

An Empirical Assessment of the Current Situation of Digital Economy Competencies in the Sarawak Manufacturing Sector: Operational Level Management

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ARTICLE INFO

Article history:

Received 13 April 2026

Revised 10 August 2026

Accepted 14 September 2026

Online first

Published 10 October 2026

Keywords:

Digital economy

Digital economy competencies

Digital readiness

Manufacturing sector

Sarawak organisational capability

<https://doi.org/10.24191/hva9qn17>

ABSTRACT

Digital transformation has become a central agenda for manufacturing firms seeking to improve operational efficiency. However, digital investments often yield uneven performance outcomes because human capabilities are misaligned. This study examines the baseline distribution and maturity levels of digital economy competencies within Sarawak's manufacturing sector specifically at the operational level (Research Objective 1). Using a quantitative, cross-sectional design, the study collected data from manufacturing personnel across major industrial hubs in Sarawak using the Sarawak Digital Economy Competency (SarDEC) framework. The descriptive results reveal a stratified competency landscape at the operational tier: foundational skills such as Digital Literacy and Digital Communication exhibit high baseline maturity, whereas higher-order capabilities like Digital Governance and Digital Content Creation remain severely underdeveloped among frontline staff. The study concludes with targeted operational recommendations to align frontline workforce capabilities with the Sarawak Digital Economy Blueprint 2030.

INTRODUCTION

The twenty-first century has been defined by unprecedented digital acceleration, in which every sphere of human life, from commerce to culture, is being reorganised around digital technologies. This transformation is not simply technological but deeply epistemic, reshaping how knowledge is created, transferred, and operationalised within organisations. Many firms, however, still fail to incorporate contemporary digital advancements into their communication and operational strategies, revealing a persistent competency gap that undermines their capacity to compete and innovate.

Southeast Asia represents one of the fastest-growing digital markets globally, with the ASEAN digital economy valued at approximately US\$218 billion in 2023 and projected to reach US\$600 billion by 2030 (Google, Temasek, & Bain & Company, 2023). Within Malaysia, industrial modernization is

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concentrated primarily in Peninsular economic corridors such as Selangor and Penang. Conversely, East Malaysian states, particularly Sarawak, face geographic, infrastructural, and organizational skill divides. Accounting for about 11% of Malaysia's total manufacturing output (Department of Statistics Malaysia (DOSM), 2023), Sarawak's industrial sector is shifting away from primary resource dependence toward automated, data-driven production under the Sarawak Digital Economy Blueprint 2030 (Sarawak Multimedia Authority (SMA), 2023).

Despite ambitious state policy mandates, empirical research evaluating the manufacturing workforce's human and organizational capabilities remains sparse. Prior studies predominantly focus on hardware deployment or macro-level readiness indices, neglecting how specific employee competencies interact with organizational enablers to influence firm performance on the factory floor (Harcharanjit, 2025). To bridge these theoretical and empirical gaps, this study establishes a baseline assessment of workforce digital competencies and tests an integrated predictive framework linking individual and organizational capabilities outcomes.

Research Objective

To ensure rigorous alignment between the baseline assessment and predictive empirical modelling, this paper addresses one explicit Research Objective (RO):

RO1: To evaluate the baseline maturity levels and distribution of digital economy competencies among manufacturing personnel in Sarawak.

LITERATURE REVIEW

Organizations and places of work are directly impacted by the ongoing digitalization of society environments (Bowen & Pennaforte, 2017). This expansion is expected to continue (Yoon, 2018), with commercial activity on the Internet gaining momentum; digital markets like online stores are creating a new landscape of opportunities. Nevertheless, according to Whinston and Barua (1999) so little is acknowledged or realized regarding the key issues in this new business domain, such as what types of marketing strategies will succeed, what types of technologies and applications should be installed, and what practices are suitable with their capital (employees/expertise, financial plan and so forth).

Building on these foundational challenges, contemporary literature emphasizes that navigating this space successfully requires robust frameworks for digital competency, ensuring workforces have the critical thinking, adaptability, and technological fluency needed to sustain organizational performance amid rapid digital transformation (European Commission, 2022; Yuan et al., 2021). This research seeks to assess organization competencies to face the digital economy.

