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Causal Influences of Big Data Analytics Adoption for Small and Medium-Sized Enterprises in the Eastern Economic Corridor (EEC) of Thailand

Pattarapon Chummee
Doctor of Business Administration Program, College of Innovation Management, Valaya Alongkorn Rajabhat University under Royal Patronage, Thailand
E-mail: pattarapon@vru.ac.th, ORCID ID: https://orcid.org/0000-0002-3962-9047

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Abstract

Background and Aim: The author provides a foundational understanding of Big Data, describing its characteristics and the inadequacy of traditional management methods. This serves as a general introduction to the topic. However, this section could more explicitly articulate the specific research problem or gap concerning Big Data Analytics (BDA) adoption within Small and Medium-Sized Enterprises (SMEs) in the Eastern Economic Corridor (EEC). While the importance of BDA for strategic decision-making and competitive advantage is mentioned, a more direct linkage to the challenges or unique circumstances of SMEs in this particular region would strengthen the problem statement. The research aims to investigate BDA adoption among SMEs in the EEC, as clearly stated. This section effectively introduces the theoretical underpinnings by referencing the Technology-Organization-Environment (TOE) framework and the Technology Acceptance Model (TAM). The author correctly identifies key components of these frameworks—technological attributes, organizational conditions, external environmental factors from TOE, and perceived usefulness and perceived ease of use from TAM. To further enhance this, a concise justification for selecting these specific frameworks, perhaps highlighting their relevance to understanding technology adoption in an SME context or their complementary nature, would add depth. The objectives are well-defined, aiming to identify critical influencing components and analyze relationships among variables, which guide the study.

Material and Methods: The author clearly outlines the methodological approach. The sample group of 340 SME entrepreneurs in the EEC, selected via purposive sampling, is appropriately described. This section precisely details the primary data collection instrument as a questionnaire, structured into six sections, differentiating between open-ended and closed-ended Likert scale questions. The inclusion of specific validation metrics - a content validity index (IOC) of 0.874 and an overall reliability (Cronbach's alpha) of 0.936 - is commendable. These values indicate a robust instrument, which is essential for the credibility of quantitative research findings. This level of detail in the abstract is suitable, providing confidence in the data collection process.

Results: The author presents key findings from the statistical analyses with precision. The result from Confirmatory Factor Analysis (CFA) highlights organizational leadership capability as the most influential observed variable, with a beta coefficient of 0.915. This emphasizes its importance in fostering technology acceptance and implementation, especially for SMEs facing competitive pressures and rapid technological changes in the EEC. Furthermore, the Structural Equation Modeling (SEM) analysis is reported to show a strong and statistically significant relationship between technological factors and perceived usefulness ($\beta = 0.653$, $p < 0.01$). The inclusion of specific fit indices (Chi-square = 686, df = 350, p-value = 0.001, and RMSEA = 0.032) confirms a good model fit. These findings provide concrete evidence of the variables influencing BDA adoption, aligning well with the study's objectives.

Conclusions: The analysis concludes that a supportive organizational system significantly influences employees' confidence and perceived ease of use with information technology. This directly connects to the findings regarding organizational leadership and perceived ease of use. The author emphasizes that when organizational structures align with technological goals, employees are more likely to integrate technology into their work. Based on these insights, the author provides actionable recommendations for SMEs in the EEC. These include prioritizing leadership development through continuous training and knowledge enhancement, enabling leaders to drive technology adoption. Additionally, the author suggests improving internal systems for flexibility and responsiveness to technological changes, fostering an innovation-friendly culture, and providing staff training in BDA. This section effectively summarizes the study's implications, highlighting how these efforts can lead to sustainable growth, market competitiveness, and effective adaptation in the digital era. However, the terms "Organization" and "Technology" are very broad. To enhance specificity and improve the discoverability of this research, it is recommended to use more precise terms. For instance, "Organizational Factors," "Organizational Readiness," or "Organizational Culture" would better capture the nuanced aspects of the organization's role in BDA adoption as discussed in the abstract, particularly the emphasis on leadership and internal systems. Similarly, "Technological Factors," "Technological Readiness," or "Technology Adoption" would be more specific than simply "Technology," aligning more closely with the study's focus on adoption. Including "Small and Medium-

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Sized Enterprises" (SMEs) and "Eastern Economic Corridor (EEC)" as keywords would also be beneficial, as these are critical contextual elements of the research, ensuring the study is easily found by those interested in this specific sector and geographic region.

Keywords: Big Data Analytics; Organization; Technology; Perceived Usefulness; Perceived Ease of Use

Introduction

The author introduces big data by defining it as the collection and processing of large, expanding volumes of information from various sources. This section clearly states that traditional management methods are inadequate, necessitating specialized technologies for analysis and decision-making. To improve this, the author could further elaborate on why conventional methods fail and provide a more explicit link between the characteristics of big data (volume, velocity, variety, veracity) and the limitations of traditional approaches. This would strengthen the foundational argument for the necessity of big data analytics. (Department of Local Administration, 2016, and Georgia Tech, 2023). This section effectively introduces the Technology-Organization-Environment (TOE) framework and the Technology Acceptance Model (TAM), highlighting their relevance to technology adoption. The author connects TOE factors like technology complexity and organizational culture, along with TAM's perceived usefulness and ease of use, to the adoption of big data analytics. The importance of senior executive support is also well-articulated, showing how it reduces uncertainty and fosters innovation. To enhance this part, the author could briefly explain how these two frameworks, though distinct, complement each other in understanding technology adoption, especially in the context of big data. This would provide a more integrated theoretical lens. (Nguyen et al., 2022; Asiri et al., 2024; and Aldraiweesh & Alturki, 2025). The support and collaboration of senior executives are particularly important, as they help reduce uncertainty during the adoption process and foster technological and innovative capacity within the organization (Asiri et al., 2024). When employees perceive the benefits of a new technology, their behavior and attitudes toward its use are likely to improve, thereby increasing overall work efficiency (Chomphuthip, 2017).

The author then transitions to the economic importance of big data, presenting global figures from the United States and then narrowing the focus to Thailand. The discussion of the skill gap and the reliance on internal data sources by Thai companies identifies crucial issues. Additionally, the mention of potential job displacement and concerns over data bias and integrity adds a critical dimension to the discussion. This section could be strengthened by explicitly framing these challenges as a gap in current practice or understanding, which the proposed research aims to address. For instance, the author could emphasize how the limited use of real-time external data in Thailand presents an opportunity for SMEs. (Kennedy Research, 2023; EIC, 2017; and NIDA, 2022).

This section effectively highlights the significant role of Small and Medium-sized Enterprises (SMEs) in Thailand's economy, especially their substantial contribution to GDP and employment. The author links the government's Thailand 4.0 initiative and its goals for SME sector growth to the importance of big data. The specific benefits of big data for SMEs, such as customer behavior analysis and cost reduction, are clearly outlined. To make this stronger, the author could briefly connect these general benefits to specific challenges or opportunities that Thai SMEs face, setting up the context for the regional focus. (SME Thailand Hub, 2019, and Coraline, 2023).

