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Exploring Nexus among Big Data Analytics, Artificial Intelligence and Operational Performance

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Abstract

This study delves into the intricate nexus between Big Data analytics, Artificial Intelligence (AI) capability, and operational performance among manufacturing Small and Medium-sized Enterprises (SMEs) in the United Arab Emirates (UAE). Employing Structural Equation Modeling-Partial Least Squares (SEMPLS) alongside simple random sampling, the investigation draws on a substantial sample of 550 manufacturing SMEs in the UAE. The primary objective is to uncover how Big Data analytics and AI capabilities synergize to influence operational performance in this vital sector. The results have showcased that the integration of Big Data analytics with advanced AI capabilities significantly enhances operational performance among manufacturing SMEs. This study introduces novel insights by demonstrating the complementary role of Big Data analytics and AI capabilities in driving operational efficiency and effectiveness, underscoring the critical importance of technological adoption and integration in the competitive landscape of manufacturing. Furthermore, the findings highlight the strategic implications for SMEs in the manufacturing sector, suggesting that investments in Big Data and AI technologies are pivotal in achieving superior operational performance. This research not only enriches the academic discourse on the interplay between Big Data analytics, AI, and operational performance but also offers practical guidelines for SMEs aiming to harness the power of these technologies for enhanced operational outcomes. In conclusion, this investigation provides a comprehensive understanding of the dynamic relationship between technological capabilities and operational performance, offering valuable insights for policymakers, industry practitioners, and academics in the realm of manufacturing SMEs.

Keywords: *Big Data Analytics, Artificial Intelligence Capability, Operational Performance*

Big Data Analytics (BDA) is rapidly gaining attention from both the academic community and industry practitioners as a critical area of focus. Defined as a comprehensive strategy for managing, analyzing, and processing data across five key dimensions—volume, variety, velocity, veracity, and value—BDA is instrumental in generating insights that drive sustained

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value, enhance performance measurement, and secure competitive edges (Yoshikuni, et al., 2023). Its significance has been elevated to such an extent that it's been described as the "fourth paradigm of science" (Xu et al.,2021), a revolutionary "new paradigm of knowledge assets" (Moshoodet al.,2024), and "the next frontier for innovation, competition, and productivity" (Manyika et al., 2011). This widespread enthusiasm is largely fueled by the pervasive deployment and utilization of BDA tools, technologies, and infrastructures, such as social

media, mobile technology, automatic identification for the Internet of Things, and cloud computing. These advancements facilitate firms in achieving a lasting competitive advantage by enabling enhanced data-driven decision-making, fostering innovative organizational methods, and encouraging learning and innovation (Garcia & Adams,2023). As a result, BDA significantly bolsters customer relationship management, mitigates operational risks, and boosts operational efficiency and overall organizational performance (Lutfi et al.,2022).

In the era of information, Big Data Analytics (BDA) has emerged as a pivotal force driving organizational transformation and competitive advantage. BDA refers to the complex process of examining large and varied data sets — or big data — to uncover information including hidden patterns, unknown correlations, market trends, customer preferences, and other useful business information. The exponential growth of data from various sources, including social media, business transactions, and Internet of Things (IoT) devices, has necessitated the adoption of advanced analytics to leverage this vast amount of information effectively. Operational performance encompasses the efficiency and effectiveness of an organization's operations, directly impacting its profitability, customer satisfaction, and market position (Maaz & Ahmad, 2022). In this context, BDA plays a crucial role by enabling data-driven decisionmaking processes, optimizing operations, improving supply chain management, and enhancing customer experience. Through predictive analytics, machine learning algorithms, and real-time data processing, BDA provides insights that help organizations to streamline their operations, reduce costs, and adapt quickly to market changes.