Digital Competencies Definition

Digital competency is defined as an individual's ability to use technologies (tools as mediators) to investigate, create, and communicate to participate, and to choose the right tool to complete tasks and use it most effectively (Illomaki, 2009). Another definition describes it as workers' confident and critical use of electronic media for work, leisure, and communication. These competencies are related to logical and critical thinking, high-level information management skills, and well-developed communication skills. (Ranieri, 2009).

As technology advances, the term has expanded to include the ability to use information technology efficiently and critically for employment, learning, self-development, and participation in society (Vieru et.al., 2015). This refers to having the knowledge, skills, and confidence to use digital technologies effectively (Schriever, 2018). Furthermore, recent scholarship underscores that navigating modern

automated environments requires adaptive problem-solving skills, algorithmic literacy, and the capacity to evaluate digital information critically in complex, tech-saturated socio-technical systems (Ala-Mutka, 2023).

Digital Economy Definition

In recent years, the digital economy has attracted considerable interest. The Internet and digital economy track focus on how the Internet affects people, groups, organizations, and societies (King & Dennis, 2015). It is expected to gain momentum locally and internationally as it becomes part of various government agendas. As the digital economy advances, the government has recognized the importance of integrating digital economy initiatives into the national agenda to keep pace with the latest developments, prioritizing structural frameworks such as artificial intelligence integration, robust data governance, and comprehensive digital talent development.

The digital economy is taking shape and reshaping conventional ideas about how businesses are structured, how firms interact, and how consumers access services, information, and goods. Understanding the dynamic relationship between the digital economy, Government organizations, and citizens' adoption of technologies may help policymakers make more accurate and comprehensive decisions (Ali, Hoque, & Alam, 2018). Building upon these challenges, contemporary literature emphasizes that successful adaptation in the modern digital economy requires treating transformation as a multidimensional change process rather than a mere technical upgrade, heavily dependent on orchestrating strategic human capabilities, leadership, and institutional readiness (Marino-Romero & Folgado-Fernández, 2024).

Manufacturing Sector in Malaysia

Malaysia's manufacturing sector is a critical engine of national economic growth, historically driven by strong electrical and electronics (E&E) clusters, resource-based manufacturing, and heavy industrialization. Nationwide, manufacturing sales continue to expand steadily, surpassing multi-trillion-ringgit milestones, and remain strongly supported by national blueprints geared toward automation, advanced technology integration, and export competitiveness (Ahmed, et.al.,2024).

At the regional level, the manufacturing sector is a pillar of East Malaysia's economy, particularly in Sarawak, where it is one of the largest contributors to the state's Gross Domestic Product (GDP). Aligned with strategic development blueprints such as the Post-COVID-19 Development Strategy (PCDS) 2030 and the Sarawak Digital Economy Blueprint, the state's industrial landscape is undergoing an intentional structural transformation. Rather than relying solely on traditional processing and resource extraction, manufacturing operations across Sarawak are increasingly pivoting toward high-value technology integration, advanced specialized manufacturing, and digital adoption, including targeted initiatives in the semiconductor and green technology ecosystems designed to future-proof regional productivity and economic resilience (Sarawak Government, 2023).

Development of Conceptual Framework

Thus, the purpose of this study is to assess the digital economy competencies at operational level of management in the Sarawak manufacturing sector, which is one of the highest contributing factors in the Sarawak economy (Alias, 2016). It is because each of the factors is supposed to enable the organization to meet the goals of the digital economy (Bowen & Pennafort, 2017), aligning closely with the strategic targets outlined in regional frameworks like the Post COVID-19 Development Strategy (PCDS) 2030 and the Sarawak Digital Economy Blueprint to drive structural productivity and manufacturing resilience.