The author justifiably narrows the study's geographical focus to the Eastern Economic Corridor (EEC), providing statistics on its economic significance and SME presence. This section clearly states that the EEC's competitive and dynamic business environment makes it a suitable area for studying big data adoption. This justification is well-placed and effectively sets the regional scope. The author could consider adding a sentence that subtly hints at a specific, unique aspect of the EEC that makes it particularly pertinent to the study, beyond general economic activity. (Office of Small and Medium Enterprises Promotion, 2024)

This section elaborates on the critical role of big data analytics integration for improving operational efficiency and competitive capabilities within EEC SMEs. The author highlights the benefits, such as data-driven decision-making, market trend anticipation, and fostering innovation. This reinforces the practical implications of big data adoption. This section effectively builds on the preceding arguments, demonstrating the tangible advantages that big data offers to businesses in the specified region. (Chen et al., 2022 and Wang et al., 2021)

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Finally, the author states the research aim, which is to examine factors influencing big data adoption by SMEs in the EEC and to develop strategic data frameworks aligned with national policy. The study's support for the Office of Small and Medium Enterprises Promotion is articulated, emphasizing data integration and knowledge creation for enhancing SME capabilities. This section also highlights the broader contribution to sustainable development. The aim is clear, and the contributions, both practical and societal, are well-defined. The author could consider explicitly stating whether the study intends to address a theoretical gap identified in the earlier discussion of TOE and TAM, beyond its practical contributions. This would further solidify its academic significance.

Research Objectives

1. To examine the components of big data analytics adoption for small and medium-sized enterprises (SMEs) in the Eastern Economic Corridor (EEC)
2. To analyze the relationships between variables related to big data analytics adoption for small and medium-sized enterprises (SMEs) in the Eastern Economic Corridor (EEC)

Literature review

This study was developed based on the works of Asiri et al. (2024), Aziz et al. (2023), Narollahi et al. (2021), Song et al. (2022), Hooi et al. (2018), Lutfi et al. (2022), Ali et al. (2020), and Wook et al. (2021). The author begins by outlining the foundational works and key latent variables guiding the study, including technological factors, organizational factors, perceived usefulness, perceived ease of use, and the adoption of big data analytics. This section provides a good initial overview of the study's scope. However, a more explicit discussion of the overarching theoretical framework (e.g., the Technology-Organization-Environment (TOE) framework, the Technology Acceptance Model (TAM), or the Diffusion of Innovations (DOI) theory) would significantly enhance the academic grounding. The author should elaborate on why these specific theories are relevant to understanding BDA adoption and how they inform the selection of the chosen variables. This would move beyond merely listing previous works to establishing a clear theoretical lens for the research.

The latent variable related to technology, as identified in the study by Maroufkhani et al. (2023), is discussed in this section, which discusses technological factors, emphasizing management's critical role in new technology adoption. The importance of senior management support, compatibility with operational practices, and access to IT infrastructure resources are highlighted as interrelated factors. To further strengthen this part, the author could explicitly link these elements to established theoretical constructs within the TOE framework, such as technological context and organizational support. Providing a clearer theoretical definition of "compatibility" regarding BDA adoption would also be beneficial. The author could explain how these technological factors are conceptualized within the chosen theoretical lens and how they are expected to causally influence BDA adoption.

The author introduces the context of BDA adoption in the manufacturing sector within the EEC, citing examples like IoT sensors and AI for predictive maintenance. While this contextualization is valuable, its placement directly after the general discussion of "technological factors" could be smoother. The author should ensure a seamless transition or consider integrating this detailed contextual information into a broader introductory section about BDA in the EEC if it does not directly explain a specific latent variable. The focus should remain on how these applications inform or reflect the adoption process, rather than just general usage. (Ministry of Digital Economy and Society, 2023)

The latent variable related to organizational factors, as discussed in the study by Chen et al. (2021), this section then addresses organizational factors, encompassing readiness in personnel, processes, systems, culture, and performance measurement. The author notes that these elements must be effectively integrated for widespread BDA use. To improve this, the author should explicitly connect these elements to the "organizational context" dimension of the TOE framework or other relevant organizational theories. Elaborating on the challenges or facilitators of integrating these diverse organizational elements, drawing from existing literature, would provide deeper insight. The discussion on achieving "greater returns on investment" could also be tied to theoretical perspectives such as the resource-based view, further strengthening the argument.

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According to the studies by Rungnapa Lertphattharapong et al. (2023) and Manager Online (2023), the author shifts to discuss BDA's broader role in the economic and social development of the EEC, referencing its contribution to research and innovation personnel and human resource development. Similar to the manufacturing context paragraph, this provides valuable background but might best fit within a general introduction to BDA's significance in the EEC, rather than as a direct explanation of "organizational factors" as a latent variable. The author should ensure that all sections of the literature review maintain a clear focus on the causal influences on BDA adoption by SMEs, aligning with the study's stated objective.

The latent variable concerning perceived usefulness is identified as a key determinant of individuals' attitudes toward technology adoption, drawing on Demirkol et al. (2025) and Phuong et al. (2025). This section correctly identifies perceived usefulness as a crucial factor. The author should explicitly state that this variable, along with perceived ease of use, is primarily derived from the Technology Acceptance Model (TAM). A brief explanation of TAM's relevance and its core tenets, especially the causal link between perceived ease of use and perceived usefulness, would significantly enhance the theoretical foundation of this part. The author should clearly articulate how perceived usefulness is expected to causally influence BDA adoption among SMEs.

Furthermore, Phakamach (2024) highlights the strategic importance of data-driven decision-making for SMEs in the EEC, linking it to the perceived benefits of accurate and timely data. This paragraph effectively contextualizes perceived usefulness within the SME environment. The author could further elaborate on how this perceived usefulness uniquely motivates SMEs, perhaps by discussing the specific challenges or competitive pressures that drive SMEs to seek such advantages. This would provide a more nuanced understanding of the causal link for this particular enterprise segment.

The latent variable concerning perceived ease of use is defined as the degree to which using a technology is believed to be effortless and convenient, referencing Luo et al. (2024) and Prastiawan et al. (2021). As with perceived usefulness, the author should firmly anchor this discussion within the TAM framework. Emphasizing how the perception of effortlessness facilitates smoother workflows and reduces user burden, and then explicitly linking these practical aspects back to their theoretical implications for adoption, would strengthen the argument. The author could also discuss the importance of initial ease of use for overcoming adoption barriers.

Moreover, Mekwilai and Aunyawong (2023) investigated factors influencing BDA adoption among SMEs in the EEC, focusing on technological readiness and support. This section effectively connects perceived ease of use to practical considerations such as technological readiness and support systems in the SME context. The author could further discuss how these support systems act as facilitating conditions that reduce the perceived complexity of BDA tools, thereby promoting easier adoption. This shows a strong understanding of practical influences on perceived ease of use.

The latent variable concerning the application of big data analytics is regarded as a vital business capability. This section describes its enhancement through deliberate development and resource integration, citing Lutifi et al. (2022). The author must clarify if "application" is synonymous with "adoption" or if it represents a subsequent stage of implementation. If "application" is the dependent variable, the author needs to establish why the previously discussed latent variables (technological, organizational, perceived usefulness, perceived ease of use) are theorized to cause or significantly influence this capability or its widespread use within the organization.

