Asian Journal of Empirical Research
Volume 15, Issue 3 (2025): 59-64

Digitalization and SME competitiveness in Sabah: A PLS-SEM analysis of infrastructure, implementation, and human capital

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Article History
Received: 24 April 2025
Revised: 19 June 2025
Accepted: 14 June 2025
Published: 21 July 2025

Keywords
Digitalization
Human resource
Sabah
SMEs.

ABSTRACT
This study investigates the factors influencing the competitiveness of small and medium-sized enterprises (SMEs) in Sabah, focusing on the roles of human resources, infrastructure, and implementation. Addressing these issues is crucial to facilitate digital transformation among SMEs in Sabah and promote more inclusive economic development. Using a quantitative approach and Partial Least Squares Structural Equation Modeling (PLS-SEM), data were collected from SMEs across various districts in Sabah. The findings reveal that both infrastructure and implementation have significant and positive effects on competitiveness, supporting established theories that emphasize the importance of tangible assets and strategic execution in enhancing firm performance. However, contrary to much of the existing literature, human resources demonstrated a significant but negative relationship with competitiveness. This suggests that within the Sabah context, challenges such as limited skills, insufficient training, or misaligned HR strategies may be hindering SMEs' ability to leverage human capital effectively. The study contributes to the literature by offering context-specific insights into SME development in a geographically and economically diverse region, and it highlights the need for more targeted policies to strengthen human resource capabilities to support sustainable competitiveness.

Contribution/Originality: The originality of this study lies in its focus on SMEs in Sabah, offering valuable insights to policymakers for formulating both short- and long-term strategies to enhance sustainable growth amid increasing global market demands. By integrating macro-level policy considerations with micro-level SME dynamics, the study contributes to a more comprehensive and unbiased understanding of the potential impacts on Sabah's economic landscape.

DOI: 10.55493/5004.v15i3.5481
ISSN(P): 2306-983X / ISSN(E): 2224-4425

How to cite: Sabu, Z., Taasim, S. I., & Daud, A. (2025). Digitalization and SME competitiveness in Sabah: A PLS-SEM analysis of infrastructure, implementation, and human capital. *Asian Journal of Empirical Research, 15*(3), 59–64. 10.55493/5004.v15i3.5481

1. INTRODUCTION

Sabah is a state rich in natural resources and ethnic diversity, yet it continues to face developmental disparities, including a significant digital divide between urban and rural areas. Rural-based SMEs in Sabah, which form a vital component of local economic development, often face various constraints such as limited digital infrastructure, lack of technological knowledge and skills, as well as insufficient capital and institutional support. These challenges have caused them to lag behind in the digital transformation process, thereby affecting their long-term competitiveness in an increasingly technology-driven market. As small players in an increasingly competitive market, SMEs must contend with larger companies that possess more advanced financial and technological resources. The lack of trained and skilled workers presents another major challenge for SMEs, hindering their development and business growth. Small enterprises often cannot afford continuous training investments, resulting in a less skilled workforce and declining productivity. According to Fenwick, Molnar, and Frangos (2024), the integration of AI into HRM also introduces significant ethical and legal considerations, particularly concerning bias, transparency, and privacy. It is imperative to address the ethical dimensions of AI in HRM, emphasizing the importance of fairness, transparency, and accountability in AI-driven decision-making processes. Organizations must establish robust ethical frameworks and governance mechanisms to ensure that AI systems are deployed responsibly, mitigating potential biases and safeguarding employee rights. Organizations need to ensure that AI systems are fair and responsible by implementing strong ethical frameworks and governance procedures. They must also ensure the responsible design, oversight, and periodic evaluation of AI systems to maintain accountability and fairness in AI-driven processes (Saraswathi et al., 2023). HR managers should also develop new job-related competencies to account for new technologies and the changing nature of work, which will help HRM transition from operational to strategic roles. Additionally, it is important to acknowledge employee concerns regarding the use of AI in HRM, emphasizing the need for transparent communication and employee involvement in the implementation process.