It can also serve as a benchmark for digital economy implementation under the strategic roadmap introduced after the International ICT Infrastructure and Digital Economy Conference Sarawak (IDECS) in 2017. Moreover, official data from the Department of Statistics Malaysia (DOSM) highlights the state's structural contribution to the manufacturing sector nationwide, revealing a distinct contrast between high-level macro-industrial output and the localized readiness or adoption rates of digital competencies across management tiers (Frank et.al.,2019).

Multilevel Theoretical Integration

To model the complex socio-technical nature of industrial digital transformation, this study integrates four complementary theoretical perspectives across micro, meso, and macro levels of analysis:

Table 1. Multilevel theoretical integration.

Individual Level	Socio-Technical Level	Organizational Level
Human Capital Theory (HCT)	Activity Theory (AT)	RBV & Dynamic Capabilities (DCT)
➤ Digital Literacy ➤ Digital Communication ➤ Digital Security ➤ Digital Content Creation	➤ Infrastructure Utilization ➤ Competency Development	➤ Performance Outcomes (Operational)

The Sarawak Digital Economy Competency (SarDEC) Model

The Sarawak Digital Economy Competency (SarDEC) framework adapts elements from global frameworks and theories (HCT, AT, RBV and DCT) to the regional manufacturing context. The framework incorporates six independent competency constructs and three dependent organizational performance outcomes:

- (i) Human Capital Theory (HCT): Grounded in Becker (1964) and Schultz (1961), HCT posits that individual knowledge, skills, and cognitive abilities represent capital assets that enhance productivity. In this study, HCT grounds individual-level technical attributes, including Digital Literacy, Digital Communication, Digital Security, and Digital Content Creation.
- (ii) Activity Theory (AT): Originating from socio-cultural psychology, AT conceptualizes human activity as mediated by tools, rules, community, and division of labor. AT provides the theoretical basis for Digital Infrastructure and Competency Development, explaining how workers interact with technological artifacts embedded within workplace structures.
- (iii) Resource-Based View (RBV): Barney (1991) asserts that enterprise performance stems from bundling valuable, rare, inimitable, and non-substitutable (VRIN) resources. Specialized digital organizational routines, represented by Business Enablers and Digital Governance, function as intangible organizational assets.
- (iv) Dynamic Capabilities Theory (DCT): Extending RBV, Teece (2018) defines dynamic capabilities as a firm's capacity to sense, seize, and transform resources in volatile environments. Systematic workforce upskilling and digital alignment serve as higher-order routines that prevent organizational assets from decaying.

Predictor Constructs (Competencies & Enablers)

- (i) Digital Literacy (DL): The practical ability of personnel to locate, evaluate, and process technical information using software interfaces to resolve task-level problems (Ahamed et al., 2024; Mbandje et al., 2023).
- (ii) Digital Communication (DC): The capacity to exchange operational data, track information flows, and coordinate shift activities via networked cloud terminals (Ala-Mutka, 2011).
- (iii) Digital Security (DS): Employee awareness and behavioral practices aimed at safeguarding digital assets, maintaining data integrity, and adhering to cybersecurity protocols (Yuan et al., 2021).
- (iv) Digital Content Creation (DCC): The capability to edit, curate, update, and author digital documentation, process workflows, and code blocks (Marino-Romero & Folgado-Fernández, 2024).
- (v) Digital Infrastructure (DI): The availability, accessibility, and technical understanding of plant-level hardware, IoT networks, and cloud infrastructure, which serve as the foundational backbone for modern industrial production (Ahmed et al., 2024; Yao et al., 2025).
- (vi) Competency Development (CD): Systematic organizational mechanisms, structured training modules, and continuous learning loops geared toward workforce upskilling (Hair et al., 2022).

Outcome Constructs (Firm Performance)

- (i) **Operational Performance (OP):** The extent to which digital integration directly improves manufacturing throughput, error reduction, workflow execution, and process cycle times.