Finally, the author discusses the characteristics of big data—volume, variety, and velocity (the 3Vs)—and their implications for operational challenges, referencing Cadden et al. (2023). While the 3Vs are fundamental to understanding big data, the author needs to explicitly explain how these characteristics specifically pose challenges for SMEs in adopting BDA, rather than just being general attributes. This paragraph currently feels somewhat detached from the core discussion of causal influences on adoption. It might be more effectively integrated as a discussion of potential barriers or complexities within a broader introduction to BDA challenges for SMEs, or framed as a moderating factor if applicable to the study's model.

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Conceptual Framework

This section introduces the influence paths between variables and formulates hypotheses. The author successfully links technological factors to perceived usefulness and perceived ease of use, drawing on relevant studies and the Technology Acceptance Model (TAM). This demonstrates a solid understanding of how technology adoption is often conceptualized in the literature. To further enhance this part, the author could elaborate on the specific mechanisms through which technological understanding, including big data applications, impacts perceived ease of use. A deeper dive into how these elements interact would provide a more nuanced theoretical argument.

The author discusses the relationship between organizational factors and perceived usefulness and perceived ease of use. The insights into management support and leadership capability are valuable for explaining how organizational context influences technology adoption. The author’s reference to how organizations effectively and securely apply internal data is a relevant point. This section could be improved by discussing alternative theoretical lenses, such as the Resource-Based View or Institutional Theory, to broaden the theoretical scope. Exploring how these theories might complement the existing arguments would enrich the framework’s academic depth.

The author addresses the influence of perceived usefulness and perceived ease of use on the adoption of big data analytics. The emphasis on user acceptance and efficiency in the application is well-placed. The author correctly identifies that the simplicity of using various technologies fosters user acceptance and enhances organizational capabilities. To strengthen this final part of the conceptual framework, the author could consider including moderating or mediating variables that might influence these relationships. For instance, factors like organizational culture, industry type, or government policies in the Eastern Economic Corridor (EEC) could play a significant role and would add further complexity and robustness to the model.

The latent variable related to technology consists of three observed variables: relative advantage, complexity, and big data security. These are based on the studies of Asiri et al. (2024), Al-shanableh et al. (2024), and Lv and Li (2021). The latent variable related to the organization consists of observed variables such as management support and leadership capability. The latent variable concerning perceived usefulness includes observed variables such as the speed of big data analysis, the resulting perception of benefits, increased work productivity, the ability to understand consumer needs, and the capability to conduct business data analysis. The latent variable related to perceived ease of use comprises observed variables, including the ease of learning big data analytics, the flexibility of big data analysis tools, the simplicity of understanding big data analytics, the adaptability of the system, and the ease of developing related skills. The latent variable related to the application of big data analytics consists of observed variables, such as the organization having already introduced the application of big data and the intention to promote the use of big data analytics within units for practical implementation. This framework is developed based on the studies of Bin-Nashwan et al. (2025), Cao et al. (2025), Al-shanableh et al. (2024), Mujalli et al. (2024), Muazu et al. (2024), Asiri et al. (2024), Aziz et al. (2023), Peng and Yan (2022), Narollahi et al. (2021), Song et al. (2022), Hooi et al. (2018), and Lutfi et al. (2022). (Figure 1)

The Influence Path between Variables of the relationship between technology and perceived usefulness is significant. According to Sheppard and Vibert (2019), there is a direct connection between these two factors. Similarly, Peng and Yan (2022) found a positive link between technology and how useful people perceive it to be, which supports the research hypothesis. This aligns with the Technology Acceptance Model (TAM), which suggests that technology not only predicts how people will use it but also improves their experience, encouraging greater use and acceptance. This can be formulated as the following hypothesis:

(1) Technological factors are positively related to perceived usefulness among small and medium-sized enterprises (SMEs) in the Eastern Economic Corridor (EEC)

The influence path between technology and perceived ease of use has been supported by several studies. Asiri et al. (2024) and Peng and Yan (2022) found that technological understanding, including the application of big data, has a direct impact on perceived ease of use. In this context, technology plays a vital role not only in marketing but also in understanding consumer behavior toward technology adoption, ultimately affecting how easy users perceive it to be.

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This finding is further supported by Hussain et al. (2025), who also observed a significant relationship between these variables. Moreover, it aligns with the Technology Acceptance Model (TAM), which explains how perceptions of ease of use can influence users' attitudes toward technology, contributing to greater user satisfaction and overall system quality, key factors in successful technology implementation. This can be formulated as the following hypothesis:

(2) Technological factors are positively related to perceived ease of use among small and medium-sized enterprises (SMEs) in the Eastern Economic Corridor (EEC)

According to the study by Al-shanableh et al. (2024), organizational factors, including management support and leadership capability, are positively associated with perceived usefulness. This is because organizations that effectively and securely apply internal data tend to achieve better data protection and are more capable of utilizing technology to its full potential. Similarly, Asiri et al. (2024) found a statistically significant positive relationship between organizational factors and perceived usefulness. Their findings suggest that the adoption of big data analytics enables SME entrepreneurs to develop knowledge and insights. Furthermore, the capabilities and attitudes of leaders play a crucial role in strategic decision-making and in maximizing the benefits of big data analytics, leading organizations to recognize the importance of adopting such technologies. This can be formulated as the following hypothesis:

(3) Organizational factors are positively related to perceived usefulness among small and medium-sized enterprises (SMEs) in the Eastern Economic Corridor (EEC)

Nasongkhla and Shieh (2023) found that organizational factors are positively associated with perceived ease of use, thereby supporting the research hypothesis. The study highlights that the integration of technology and social media within organizational settings contributes to ease of use, enhances the working environment, and facilitates the adoption of technology across all areas of operation. Additionally, it promotes continuous learning across all age groups. Support from colleagues further contributes to making technology easier to use, reinforcing the organization's capacity to adopt and utilize new systems effectively. This can be formulated as the following hypothesis:

(4) Organizational factors are positively related to perceived ease of use among small and medium-sized enterprises (SMEs) in the Eastern Economic Corridor (EEC)

According to Al-shanableh et al. (2024), perceived usefulness has a significant influence on the level of technology acceptance, which in turn affects the capability to use technology effectively. The perceived variety and benefits of technology contribute directly to the adoption of big data analytics, as users tend to experience greater ease and efficiency in application, particularly when engaging with advanced technologies. Similarly, Asiri et al. (2024) found a positive relationship between perceived usefulness and the adoption of big data analytics, noting that such technologies enable SMEs to apply knowledge more effectively in developing their businesses. In today's rapidly evolving business environment, the increasing complexity and pace of change have heightened the value and impact of big data analytics, making them essential for enhancing organizational efficiency and competitive advantage. This can be formulated as the following hypothesis:

(5) Perceived usefulness is positively related to the adoption of big data analytics among small and medium-sized enterprises (SMEs) in the Eastern Economic Corridor (EEC)