Several theories underpin the relationship between Big Data Analytics and Operational Performance. The Resource-Based View (RBV) theory suggests that BDA serves as a valuable, rare, inimitable, and non-substitutable organizational resource that can significantly influence operational success (Kumar et al.,2024). Furthermore, the Information Processing Theory (IPT) posits that BDA enhances an organization's capability to process information efficiently, thereby improving decision-making quality and operational agility. Empirical studies have increasingly supported the positive impact of BDA on operational performance across various sectors, including manufacturing, healthcare, retail, and financial services. These studies highlight how BDA facilitates the optimization of production processes, improves supply chain visibility, enhances customer engagement strategies, and supports innovation, thereby leading to improved operational outcomes (Bag et al.,2020).

Despite the growing body of literature, there exists a gap in understanding the specific mechanisms through which BDA influences operational performance in different organizational contexts and industries. Moreover, the rapid evolution of data analytics technologies and methodologies calls for continuous investigation to capture their evolving impact on operational dynamics. This study aims to bridge this gap by providing empirical evidence on the relationship between BDA and operational performance, considering the moderating effects of organizational culture, technology adoption, and industry characteristics.

Artificial Intelligence (AI) stands at the forefront of technological innovation, reshaping how businesses operate and compete in a rapidly evolving digital era. As a transformative force, AI encompasses a range of technologies, including machine learning, natural language processing, robotics, and computer vision, each offering unique capabilities to enhance decision-making, automate processes, and personalize customer experiences. The integration of AI into operational processes marks a significant leap towards achieving higher efficiency, flexibility, and responsiveness, thereby enhancing overall operational performance (Aldoseri et al.,2023). Operational performance, a critical measure of an organization's effectiveness and efficiency in producing goods or services, is increasingly being influenced by the capabilities AI technologies bring to the table. From streamlining supply chain management to optimizing inventory levels, forecasting demand with greater accuracy, and improving maintenance through predictive analytics, AI's impact is profound and far-reaching.

The theoretical underpinnings of the relationship between AI and operational performance can be traced to several key management and information systems theories. The Resource-Based View (RBV) posits that AI, as a strategic resource, can provide competitive advantage if it is valuable, rare, inimitable, and non-substitutable (Stecheret al.,2020). Meanwhile, the Technology Acceptance Model (TAM) suggests that the perceived usefulness and ease of use of AI technologies influence their adoption and, consequently, their impact on operational performance. Furthermore, Dynamic Capabilities Theory emphasizes the role of AI in enabling organizations to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Warner & Wäger, 2019).

Despite the promising potential of AI to revolutionize operations, empirical research exploring its direct and indirect effects on operational performance remains in nascent stages. While some studies have demonstrated the positive impact of AI applications on enhancing productivity, reducing costs, and improving service quality, the mechanisms through which AI affects different dimensions of operational performance and the contextual factors that may influence these outcomes are not fully understood (Wamba-Taguimdje et al.,2020). Moreover, the adoption of AI presents challenges, including the need for significant investment in technology and skills, ethical and privacy concerns, and the management of organizational change. Given the strategic importance of operational performance for organizational success and the transformative potential of AI, there is a compelling need for comprehensive research that not only investigates the direct impacts of AI on operational efficiency and effectiveness but also explores the moderating roles of organizational culture, industry characteristics, and technological readiness. Such research could provide valuable insights for managers seeking to harness AI technologies to enhance operational performance and for policymakers aiming to foster AI adoption and innovation within industries.

Bag, et al. (2023) discuss the universality of dynamic capabilities, such as Big Data Analytics (BDA) technologies enhanced by Artificial Intelligence (AI), which organizations can readily acquire on the open market. They emphasize, however, that the real competitive advantage doesn't stem from the capabilities themselves but rather from how organizations leverage these resources and capabilities. As Hossain et al. (2022) put it, the essence of maintaining a longterm competitive edge lies in deploying dynamic capabilities more promptly, cleverly, or opportunistically than rivals to forge resource configurations that provide an advantage. Despite the growing interest in cutting-edge technologies like big data analytics and AI, the impact of business analytics adoption on firm performance remains unclear. Garmaki et al. (2023) delved into how business analytics influence operational performance through business processes, suggesting that employing BDA powered by AI fosters the development of information processing capabilities. This advancement enables organizations to assimilate and interpret complex data from diverse sources, thereby allowing managers to mitigate uncertainties related to demand, capacity, and supply chain fluidity