This study is conducted to identify and analyze the key barriers hindering the digitalization process among SMEs in Sabah. By understanding these obstructive factors, the study aims to contribute toward formulating more effective and targeted policy interventions, support strategies, and training programs. Furthermore, the findings of this study are expected to provide valuable insights for stakeholders, including the government, entrepreneurial development agencies, and industry players, in strengthening a more inclusive and sustainable digital ecosystem.

2. LITERATURE REVIEW

Digitalization has emerged as a transformative force reshaping various facets of organizational operations, with Human Resource Management standing as a pivotal domain undergoing substantial evolution. This transformation entails a fundamental shift in the structure of management, driven by the integration of digital technologies, impacting how organizations manage their workforce and optimize human capital (Romanov, 2021). The digital transformation of Human Resource Management encompasses a wide array of processes, including recruitment, training and development, performance management, and employee engagement, all of which are increasingly reliant on sophisticated digital tools and platforms (Zhang & Chen, 2024). The integration of technology into HRM practices has led to streamlining processes, improving efficiency, and facilitating data-driven decision-making (Prasad, Hamraaia, Sharma, Sahana, & Pereira, 2024). It is crucial for HR professionals to continuously learn and develop their skills in order to fully utilize AI (Sayyad & Srinivas, 2024).

The integration of Artificial Intelligence into Human Resource Management signifies a profound shift, revolutionizing talent acquisition, development, and retention strategies (Kadirov, Shakirova, Ismoilova, & Makhmudova, 2024). AI algorithms possess the capability to analyze extensive datasets, discern patterns, and predict outcomes, thereby significantly enhancing the recruitment process by forecasting candidate success with remarkable accuracy (Kadirov et al., 2024). This enables HR departments to identify and attract top-tier talent, streamlining the selection process and minimizing biases, and fostering a more diverse and inclusive workforce (Kadirov et al., 2024). AI-powered HR technologies also enhance employee satisfaction and retention through individualized HR procedures, fair decision-making, and efficient task management (Sayyad & Srinivas, 2024). The application of machine learning algorithms enables the automation of resume screening, refining candidate evaluation procedures through video and behavioral analysis, thus ensuring a deeper alignment between job requirements and applicant proficiencies (Sayyad & Srinivas, 2024). Natural Language Processing further revolutionizes candidate engagement through AI-driven chatbots, which facilitate instant interactions and provide immediate assistance, thereby enhancing the candidate experience and engagement (Kadirov et al., 2024). AI further facilitates the identification of employees at risk of attrition by analyzing engagement levels and workload patterns, enabling proactive retention measures through customized career growth opportunities and compensation adjustments (Rajan & Nagajothi, 2024). Integrating blockchain with AI can ensure data security and transparency within HR functions (Rajan & Nagajothi, 2024).

Moreover, AI algorithms play a crucial role in analyzing employee performance data, identifying skill gaps, and prescribing personalized learning paths, leading to improved employee performance and career advancement. AI-driven sentiment analysis tools offer invaluable insights into employee morale, facilitating proactive interventions to address potential issues and foster a positive work environment (Rajan & Nagajothi, 2024). AI can significantly improve the quality of work life for employees and boost company performance by automating routine tasks. This enables HR professionals to foster continuous improvement by linking employee objectives to organizational goals and offering continuous, customized feedback based on data. However, integrating AI into HRM also poses a number of difficulties that must be addressed.

Furthermore, the application of predictive analytics in talent retention strategies has enabled organizations to proactively mitigate burnout risks, thereby reducing turnover costs and fostering a stable, experienced workforce (Kadirov et al., 2024). Sentiment analysis and predictive analytics represent new AI applications in HRM that can provide individualized employee experiences and intelligent decision support (Saraswathi et al., 2023). By identifying those at risk of leaving, businesses can offer tailored professional development and compensation, which greatly improves job satisfaction and dedication. Kadirov et al. (2024) Robotics Process Automation has emerged as a transformative force in HR administration, automating routine tasks, freeing up HR professionals to focus on strategic initiatives, and enhancing operational efficiency. RPA can automate many HR administrative activities, allowing HR experts to concentrate on strategic goals and improve operational effectiveness. The digitization of HRM also needs to be carefully managed to mitigate risks and ensure alignment with other business functions.