According to the studies by Shabaz et al. (2019) and Hayek et al. (2024), perceived ease of use significantly influences the adoption of big data analytics. The simplicity of using various technologies fosters user acceptance, which enhances the effectiveness of the system for individual users and positively impacts organizational capabilities. This leads to increased organizational profitability, reduced operational costs, better risk management, and more efficient decision-making processes. Consequently, the adoption of big data analytics depends largely on the ease of use experienced through the synthesis of big data. It is important to note that perceptions of ease of use may vary among individuals. Furthermore, these studies also found that the relationship between perceived ease of use and system users extends internationally, as successful adoption of big data analytics requires systems to be both easy and convenient to use. This can be formulated as the following hypothesis:

(6) Perceived ease of use is positively related to the adoption of big data analytics among small and medium-sized enterprises (SMEs) in the Eastern Economic Corridor (EEC)

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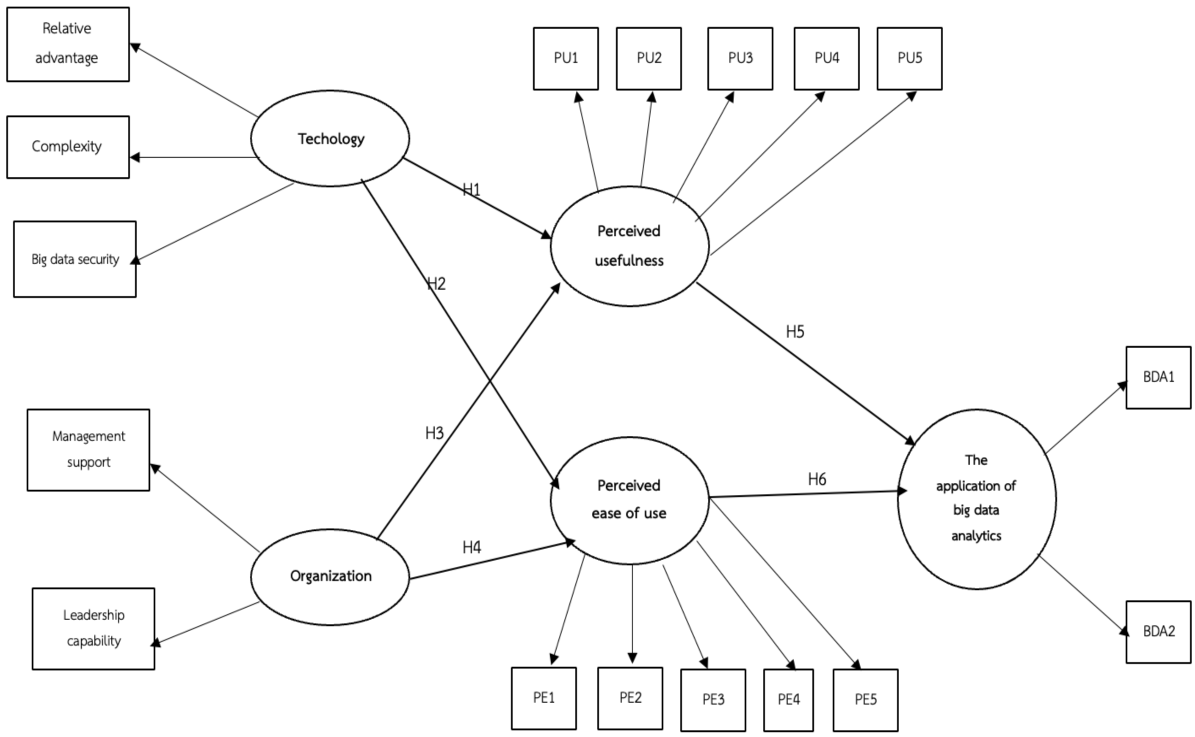

Figure 1 Conceptual framework

Methodology

This research is categorized as applied research, focusing on discovering answers by seeking factual information or exploring relationships between data or variables. The primary aim is to utilize the findings and insights obtained from the study to generate meaningful and practical benefits. As such, a cross-sectional research design was employed, which is appropriate for collecting data from businesses where access and data collection are limited to a single occasion.

Population and sample size

Regarding the population and sample size, the author clearly defines the target population as entrepreneurs from small and medium-sized enterprises (SMEs) in the Eastern Economic Corridor (EEC). This clarity is a strength. The sample size determination, based on Hair et al.'s (1998) guideline of 5 to 20 times the number of observed variables, resulted in 340 participants for 17 observed variables. While this rule of thumb provides a practical estimate, for structural equation modeling (SEM), it is often beneficial to also consider alternative methods, such as power analysis, to ensure the sample size is sufficient for detecting expected effects given the model complexity. The author states that data collection involved one respondent per business. This approach, while efficient, introduces the potential for common method bias, as a single individual provides data for both predictor and outcome variables. In future work, the author could consider strategies to mitigate this, such as collecting objective firm-level data where possible, employing different data sources, or utilizing statistical remedies like marker variable techniques. The purposive sampling method ensures that respondents possess relevant knowledge, which is critical for obtaining insightful data. However, the author might also briefly discuss the implications of purposive sampling on the generalizability of the findings to the broader SME population within the EEC.

Research Instrument

The research instrument consisted of a questionnaire with six sections. The inclusion of open-ended questions in Section 1 is a positive aspect, as it allows for richer, qualitative insights from the respondents' experiences. The author should clarify how these open-ended responses will be analyzed, such as through thematic analysis or content analysis, to ensure their findings are systematically integrated into the study. Sections 2 through 6 utilized a five-point Likert scale, which is a standard and

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appropriate measurement for perceptual variables. The questionnaire items were developed based on an extensive review of prior research, which enhances the theoretical grounding and validity of the constructs being measured. The list of recent scholarly works cited demonstrates a contemporary understanding of relevant literature. The questionnaire items were developed based on an extensive review of prior research, drawing on studies conducted by Bin-Nashwan et al. (2025), Cao et al. (2025), Al-Shanableh et al. (2024), Mujalli et al. (2024), Muazu et al. (2024), and Asiri et al. (2024), etc.

Instrument Quality Assessment

For instrument quality assessment, the author performed content validity by having five experts evaluate the questionnaire, yielding an index of item-objective congruence (IOC) of 0.874. The detailed IOC scores for each dimension provide good evidence of content coverage and clarity. The reliability of the instrument was assessed using Cronbach's alpha coefficient, which resulted in a high value of 0.936, indicating strong internal consistency. This demonstrates the instrument's reliability. However, this section would benefit from a discussion of construct validity, specifically convergent and discriminant validity, which are essential for research employing structural equation modeling. The author should elaborate on how these forms of validity were assessed (e.g., through average variance extracted (AVE) and composite reliability (CR) for convergent validity, and the Fornell-Larcker criterion or heterotrait-monotrait ratio (HTMT) for discriminant validity) to ensure that the latent constructs are measured accurately and distinctly.