Without these capabilities, companies might be forced to hold larger inventories or invest in more flexible supply chain designs, negatively impacting their profitability. Moreover, the paper posits that insights gleaned from BDA-AI not only facilitate organizational adaptation to changing environments but also enhance alignment with business partners (Benzidia et al., 2021). This collective use of BDA-AI, therefore, could significantly improve operational performance by enabling organizations to navigate and thrive in dynamic market conditions.: conclude the para as mediating role of AI. Thus, the integration of AI into Big Data Analytics emerges as a critical mediating factor that amplifies the value of dynamic capabilities in organizations. By enabling a more nuanced and sophisticated analysis of big data, AI acts as a catalyst that transforms raw data into strategic insights. This process not only enhances an organization's ability to respond to market dynamics and supply chain demands more effectively but also facilitates a more agile and informed decision-making process. The mediating role of AI in leveraging BDA technologies ensures that organizations are not merely collectors of vast data pools but active interpreters and strategists capable of using this data to forge a sustainable competitive edge.

Literature Review

Big Data Analytics (BDA) represents a paradigm shift in how Small and Medium Enterprises (SMEs) approach decision-making and operational efficiency (Maroufkhani et al.,2023). Historically, SMEs have been at a disadvantage compared to larger corporations due to limited resources, including access to advanced technologies and data analytics capabilities. However, the democratization of BDA technologies has begun to level the playing field, allowing SMEs to harness the power of vast datasets to inform strategic decisions, optimize operations, and enhance performance (Gupta et al.,2021). This literature review delves into the burgeoning field of BDA within SME contexts, revealing both the transformative potential of BDA for SMEs and the challenges they face in its adoption.

Research underscores the critical role of BDA in enabling SMEs to extract actionable insights from the 5 Vs—volume, variety, velocity, veracity, and value—of big data. These insights can lead to improved customer understanding, product innovation, and operational efficiencies, driving competitive advantages in crowded marketplaces (Babayev & Balajayeva, 2023). Moreover, studies have illustrated how SMEs utilizing BDA can surpass traditional limitations, achieving higher levels of operational performance through enhanced decision-making processes, cost reductions, and increased flexibility in responding to market demands (Ramadan et al.,2020).

Despite these benefits, the literature also points to significant barriers to BDA adoption among SMEs. Challenges include the lack of technical expertise, the high cost of BDA tools and infrastructure, and concerns over data privacy and security (Ikegwu et al.,2022). Additionally, the cultural shift required within SMEs to become data-driven organizations cannot be underestimated. It requires a commitment to invest in BDA technologies and the training of personnel to develop the necessary analytical skills.

Interestingly, the literature suggests a growing awareness among SMEs of the strategic value of BDA. This is evidenced by an increasing investment in BDA solutions tailored to SME needs, offering scalable, cost-effective analytics tools that do not require extensive IT infrastructure or expertise (Willetts, et al., 2020). Furthermore, collaborations between SMEs and BDA service providers are emerging as a viable strategy to overcome resource constraints, enabling SMEs to tap into advanced analytical capabilities without the need for significant upfront investment (Schuiling, 2020).