This necessitates the cultivation of human-machine collaboration, wherein AI augments human capabilities, empowering employees to focus on higher-value tasks and fostering innovation (Fenwick et al., 2024). AI-human collaboration is essential for the successful use of AI in HRM, as well as addressing the impact on employees through factors such as AI type, process, and organizational AI strategy. To alleviate skepticism and negative perceptions surrounding AI adoption, managers must establish transparent communication strategies that clearly outline the impact on job design, expectations, and the purpose of using AI (Chowdhury et al., 2023). For HRM to embrace AI, there must be a comprehensive approach that incorporates ethical considerations, strategic alignment, and employee empowerment. Additionally, HRM plays a critical role in managing the cultural transformation that accompanies digitalization, cultivating a growth-oriented mindset, promoting continuous learning, and fostering a culture of innovation and adaptability.

Ultimately, organizations should cultivate an innovative culture that encourages workers to embrace AI, find new applications through creative thinking, and dynamically adjust to changes brought about by HR business process and practice transformation (Chowdhury et al., 2023). Meanwhile, Kadirov et al. (2024) by encouraging creativity and empowering people to adapt, businesses can make sure that they can fully utilize AI's potential and promote innovation at all levels of the organization. Moreover, the integration of AI with other technologies, such as the Internet of Things and blockchain, is expected to further enhance HR practices, making them more secure, transparent, and efficient. AI combined with IoT and blockchain could provide safe, open, and effective HR procedures.

3. METHODOLOGY

This study adopts a quantitative research design to identify and analyze the key barriers to digitalization among small and medium enterprises (SMEs) in Sabah. A cross-sectional survey method was employed to collect primary data, enabling the researchers to obtain measurable insights from a large population within a specific period. The target population comprises SMEs located in the districts of Sabah. A stratified random sampling method was applied to ensure representation across various sectors such as retail, agriculture, manufacturing, and services. Based on the Krejcie and Morgan (1970) sampling table, a minimum of 200 SMEs was targeted to ensure statistical significance and the generalizability of the findings. Data were collected over a period of two months via both online surveys and face-to-face distribution, facilitated by collaboration with local entrepreneurship agencies and SME support centers. Respondents were briefed on the objectives of the study, and informed consent was obtained prior to participation. Data were analyzed using the Statistical Package for the Social Sciences (SPSS) version 26. Descriptive statistics were used to summarize demographic data and the general perception of barriers. Inferential analysis, including Exploratory Factor Analysis (EFA) and multiple regression, was conducted to identify the key constructs and examine the influence of each barrier on digitalization readiness.

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0 software. This method was selected due to its suitability for exploratory research and its ability to accommodate complex models involving both formative and reflective latent constructs. The analysis was conducted in several stages. First, the measurement model was assessed to evaluate internal consistency reliability, convergent validity using Average Variance Extracted (AVE), and discriminant validity through the Fornell-Larcker criterion, cross-loadings, and the Heterotrait-Monotrait ratio (HTMT). Next, the structural model was examined by analyzing path coefficients, R^2 values, effect sizes (f^2), and predictive relevance (Q^2). Finally, bootstrapping with 5,000 samples was performed to determine the significance levels of the hypothesized relationships in the model.

4. RESULT

Table 1, 46.4% of respondents are running sole proprietorship businesses, while 50.8% do not know the type of business they operate. Table 1 is designed to assess the business profiles of the respondents and their understanding of the types of businesses. The survey results show that 69.3% of respondents employ fewer than five employees, and 30.7% employ between five and seventy-five employees. The study also evaluates the operational years of the businesses, with 49% of respondents having been in business for less than a year. Meanwhile, 31.3% have been operating for between one to six years, 7.8% for five to ten years, and 9.9% for more than ten years.

Table 1. Descriptive statistics of respondents' business profiles.