Statistical Methods for Data Analysis

Finally, the statistical methods for data analysis involved confirmatory factor analysis (CFA) and structural equation modeling (SEM). The author correctly identifies CFA as crucial for confirming the factor structure and bridging the gap between theoretical constructs and observable data. The explanation of SEM as a robust framework for testing complex relationships among constructs is also appropriate. A key omission in this section is the specific mention of model fit indices that will be used to evaluate the CFA and SEM models. To rigorously assess how well the proposed model fits the empirical data, the author should specify which fit indices will be reported and interpreted. Common model fit indices include the chi-square to degrees of freedom ratio ($\chi2$/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Explicitly stating these measures will enhance the transparency and academic rigor of the methodology section, ensuring the audience understands the criteria for model evaluation. (Brown, 2015; Hancock and Mueller, 2001; and Schumacker & Lomax, 2016)

Research Result

The author presents the CFA results in Table 1 effectively, providing a foundational understanding of the measurement model. This section correctly identifies the acceptable to high reliability values (Cronbach's Alpha and Composite Reliability) and the adequate convergent validity (AVE values). These indicators are essential for establishing the robustness of the constructs. However, a more detailed interpretation of the factor loadings, beyond just highlighting the highest ones, would benefit this section. All latent variables demonstrated acceptable to high reliability, with Cronbach's Alpha values exceeding 0.66 and Composite Reliability values above 0.65, indicating good internal consistency. The AVE values, mostly above 0.70, confirm adequate convergent validity, showing that the observed variables effectively represent their underlying constructs.

Table 1 Confirmatory factor analysis

Latent Variables	CR	AVE	Cronbach's Alpha	Observed Variables	Model Fit Indices
1 Technology	0.761	0.658	0.866	Relative Advantage (0.359), Complexity (0.392), Big Data Security (0.646)	χ^2/df = 0, GFI = 1.000, AGFI = 1.000,

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	Latent Variables	CR	AVE	Cronbach's Alpha	Observed Variables	Model Fit Indices
						RMSEA = 0.000
2	Organizational Factors	0.847	0.737	0.848	Top Management Support (0.841), Leadership Capability (0.915)	χ^2/df = 0, GFI = 1.000, AGFI = 0.999, RMSEA = 0.030
3	Perceived Usefulness (PU)	0.915	0.740	0.940	PU1: Ease of Big Data Analytics (0.838), PU2: Business Capability Enhancement (0.589), PU3: Efficiency Improvement (0.995), PU4: Understanding Consumer Needs (0.853), PU5: Process Monitoring Support (0.232)	χ^2/df = 2.03, GFI = 1.000, AGFI = 1.000, RMSEA = 0.050
4	Perceived Ease of Use (PEOU)	0.744	0.776	0.662	PE1: Ease of Big Data Analytics (0.546), PE2: System Convenience (0.767), PE3: Ease of Understanding (0.863), PE4: Flexibility (0.567), PE5: Ease of Skill Development (0.464)	χ^2/df = 0, GFI = 1.000, AGFI = 1.000, RMSEA = 0.000
5	Big Data Analytics Application	0.735	0.762	0.879	BDA1: Recommendation of BDA (0.808), BDA2: Implementation of Big Data Analytics (0.961)	χ^2/df = 0, GFI = 1.000, AGFI = 1.000, RMSEA = 0.000

This section discusses the highest factor loadings for each latent variable, which is a good starting point for interpretation. For instance, the author notes the prominence of Big Data Security within Technology, Leadership Capability for Organizational Factors, Efficiency Improvement for Perceived Usefulness, and Ease of Understanding for Perceived Ease of Use. The author also points out the strong loading of the Implementation of Big Data Analytics for the application construct. These observations are insightful. However, this section could further elaborate on observed variables with comparatively lower loadings. For example, in the Technology variable, Relative Advantage (0.359) and Complexity (0.392) show lower factor loadings compared to Big Data Security (0.646). From a technology management perspective, a deeper analysis is needed here. This could suggest that for SMEs in the EEC, the direct perception of a new technology's relative benefits or its inherent complexity might be less prominent drivers than fundamental security concerns when considering adoption. This invites questions about the initial awareness or the perceived value proposition of Big Data Analytics in this specific regional context.

Similarly, within Perceived Usefulness, Process Monitoring Support (0.232) has a remarkably low loading. This section needs to consider why SMEs might not perceive Big Data Analytics as highly useful for process monitoring, even if other aspects like efficiency improvement are strongly perceived. This could indicate a gap in understanding how Big Data Analytics can be strategically applied beyond immediate gains, or it might reflect the current operational priorities of these SMEs. In the Perceived Ease of Use construct, observed variables such as Ease of Big Data Analytics (0.546) and Ease of Skill Development (0.464) also exhibit moderate loadings. This section could discuss whether these moderate

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loadings imply that while understanding the system is crucial, the initial ease of adoption or the perceived ease of developing necessary skills still present some challenges for SMEs.

Finally, within the Big Data Analytics Application construct, "Implementation of Big Data Analytics" has the highest loading at 0.961. This confirms that the actual application and integration of big data analytics into business processes is the most prominent indicator of adoption. Overall, these results demonstrate that concerns such as data security, leadership quality, operational efficiency, system comprehensibility, and practical implementation are pivotal factors influencing the acceptance and use of big data analytics among SMEs in the study area.

This section provides a good explanation of the model fit indices (χ^2/df, GFI, AGFI, RMSEA) and confirms the excellent fit of the measurement models. This ensures that the constructs are well-represented by the observed data, which is a critical prerequisite for structural model analysis. The author effectively demonstrates that the data align with the proposed theoretical structure.

To further enhance the academic contribution of this results section, the author could integrate the interpretation more explicitly with relevant technology adoption theories, such as the Technology-Organization-Environment (TOE) framework or the Technology Acceptance Model (TAM). For instance, when discussing the strong loading of Leadership Capability, this section could link it to the organizational dimension of the TOE framework, emphasizing how top management support and strategic vision are paramount for successful technology assimilation in smaller enterprises. Similarly, the findings related to Perceived Usefulness and Perceived Ease of Use directly relate to the core constructs of TAM, and this section could explicitly draw these connections, discussing how these perceptions ultimately drive the intention to use Big Data Analytics among SMEs.

Results of Structural Equation Modeling Analysis

Regarding the first paragraph, the author highlights that technology has the strongest influence on entrepreneurs' perceptions, specifically on Perceived Usefulness (PU) and Perceived Ease of Use (PE). This finding aligns well with the core tenets of the Technology Acceptance Model (TAM), where perceived characteristics of a technology are primary drivers of its acceptance. This section could further elaborate on how modernity and processing efficiency, as technological attributes, directly map to the "perceived usefulness" construct, perhaps referencing established literature that defines these facets within information systems. This would strengthen the theoretical grounding of the claims.

In the second paragraph, the author notes that organizational factors, such as top management support and leadership capability, show a moderate influence on Perceived Usefulness and a comparatively lower impact on Perceived Ease of Use. This finding suggests that while organizational backing is present, it does not fully translate into simplifying the technology for users. This section could benefit from discussing this nuanced relationship in the context of organizational readiness for technology adoption. Drawing upon insights from institutional theory or resource-based view could provide a richer explanation for why resources might be available but not fully leveraged to reduce technological complexity for end-users, especially in the context of SMEs that may face resource constraints in training or dedicated IT support.