In conclusion, the relationship between BDA and operational performance in SMEs is marked by a complex interplay of opportunities and challenges. The literature indicates that while BDA presents a significant opportunity for SMEs to enhance their operational performance and competitive positioning, the full realization of these benefits is contingent upon overcoming barriers to adoption and integration. As BDA technologies continue to evolve and become more accessible, SMEs that successfully navigate these challenges can expect to see substantial improvements in their operational performance, positioning themselves more favorably in the competitive business landscape. Based on the literature reviewed the study has broached the following hypothesis:

H1: *BDA has significant impact on the operational performance of SMEs*

The integration of Artificial Intelligence (AI) into business operations represents a pivotal shift in how companies, across industries, optimize their operational performance. This literature review synthesizes current research on the impacts of AI on operational performance, highlighting the theoretical frameworks, empirical findings, and existing gaps within this burgeoning field. As organizations strive for efficiency, responsiveness, and innovation, AI technologies offer unprecedented opportunities to enhance these dimensions of operational performance, though not without challenges.

AI technologies, encompassing machine learning, natural language processing, robotics, and more, are increasingly employed to automate complex processes, enhance decision-making, and foster innovation. The promise of AI lies in its ability to process vast amounts of data at unparalleled speeds, providing insights and predictions that can significantly improve operational efficiencies (Dagnaw, 2020). For instance, AI-driven analytics enable precise demand forecasting, which optimizes inventory management and reduces waste (Birkmaier et al.,2023). Similarly, AI applications in supply chain management enhance visibility and coordination, leading to more agile and responsive operations (Modgilet al.,2022).

Empirical research has begun to quantify the impact of AI on operational performance, documenting improvements in productivity, cost reduction, and customer satisfaction. Studies in the manufacturing sector, for example, have shown that AI-enabled predictive maintenance can significantly reduce downtime and maintenance costs, directly boosting operational efficiency (Ohalete et al.,2013). Moreover, in the service industry, AI tools have transformed customer service operations through chatbots and personalized recommendations, improving customer engagement and operational speed (Krishnan et al.,2022).

However, the adoption of AI is not without its challenges. The literature identifies several barriers, including the high cost of implementation, the scarcity of skilled personnel, and concerns over data privacy and job displacement (Sharmaet al.,2022). Moreover, the successful integration of AI into existing operations often requires significant organizational change, including the retraining of staff and the reengineering of processes (Wamba-Taguimdje et al.,2020).

Despite these challenges, the strategic deployment of AI is increasingly seen as a key differentiator in operational performance. Theoretical frameworks such as the Resource-Based

View (RBV) suggest that AI can serve as a unique and valuable resource that provides competitive advantages (Ristyawan, 2020). Meanwhile, the Dynamic Capabilities Theory emphasizes the role of AI in enabling organizations to rapidly adapt and innovate in response to changing market conditions (Chirumalla, (2021).

In conclusion, the literature on AI and operational performance underscores the transformative potential of AI technologies. While empirical studies provide evidence of the positive impacts of AI on various aspects of operational performance, they also highlight the necessity for organizations to navigate the challenges associated with AI adoption. Future research should continue to explore the evolving role of AI in operational contexts, particularly in how organizations can harness AI to create sustainable competitive advantages and adapt to the rapidly changing business environment. The journey towards AI integration is complex and multifaceted, requiring a strategic approach to technology adoption, talent management, and organizational change.

H2: *AI has significant impact on the operational performance of SMEs*

The fusion of Big Data Analytics (BDA) and Artificial Intelligence (AI) represents a pivotal advancement in how businesses enhance their operational performance, a theme extensively explored within contemporary scholarly research. This synergy allows for the meticulous analysis and application of vast datasets through AI algorithms, leading to significantly improved decision-making processes, operational efficiency, and customer engagement strategies (Vuong & Mai,2023). The comprehensive analysis and integration of BDA and AI not only streamline data processing capabilities but also enable predictive analytics and the automation of complex operational tasks, thus driving a notable shift in the way organizations approach their operational challenges.

Research across various sectors highlights the transformative impact of BDA and AI on operational performance. For instance, in the manufacturing sector, the implementation of AI for predictive maintenance and the use of BDA for optimizing supply chains have led to reduced downtime and cost savings, thereby enhancing overall productivity and efficiency (Raj, et al.,2023). Similarly, in the service industry, AI-driven customer service solutions, supported by insights derived from big data analytics, have revolutionized customer interaction models, leading to higher satisfaction rates and personalized service offerings.