Domain	Category	Number	Percentage
Business type	Sole proprietorship	221	46.4
	Private limited company	6	1.3
	Partnership	7	1.5
	Not registered	242	50.8
Business size	< 5 employees	330	69.3
	5 – 75 employees	146	30.7
Location	Kudat	116	23.9
	West Coast	67	13.8

Domain	Category	Number	Percentage
	Inland	37	7.6
	Tawau	162	33.3
	Sandakan	104	21.4
Years of business operation	<1 year	238	49.0
	1-5 years	152	31.3
	6-10 years	38	7.8
	>10 years	48	9.9
Business registration	Registered	317	65.2
	Not registered	159	32.7

In this study, there are four main constructs: human resources (5 items), infrastructure (6 items), implementation (5 items), and competitiveness (5 items). All constructs are assessed using a reflective measurement approach. The measurement model is used to evaluate the validity and reliability of the constructed model. According to Hair, Black, Babin, and Anderson (2019) and Ramayah, Cheah, Chuah, Ting, and Memon (2018), several conditions must be fulfilled.

i) Individual item reliability (Outer loading).
ii) Internal consistency reliability.
iii) Convergent validity.
iv) Discriminant validity.

The measurement model is illustrated in Figure 1. In this study, the model measures how human resources, infrastructure, and implementation predict competitiveness. The reliability of individual items in this study was assessed using outer loading values for each sub-construct. Following the recommended threshold of 0.60 (Hair, Hult, Ringle, & Sarstedt, 2017), items with loadings below this value were removed to ensure measurement accuracy. As a result, two items under the competitiveness construct (D2 and D5) were excluded from further analysis. The remaining items demonstrated acceptable outer loading values, indicating adequate individual item reliability. Internal consistency reliability was evaluated using composite reliability (CR).

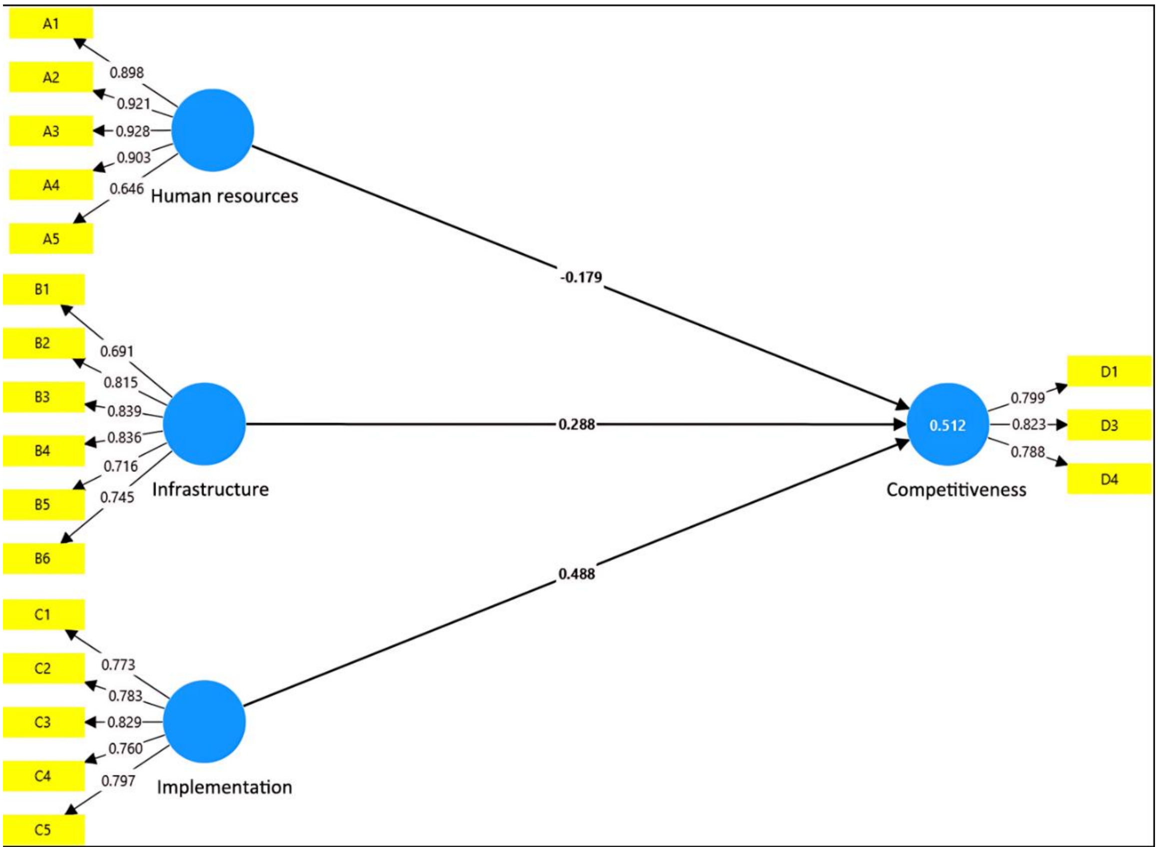

Figure 1. Model structural.