The third paragraph explains that Perceived Usefulness has a stronger effect on the application of big data analytics than Perceived Ease of Use. This section accurately reflects that entrepreneurs prioritize the outcomes and benefits derived from technology. From a technology management perspective, this is a common observation in mature technology adoption phases where the value proposition outweighs initial usability hurdles. The author could contextualize this finding by referencing adoption theories that emphasize value realization over initial friction, particularly for strategic technologies like Big Data Analytics that promise tangible business improvements.

When examining the observed variables of technology in the fourth paragraph, the author identifies technological complexity as the most influential factor, negatively affecting acceptance. This is a consistent finding in technology adoption research, where high complexity is a significant barrier. This section correctly identifies data security as a critical consideration. The relatively low influence of competitive advantage is an interesting finding, suggesting Big Data Analytics is seen more as an enabler than a direct source of competitive edge. This section could further discuss this by referencing literature on the strategic impact of IT, distinguishing between foundational IT capabilities and those

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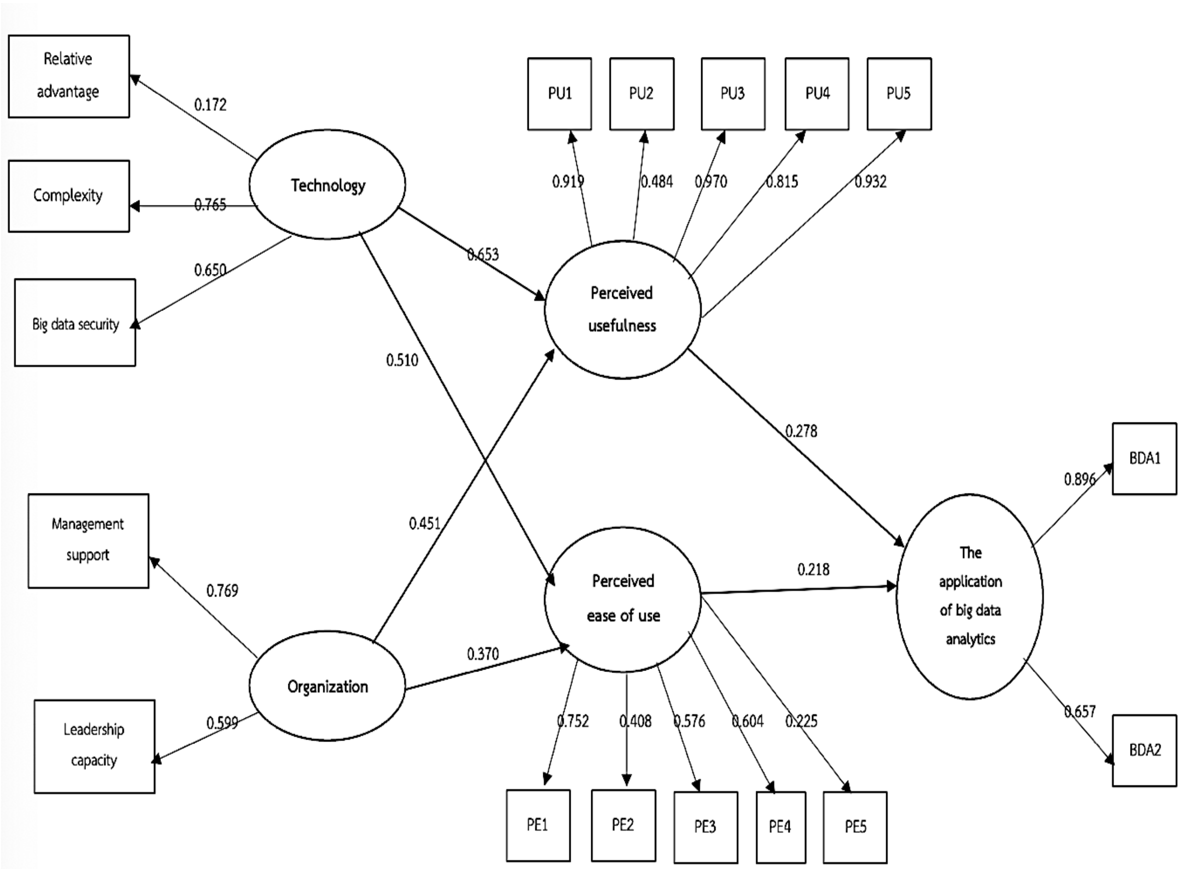
that directly confer competitive advantage. Perhaps Big Data Analytics is currently viewed as a necessary foundational capability for SMEs in the EEC, rather than a differentiator.

For the fifth paragraph, the author observes that top management support carries the highest weight among organizational factors, followed by leadership capability. This underscores the pivotal role of senior leadership in championing technology initiatives. This finding is consistent with organizational change management theories, which emphasize leadership commitment as a critical success factor for enterprise-wide technology adoption. The author could briefly connect these findings to concepts like transformational leadership or strategic alignment, which highlight how leadership vision and resource allocation drive successful technological integration.

The sixth paragraph details the observed variables for Perceived Usefulness, with process efficiency improvement, data monitoring capability, and rapid data analysis showing high loadings. These findings directly reflect the anticipated operational benefits of Big Data Analytics. This section could further elaborate on how these specific improvements contribute to the overall perceived value, perhaps by linking them to specific operational efficiency models or data-driven decision-making frameworks.



Chi-square=686, df=350, P-value=0.001, RMSEA=0.032

Figure 2 Synthesized Conceptual Framework

In the seventh paragraph, the author discusses the observed indicators for perceived ease of use. The ease of data analysis is the most influential, while the development of user skills has the least influence. This highlights the importance of intuitive system design. This section could explore the implications for training and user support within SMEs. The low influence of user skill development might suggest a need for more user-friendly interfaces or that SMEs struggle with dedicated training initiatives, relying more on inherent system simplicity. This aligns with challenges often faced by resource-constrained organizations in technology management.

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The eighth paragraph focuses on the application of big data analytics, where the availability of guidelines or recommendations for use is the most influential factor, followed by actual usage. This suggests that clear operational protocols are essential for effective implementation. This section correctly concludes that the application of big data analytics is shaped by a confluence of technological, perceptual, and managerial factors. This multi-faceted view is consistent with comprehensive technology adoption frameworks that consider various organizational and individual influences. This section could emphasize the practical implications of providing clear guidelines for SMEs, linking them to implementation success factors in information systems.

The ninth and tenth paragraphs report the model fit indices, indicating a strong alignment with standard criteria. The author clearly states that the absolute and relative fit measures exceed common thresholds, and the error-based indices are below the acceptable threshold. (GFI = 0.992, AGFI = 0.983, NFI = 0.983, NNFI = 0.983, CFI = 0.957, IFI = 0.960, RFI = 0.972, RMSEA = 0.032, RMR = 0.032, SRMR = 0.032, $\chi^2/df = 1.96$) This section confirms the model's appropriateness and reliability. To further strengthen this part, the author could briefly reiterate the theoretical significance of having a well-fitting model, explaining how it lends credibility to the proposed causal relationships and strengthens the generalizability of the findings within the technology management domain. This would reinforce the methodological rigor.