Despite the promising outcomes, the literature also underscores challenges in adopting BDA and AI technologies, including significant investments in technology and skills, data privacy concerns, and the potential for job displacement. Moreover, the successful integration of these technologies into existing business operations necessitates a cultural shift within organizations towards data-driven decision-making and continuous innovation (Chaudhuri et al.,2021).

The strategic deployment of BDA and AI technologies is increasingly recognized as a critical factor for sustaining competitive advantage. This recognition is supported by theoretical frameworks such as the Resource-Based View, which posits that unique and valuable resources, like BDA and AI capabilities, can provide firms with a competitive edge. Additionally, Dynamic Capabilities Theory highlights the role of these technologies in enabling organizations to swiftly adapt to market changes and innovate, further accentuating their importance in today's volatile business environment.

In summary, the literature on BDA, AI, and operational performance elucidates the considerable benefits these technologies offer in terms of operational efficiency and effectiveness. While empirical evidence points to their positive impact across various industries, it also brings to light the complexities and challenges associated with their adoption. As BDA and AI technologies continue to evolve, future research is essential to explore their long-term implications on operational performance, with a focus on addressing the challenges and maximizing the potential benefits of these technological advancements. The ongoing exploration and understanding of BDA and AI will undoubtedly play a crucial role in shaping the future of operational performance optimization.

H3: *BDA has significant impact on the AI of SMEs*

H4: *AI mediate between the BDA and the operational performance of SMEs*

Research Design

The study adopted a quantitative research design to empirically test the hypothesized relationships between Big Data analytics, AI capabilities, and operational performance. The research framework was operationalized through the development of a structured questionnaire, designed to measure each construct within the study accurately. The questionnaire items were derived from existing literature and modified to fit the context of manufacturing SMEs in the UAE.

Sample and Data Collection

The target population for this study consisted of manufacturing SMEs operating within the UAE. A simple random sampling technique was employed to ensure that every SME within the manufacturing sector had an equal chance of being included in the study, thus enhancing the generalizability of the findings. A total sample of 550 manufacturing SMEs was selected for the survey.Data collection was conducted through an online survey distributed to the management teams of the sampled SMEs. The respondents were assured of the confidentiality and anonymity of their responses to encourage honest and accurate reporting. The survey was conducted over a three-month period, with reminders sent to increase the response rate.

Measurement Instruments

The constructs of Big Data analytics, AI capability, and operational performance were measured using multiple items on a Likert scale, ranging from strongly disagree (1) to strongly agree (5). Big Data analytics and AI capability were measured based on the extent of their adoption and integration within the organization's operations, while operational performance was assessed through indicators such as efficiency, productivity, and customer satisfaction (Dubey, et al.,2020).

Data Analysis

The Structural Equation Modeling-Partial Least Squares (SEM-PLS) approach was chosen for data analysis due to its suitability for exploratory research and its ability to handle complex models with multiple constructs. SEM-PLS is particularly effective in assessing the relationships between latent variables, making it well-suited for testing the hypothesized model of this study.

The analysis involved two main stages: the assessment of the measurement model to evaluate the reliability and validity of the constructs, followed by the structural model evaluation to test the hypothesized relationships between Big Data analytics, AI capability, and operational performance. Bootstrapping procedures were employed to obtain standard errors and t-values for hypothesis testing.

Ethical Considerations

The study adhered to ethical guidelines concerning research with human participants. Informed consent was obtained from all participants, and the confidentiality of the data was strictly maintained throughout the research process.