All four constructs human resources, infrastructure, implementation, and competitiveness recorded CR values exceeding 0.70, confirming that each construct demonstrated strong internal consistency and reliability. Among them, human resources recorded the highest reliability value, further supporting the robustness of the measurement scale. Convergent validity was assessed through the Average Variance Extracted (AVE). All constructs reported AVE values above the threshold of 0.50, indicating that more than half of the variance in the indicators was captured by their respective constructs. These findings confirm that the constructs possess sufficient convergent validity and are conceptually sound for further structural model evaluation.

The path coefficient is used to identify the relationships between constructs. To test the significance of the path coefficient, this study employed the standard bootstrapping procedure with 5,000 samples (Hair et al., 2017; Ramayah et al., 2018). The p-value must be below 0.05 to be considered significant. In this study, the t-value is based on a 95% confidence level, with the critical value set at 1.64. To confirm that the relationship between constructs is significant, the t-value must exceed 1.64, and the p-value must be less than 0.05.

Table 2. Hypothesis testing results.

Hypothesis	Beta	Standard deviation	T-statistic	P-value	Result
H1: Human resources → Competitiveness	-0.179	0.037	4.883	0.00	Supported
H2: Infrastructure → Competitiveness	0.288	0.044	6.503	0.00	Supported
H3: Implementation → Competitiveness	0.488	0.043	11.391	0.00	Supported

Based on the results presented in Table 2, all three hypotheses are supported, indicating statistically significant relationships between the independent constructs and competitiveness.

Specifically, infrastructure and implementation both show positive and significant effects on competitiveness, with implementation having the strongest influence ($\beta = 0.488$, $t = 11.391$, $p < 0.001$). This suggests that effective implementation strategies play a crucial role in enhancing competitiveness. Infrastructure also contributes positively ($\beta = 0.288$, $t = 6.503$, $p < 0.001$), emphasizing the importance of physical and organizational systems in competitive performance. Interestingly, human resources show a negative but significant effect on competitiveness ($\beta = -0.179$, $t = 4.883$, $p < 0.001$). This may indicate potential issues related to workforce quality, training, or management practices that could hinder rather than support competitiveness. Overall, the findings highlight that while infrastructure and implementation drive competitiveness, human resource factors require further evaluation and improvement to better support organizational success.

5. CONCLUSION

In relation to the literature review, the findings of this study offer both support and new insights, particularly within the context of SMEs in Sabah. The positive and significant relationships between infrastructure and implementation with competitiveness are consistent with prior studies that emphasize the importance of robust infrastructure and effective strategy execution in achieving a competitive advantage (Barney, 1991; Porter, 1985). These results reinforce the argument that tangible resources and efficient operational practices are critical enablers of competitiveness, especially for SMEs operating in geographically diverse and logistically challenging regions like Sabah. However, the negative relationship between human resources and competitiveness deviates from much of the established literature, which generally positions human capital as a cornerstone of firm success (Becker, 1993; Wright & McMahan, 2011). In the case of SMEs in Sabah, this finding may reflect practical limitations such as insufficient training, lack of skilled labor, or a misalignment between workforce capabilities and strategic business objectives. This outcome suggests that while infrastructure and implementation are strengths, human resources may be an underutilized or mismanaged component, pointing to a potential disconnect between HR practices and competitive outcomes. Therefore, while this study supports key theoretical models, it also extends the literature by highlighting the unique dynamics faced by SMEs in Sabah. It underscores the need for targeted interventions to enhance human capital development and strategic HR integration, ensuring that human resources contribute effectively to the competitiveness of SMEs in the region.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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