Hypothesis Testing Results

The author begins by presenting the hypothesis testing results, which is a standard approach. However, this introductory sentence could be expanded to provide a brief overview of the analytical method employed and its relevance to assessing the proposed relationships. For example, if a structural equation modeling approach was used, mentioning this upfront would set a clearer context for the subsequent discussion of path coefficients.

Regarding Hypothesis 1, which posits that technological factors are positively associated with perceived usefulness among small and medium-sized enterprises (SMEs) in the Eastern Economic Corridor (EEC), the analysis strongly supports this. The statistical results show a correlation coefficient of 0.653, significant at the $p<0.01$ level. This section indicates a reliable and robust positive relationship. To enhance this part, the author could elaborate on the specific technological characteristics measured that contribute to this strong perceived usefulness. For instance, this could relate to the system quality, information quality, or service quality of the Big Data Analytics (BDA) systems, aligning with dimensions from the DeLone and McLean Information System Success Model. Discussing *why* a strong positive relationship exists, perhaps linking it to the specific technological readiness or infrastructure present in the EEC, would add valuable insight from a technology management perspective.

For Hypothesis 2, which suggests technological factors are positively associated with perceived ease of use among SMEs in the EEC, the statistical analysis supports this with a path coefficient of 0.510 ($p<0.01$). This indicates a moderate but statistically significant positive relationship. This section could benefit from a deeper exploration of what aspects of technological factors specifically contribute to ease of use. Is it the user-friendliness of the BDA interface, the availability of technical support, or the compatibility with existing IT systems? Drawing connections to the Technology Acceptance Model (TAM), where perceived ease of use is a critical determinant of technology acceptance, would strengthen the theoretical grounding of this finding.

Moving to Hypothesis 3, the assertion that organizational factors are positively associated with perceived usefulness among SMEs in the EEC is well-supported. The path coefficient of 0.451 ($p<0.01$) points to a moderately strong and statistically significant positive relationship. The author should consider discussing which organizational aspects, such as management support, organizational structure, or internal capabilities, are most influential. This could be framed within the Technology-Organization-Environment (TOE) framework, highlighting how internal organizational readiness and resources facilitate the perceived value of BDA. This section could explain how a supportive organizational environment makes BDA seem more beneficial.

In Hypothesis 4, organizational factors are found to be positively associated with perceived ease of use among SMEs in the EEC, with a path coefficient of 0.370 ($p<0.01$). This result suggests a meaningful positive association. The author could provide more specific examples of organizational

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elements that contribute to ease of use. For instance, robust training programs, clear communication channels, or a culture that embraces technological change could make BDA seem less complex for employees. Connecting this to the importance of human capital and change management within technology adoption literature would provide a richer interpretation.

Concerning Hypothesis 5, which states that perceived usefulness is positively associated with the application of BDA among SMEs in the EEC, the findings strongly support this. A path coefficient of 0.278 ($p<0.01$) indicates a significant positive relationship. While statistically significant, this coefficient is lower than some others. This section could benefit from a discussion about the practical implications of this magnitude. It might suggest that while usefulness is important, other factors could also significantly influence the actual application or usage intensity of BDA, or that the path from perceived usefulness to actual application is mediated by other variables not explicitly tested here. This also directly aligns with the core tenets of the TAM, where perceived usefulness is a direct predictor of technology adoption and usage.

Finally, for Hypothesis 6, which suggests perceived ease of use is positively associated with the application of BDA among SMEs in the EEC, the quantitative analysis supports this with a path coefficient of 0.218 ($p=0.010$). This section correctly explains that SMEs' perception of BDA systems as easy to use contributes to their willingness to adopt these technologies. Similar to Hypothesis 5, the author could elaborate on the practical significance of this coefficient given its magnitude. This finding reiterates the importance of designing BDA systems that are intuitive and require minimal specialized expertise, especially for SMEs where resources for extensive training might be limited. The author could also discuss whether the influence of perceived ease of use is direct or if it primarily operates through perceived usefulness, a common relationship explored in technology acceptance literature.

Discussion

For the technological dimension, the author notes that the variable representing big data security exhibited a high factor loading of 0.646. This finding aligns with Asir et al. (2024), who underlined the critical need to safeguard digital assets and data from cyberattacks to maintain data integrity and privacy within organizations. This suggests that data security is fundamental for building trust among consumers and organizations, especially as vast data volumes are increasingly utilized for strategic decision-making. Risks such as cyberattacks and data leaks can severely damage an organization's reputation and stakeholder trust. From a theoretical perspective, this highlights the importance of risk perception in technology adoption, where perceived security reduces uncertainty and enhances confidence, thereby fostering willingness to integrate new systems. Therefore, effective data security management should encompass not only robust technological infrastructure but also continuous personnel development to ensure the proper and efficient protection of organizational data, reflecting a holistic approach to technology implementation.

In the organizational dimension, the variable for leadership competency demonstrated a notably high factor loading of 0.915. This strongly supports the findings of Schmidt et al. (2022), who observed that effective leaders possessing a blend of systems thinking, clear vision, and technological expertise are key facilitators in the adoption of big data analytics within organizations. This indicates that leadership plays a pivotal role in establishing strategic direction, motivating teams, and cultivating competencies in technology, data management, and human capital skills. This also fosters an organizational culture that embraces innovation and continuous learning, which is essential for enhancing sustainable competitiveness in the digital era. This finding aligns with the Resource-Based View, where competent leadership is seen as an invaluable internal resource that enables an organization to effectively leverage new technologies.

Concerning the perceived usefulness dimension, the author found that the variable "enhancing efficiency" (PU3) exhibited the highest factor loading of 0.995. This result corroborates the study by Samdhiya et al. (2024), who highlighted that big data analytics can significantly improve productivity, enable faster responses to customer demands, and stimulate innovation and product development. This suggests that users, particularly within SMEs, highly value tangible efficiency outcomes derived from utilizing such technologies. These outcomes include loss reduction, improved accuracy in decision-making, and enhanced market responsiveness, reflecting their practical experiences and perceptions of

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value. This strongly supports the core tenets of the Technology Acceptance Model (TAM), where perceived usefulness is a primary determinant of technology adoption, particularly when the benefits are directly observable and impactful on operations.

For the perceived ease of use dimension, the variable "ease of understanding" (PE3) showed the highest factor loading of 0.863. Kling et al. (2025) emphasized that knowledge and skills that are easy to grasp can lead to a competitive advantage by reducing complexity in technology usage. Thus, ease of use acts as a critical factor in lowering user resistance and increasing the likelihood of technology adoption. For SMEs in the Eastern Economic Corridor, where resources might be limited, the simplicity of technology understanding is particularly vital. This finding further reinforces the importance of perceived ease of use within the TAM framework, as it directly influences the effort users anticipate investing in learning and utilizing new systems. Organizations should, therefore, focus on developing user-friendly tools and conducting ongoing training to ensure knowledge is effectively transferred to personnel, thereby facilitating smoother adoption.