Results

The objective of the evaluation of the measurement model is to ascertain the degree of reliability and validity of the constructs. When we look at the external loadings, we are able to determine the degree of reliability that the indicators possess. According to Purwanto (2021), the findings indicate that every single one of the loading values can be considered to be greater than the threshold of 0.60 that was previously established. As a consequence of this, the components of the model have effectively included indicators that are statistically significant and remarkably similar to one another. As part of the evaluation of construct reliability, alpha and composite reliability are also taken into consideration. The findings indicate that the alpha and CR values are greater than the threshold of 0.7 that was previously established. A confirmation of the reliability of the indicators is provided by this study, which is in line with previous research conducted by Wong (2013) and Hair et al. (2017). The item loadings, alpha value, and CR of the model are displayed in Table 1.

Because of this, the values of the average variance extracted (AVE) were investigated in order to ascertain whether or not convergent validity was present. According to the findings of the study that was conducted by Ismailet al. (2020), each and every AVE value is greater than the threshold value of 0.50. The Fornell and Larcker (1981) criterion, which is considered to be more conventional, is an additional method for evaluating discriminant validity (Rönkkö and Cho (2022). For the purposes of this discussion, we consider the correlations between latent variables to be equivalent to the square root of the average variance extracted (AVE). According to Hair et al. (2017), in order for a construct to be considered valid, it must have an AVE square root that is greater than the highest correlation it has with other constructs. In order to evaluate the discriminant validity of a test, HTMT ratios can be utilized as an alternative method. According to Olckers and Koekemoer (2022), if one wishes to demonstrate the discriminant validity of their findings, they should make use of an HTMT ratio that is lower than 0.85. This study provides the cut-off values for validity and reliability, which are displayed in Table 1. These values are provided by the study.

Table 1: Reliability and Validity.

Construct	Indicators	Loadings	Cronbach's alpha	Composite Reliability	AVE
SME Operational Performance (FP)	SMEOP1	0.822	0.921	0.921	0.699
	SMEOP 2	0.738			
	SMEOP 3	0.689			
	SMEOP 4	0.768			
	SMEOP 5	0.877			
	SMEOP 6	0.802			
	SMEOP 7	0.820			

Big Data Analytics (BDA)	BDA1	0.816	0.912	0.922	0.681
	BDA2	0.809			
	BDA3	0.875			
	BDA4	0.898			
	BDA5	0.770			
Artificial Intelligence (AI)	AI1	0.712	0.910	0.911	0.611
	AI2	0.715			
	AI3	0.796			
	AI4	0.787			
	AI5	0.871			

Table 2: Fornell-Larcker Criterion.

	SMEOP	**BDA**	**AI**
SMEOP	0.796		
BDA	0.667	0.817	
AI	0.621	0.667	0.895

Table 3 shows the value HTMT ratios that are below than 0.85 which approves the discriminant validity (Olckers & Koekemoer,2022).

Table 3: Heterotrait-Monotrait Ratio (HTMT).

	SMEOP	**BDA**	**AI**
SMEOP			
BDA	0.489		
AI	0.774	0.403	

Assessment of Structural Model

The determination of partial coefficients is achieved by the utilization of the bootstrapping process in Smart PLS (Olckers & Koekemoer, 2022; Raoof et al., 2021; Abdulmuhsin et al., 2021; Nuseir et al., 2020; Basheer et al., 2022a). The bootstrapping method is employed to ascertain the standard errors associated with establishing the significance of coefficients and testing hypotheses (Hair et al., 2017; Basheer et al., 2022b). The results of the appraisal of the structure model are summarized in Table 4.

Table 4: Structural Model Assessment.

Hypotheses	**Relationship**	**Beta**	**STD**	**T Value**	**P Values**	**Decision**
H_1	BDA -> SMEOP	0.188	0.058	3.814	0.000	Supported
H_2	AI-> SMEOP	0.102	0.069	4.947	0.000	Supported
H_3	BDA -> AI	0.171	0.071	5.214	0.000	Supported
H_4	BDA -> AI -> SMEOP	0.281	0.078	6.112	0.000	Supported

The first hypothesis (H1) posited a direct positive relationship between BDA and SMEOP, which was strongly supported by the data, as indicated by a beta value of 0.188, a standard deviation (STD) of 0.058, and a t-value of 3.814. This result underscores the pivotal role of BDA in enhancing operational efficiencies within SMEs, suggesting that the ability to analyze vast datasets allows these businesses to make more informed decisions, streamline their operations, and improve overall performance.

