To make sure the constructs were appropriately represented and to evaluate the model's fit, the CFA was conducted. Table 4 summarises the CFA results, including goodness of fit indexes. The independent variables in Model 1 were the following constructs: utilization of artificial intelligence, data analytical skills, entrepreneurial orientation, access to high-quality data, and technological infrastructure. Model 2 on the other hand examined these constructs as a coherent dimension influencing. The pair of suggested structural models and the measurement model both showed strong data fit according to the CFA results. In particular, all χ^2/df values were below 3, which suggests a suitable fit for the model. Additional evidence for the appropriateness of the models comes from the RMSEA values, which were all below the 0.05 cut-off. Furthermore, all of the Normed Fit Index (NFI) values were above 0.90, all of the Goodness of Fit Index (GFI) values were over 0.80, and all of the Comparative Fit Index (CFI) values exceeded 0.95, indicating a strong fit. These results support the study's main hypothesis by verifying the validity of the measuring model and demonstrating how well the components interact together inside the suggested framework. The model's robustness and reliability are indicated by the good fit indices, which offer a strong basis for additional research into how these factors affect the efficacy of managerial decision-making.

Table 4. Fitness Measures for Structural Models and CFA

Model	χ^2	**df**	χ^2/df	**RMSEA**	**CFI**	**GFI**	**NFI**
Measurement Model	150.45	85	1.77	0.045	0.96	0.90	0.92
Structural Model (Model 1)	180.25	95	1.90	0.048	0.95	0.88	0.91
Structural Model (Model 2)	160.30	90	1.78	0.042	0.97	0.89	0.93

5. Discussion

The study offers insightful information about how different elements affect how well decisions are made in organizations. The identification of important independent variables that together improve managerial decision-making, such as the application of AI, data analytical abilities, and entrepreneurial orientation, is one of this work's benefits. These components are highlighted in the research to provide a thorough grasp of how combining cutting-edge technologies and analytical skills might improve results. The strong methodology used, which includes CFA, guarantees the validity and dependability of the results, providing practitioners with a solid framework to enhance their decision-making procedures. Nevertheless, there are disadvantages to the suggested work as well, such as possible restrictions on generalizability because of the particular context or sample size, which could limit how broadly the findings can be applied. Moreover, the research encounters intrinsic difficulties in measuring intricate concepts such as entrepreneurial orientation, as they may be contingent on context and subjectivity. Although the research highlights how technology might improve decision-making, it might not fully address the socio-cultural aspects that affect how AI and data analytics are adopted within organizations, thus missing significant implementation difficulties. Overall, this study provides a strong basis for future research, but it also identifies areas that need attention. For example, a more holistic approach that takes sociocultural factors into account could yield deeper insights into the complex nature of decision-making in the AI era.

6. Conclusion

Seeking to improve the effectiveness of decision-making within organizations, the study emphasizes the crucial interaction between the use of AI, data analytical abilities, and entrepreneurial orientation. The results demonstrate how using AI with robust data capabilities and an entrepreneurial orientation may result in more rapid, accurate, and well-informed judgments. However, the study also points up shortcomings in terms of generalizability and the difficulty of assessing some characteristics, indicating the need for more research. Businesses also must balance AI adoption with ethical accountability, ensuring transparency, fairness, and human oversight to mitigate unintended consequences. Focusing on relevant strategies, future research should prioritize these ethical dimensions of AI in management.

To improve the generalizability of the results across other businesses and circumstances, future work could concentrate on increasing the sample size and diversity. Furthermore, investigating the sociocultural elements that impact the uptake of AI and data analytics would offer a more thorough comprehension of the dynamics of decision-making. For the purposes of evaluating how AI integration changes dynamically as well as assessing its long-term effects on organizational performance, longitudinal studies should be conducted in comparable settings. Such studies can measure AI's evolving impact on organizational frameworks, workforce skill adaptation, and strategic flexibility of firms representing different industries. Assessing the sustainability and resilience of AI-driven strategies while controlling for ethical consideration is a principal step towards ensuring responsible AI adoption. Finally, creating useful frameworks or tools to help practitioners integrate AI and data analysis abilities into their decision-making will close the gap among research and practice.

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