In the dimension of big data analytics application, the author notes that the variable BDA2 showed a high factor loading of 0.961, underscoring the importance of the actual implementation of analytics technologies in organizations. This finding supports Chen (2024), who discovered that employee readiness and capability to adopt such technologies significantly affect organizational performance and internal collaboration. It can be inferred that the application of big data analytics represents a practical behavioral outcome that reflects an organization's readiness and capacity to convert data into decisions and performance improvements. Employee capabilities contribute to increased efficiency, foster interdepartmental communication and cooperation, and enhance organizational agility in responding to technological and market changes, aligning with theories of organizational learning and dynamic capabilities.

About the second research objective, the results provide compelling evidence to support all six hypothesized relationships, as discussed below.

First, the analysis found that technological factors are significantly and positively related to perceived usefulness among SMEs in the Eastern Economic Corridor (β=0.653, p<0.01). This finding is consistent with Sheppard, B., & Vibert, C. (2019), who highlighted the role of technology in enhancing user experience and behavioral engagement. This suggests that technological readiness, particularly the availability of robust digital infrastructure and advanced analytics tools, enables SMEs to recognize the practical benefits of technology in improving operational efficiency, lowering costs, and establishing competitive advantages. The strong positive relationship underscores that well-developed technological resources are crucial enablers for SMEs to perceive the tangible value of Big Data Analytics.

Second, technological factors were also shown to have a significant positive association with perceived ease of use (β=0.510, p<0.01). This supports the findings of Muazu et al. (2024), who emphasized that technologies designed with user-friendliness in mind can boost user confidence and willingness to adopt. Accordingly, stable, intuitive systems supported by accessible technical assistance can help alleviate user concerns and increase motivation to engage with the technology. This promotes more effective and long-term usage among SMEs, highlighting that the inherent design and support of technology are critical for its perceived simplicity, which in turn facilitates adoption.

Third, organizational factors demonstrated a significant positive relationship with perceived usefulness (β=0.451, p<0.01). This aligns with the research of Al-shanableh et al. (2024), which highlighted the importance of leadership and managerial support in enhancing perceptions of technology value. Strong leadership and well-structured organizations help to build technological awareness, ease concerns regarding data security, and encourage the full utilization of digital tools. This ultimately strengthens SMEs' competitive capabilities in the region. This relationship suggests that an enabling organizational environment, through strategic direction and support, plays a key role in shaping how employees perceive the benefits of new technologies.

Fourth, the analysis found that organizational factors also positively influence perceived ease of use (β=0.370, p<0.01). This supports Nasongkhla and Shieh (2023), who indicated that organizational support, particularly in the form of training and capacity-building, can reduce complexity in technology adoption. An open organizational culture and thoughtful resource allocation contribute to building user

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confidence and simplifying the integration of new systems. This is especially beneficial for SMEs that often face constraints in human and financial resources. This finding underscores that organizational efforts can directly mitigate the perceived difficulty of adopting new technologies, making them more accessible to employees.

Fifth, perceived usefulness was found to be significantly and positively related to the actual application of big data analytics (β=0.278, p<0.01). This finding corresponds with the work of Meitasari and Manurang (2023), who argued that when SMEs recognize the practical benefits of technologies, such as customer data analysis, market forecasting, and operational optimization, they are more likely to commit to learning and implementing those technologies. While the strength of this relationship is moderate, it nevertheless highlights perceived usefulness as a key driver of technology adoption. This enables SMEs to make more informed decisions and respond more effectively in dynamic and competitive environments, reaffirming the central tenet of the Technology Acceptance Model that perceived utility drives actual usage.

Lastly, perceived ease of use was also positively associated with the application of big data analytics (β=0.218, p=0.010). This supports the findings of Bin-Nashwan et al. (2025), who asserted that ease of use plays a critical role in lowering adoption barriers and increasing user interest. In the specific context of SMEs in the Eastern Economic Corridor, where limitations in personnel and resources are common, technologies that offer intuitive user interfaces and simplified processes are more likely to be embraced. Although the strength of this relationship is comparatively lower than that of perceived usefulness, it nonetheless underscores the importance of user experience in facilitating digital transformation among SMEs facing rapidly evolving market and technological landscapes. This indicates that while tangible benefits are a primary driver, the simplicity of interaction remains an important factor for actual technology integration, especially for resource-constrained organizations.

Conclusions and recommendations

The author begins the conclusion by highlighting a key finding from the confirmatory factor analysis (CFA): the significant role of leadership capability, which exhibited a strong beta value of 0.915. This section accurately emphasizes the importance of leadership in promoting the acceptance and adoption of new technologies. However, this discussion could be strengthened by explicitly connecting this finding to established technology adoption theories. For instance, the author might discuss how strong leadership aligns with the concept of top management support, which is consistently identified in technology management literature as a critical success factor for innovation diffusion. Furthermore, the author could consider how different leadership styles, such as transformational leadership, might specifically foster an environment conducive to technology assimilation, going beyond merely encouraging acceptance to actively championing change. This deeper theoretical integration would provide a more robust academic foundation for the stated finding.

Moreover, the structural equation modeling (SEM) results, showing a strong positive relationship between technological factors and perceived usefulness (β=0.653,p<0.01), are presented as directly influencing the Big Data Analytics application. While the finding is clear, the term "technological factors" remains somewhat broad. The author could gain from specifying what these factors encompass in the context of Big Data Analytics, perhaps detailing aspects like system quality, information quality, or infrastructure availability, which are distinct components within information system success models. This section correctly identifies perceived usefulness as a key pathway; however, an explicit mention of the Technology Acceptance Model (TAM) would greatly enrich the theoretical discussion, as perceived usefulness is a central construct within this widely recognized framework. Explaining how appropriate organizational structures and systems build trust and ease of use could also benefit from links to organizational readiness for technology adoption, a concept that explores how an organization's internal characteristics facilitate or hinder the implementation of new systems.

Based on these insights, the author recommends prioritizing the development of leadership competencies through ongoing training and continuous support. This recommendation is logical given the findings. To enhance its academic depth, the author could suggest incorporating specific elements into leadership training that directly relate to technology change management, such as fostering technological foresight or enabling leaders to articulate the strategic value of Big Data Analytics. This

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approach would move beyond generic skill development to targeted interventions. The author could also discuss the role of opinion leaders within the organization, a concept from Diffusion of Innovation theory, to maximize the impact of leadership initiatives.

In addition, this section proposes that SMEs should adapt their organizational systems to be more flexible and responsive to new technologies. The author rightly suggests fostering an innovation-driven organizational culture and investing in workforce training in Big Data Analytics. These recommendations could be further refined by referring to concepts such as organizational learning, where continuous knowledge acquisition and sharing are vital for adapting to technological changes. The author could also explore the idea of dynamic capabilities, which refers to an organization's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. Providing a more structured approach to culture change, perhaps referencing specific frameworks for fostering innovation, would also be beneficial. The final aim of supporting sustainable growth and competitiveness through digital transformation is a strong overarching goal, and linking the recommendations directly to strategic advantages derived from technology adoption would strengthen this concluding thought.

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