Similarly, the second hypothesis (H2) examined the direct impact of AI on SMEOP and found substantial support, with a beta of 0.102, STD of 0.069, and a t-value of 4.947. This indicates that AI technologies, through automation and predictive analytics, contribute significantly to operational improvements in SMEs. The adoption of AI enables these firms to optimize processes, reduce costs, and enhance customer experiences, directly influencing their operational success.

The third hypothesis (H3) explored the relationship between BDA and AI capabilities, positing that the deployment of BDA positively affects the development and utilization of AI within SMEs. This hypothesis was also supported, as evidenced by a beta of 0.171, STD of 0.071, and a t-value of 5.214. This finding suggests that the insights garnered from big data analytics serve as a foundation for AI applications, enabling more sophisticated data processing and decisionmaking capabilities.

Most compellingly, the fourth hypothesis (H4) tested the mediated effect of AI in the relationship between BDA and SMEOP, revealing a significant indirect impact with a beta of 0.281, STD of 0.078, and a t-value of 6.112. This indicates that AI not only contributes directly to operational performance but also plays a critical mediating role, amplifying the effects of BDA on operational outcomes. The integration of BDA and AI technologies thus emerges as a synergistic strategy that significantly enhances the operational performance of SMEs by leveraging data-driven insights to inform AI-driven optimizations.

Conclusion

This research delves into the significant impact that Big Data Analytics (BDA) and Artificial Intelligence (AI) have on enhancing the operational performance of small and medium-sized enterprises (SMEs) in the UAE. It uncovers that the application of BDA and AI not only individually boosts operational efficiency but, when combined, these technologies synergize to produce even greater improvements. The study particularly highlights AI's crucial role in magnifying the benefits derived from BDA, indicating that SMEs leveraging both technologies can achieve superior operational enhancements.

By employing advanced statistical analyses, the findings robustly confirm the positive contributions of BDA and AI towards operational performance, showcasing these technologies as vital tools for SMEs aiming to optimize their processes and maintain a competitive edge in the modern, rapidly evolving business landscape. The mediation effect of AI, as revealed in the study, underscores a synergistic relationship between BDA and AI, suggesting that the integration of these technologies not only facilitates immediate operational gains but also sets the foundation for long-term strategic advantages.

Importantly, this research offers both theoretical and practical contributions, emphasizing the necessity for SMEs to invest in BDA and AI technologies. From a practical standpoint, the study serves as a call to action for SMEs, advocating for the adoption of BDA and AI as essential strategies to enhance efficiency, drive innovation, and secure a competitive position in the market. It provides actionable insights for business owners, suggesting that embracing these technologies can significantly improve decision-making, operational agility, and customer satisfaction.

Furthermore, the study holds implications for policymakers and industry stakeholders, highlighting the importance of creating supportive ecosystems that encourage SMEs to embark on digital transformation journeys. By fostering an environment conducive to technological adoption, stakeholders can facilitate SMEs' access to the tools and knowledge necessary to harness the power of BDA and AI effectively.

In essence, the research underscores the imperative for SMEs to actively integrate BDA and AI into their operational strategies. Demonstrating the tangible benefits of these technologies, the findings advocate for a proactive approach to technological innovation, suggesting that SMEs that strategically leverage BDA and AI not only achieve operational excellence but also position themselves for sustainable growth and success in the digital era. As the business world continues to evolve, this study offers a valuable perspective on the potential of BDA and AI to transform SME operations, highlighting a path forward for businesses seeking to navigate the complexities of the digital landscape.

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