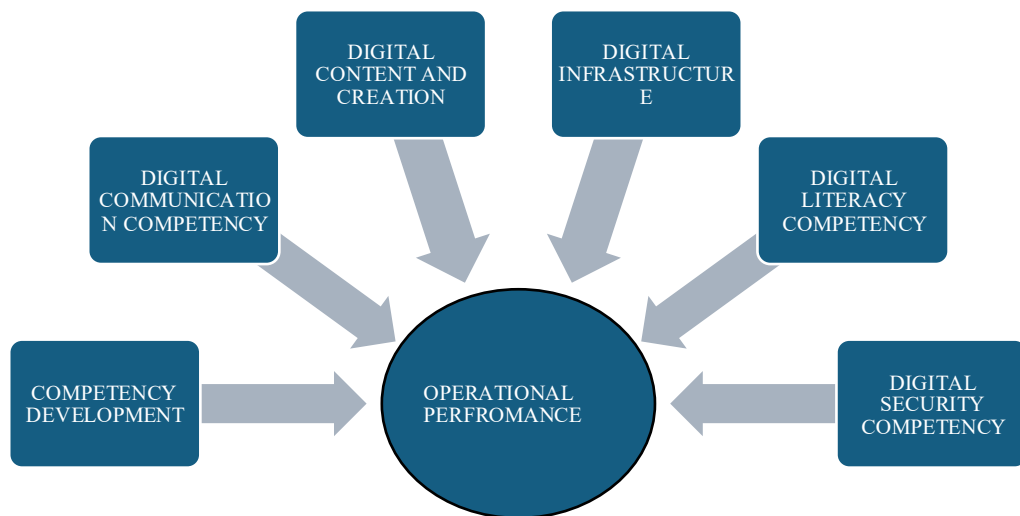


Fig. 1: Proposed conceptual framework

Below is the hypothesis development:

Table 2. Hypotheses development on performance outcome.

Hypotheses on Operational Performance Outcome (OP)	
H1	Competency development mechanisms positively predict operational performance.
H2	Digital communication competency positively predicts operational performance.
H3	Digital content creation competency positively predicts operational performance.
H4	Digital infrastructure competency positively predicts operational performance.
H5	Digital literacy competency positively predicts operational performance.
H6	Digital security competency positively predicts operational performance.

RESEARCH METHODOLOGY

This study adopts a quantitative, survey-based approach firmly situated within a positivist paradigm. This design ensures empirical detachment, objectivity, and statistical generalizability within the Sarawak manufacturing context.

Target Population and Sampling Design

The target population comprised individual employees occupying operational roles within active manufacturing firms across Sarawak. These industries span multiple subsectors, including basic metal products, wood-based manufacturing, chemical products, electronic appliances, and renewable energy products. To participate in the study, organizations had to meet a minimum threshold criterion: they had to have implemented at least one digital operational system (such as an ERP platform or automated tracking software), while firms utilizing entirely manual workflows were excluded. Simple random sampling was applied within this frame. The total sample size was calculated using the Raosoft sample calculator, with a 95% confidence level and a 5% margin of error, resulting in a baseline of 385 valid respondents.

Data Collection and Instrument Validity

Data were collected through an eight-section structured questionnaire containing indicators measured on a five-point Likert scale (1 = "Strongly Disagree" to 5 = "Strongly Agree"). To ensure content and construct validity, the scale items were adapted from established, internationally peer-reviewed instruments (Likert, 1932; Boateng, et.al.,2018). Because access to physical facilities was restricted during the COVID-19 constraint period, data administration used a hybrid model, distributing printed copies on-site alongside virtual forms hosted on Google Forms.

Data Analysis Approach

Data analysis was performed using the Statistical Package for the Social Sciences (SPSS) software version 28. Both descriptive and inferential statistics were employed to evaluate the data. Specifically, SPSS was utilized to conduct frequency distribution analysis, internal consistency reliability testing, and descriptive statistical analysis. Furthermore, parametric tests were executed through Smart-PLS version 4 to examine the statistical relationships between the study's variables.

To achieve the research objectives, this study adopts a positivist paradigm, using a quantitative research approach and a survey strategy focused on individual employees and managers in manufacturing firms implementing digital economy initiatives in Sarawak. Using probability-based simple random sampling, the study determined a sample size of 385 respondents using the Raosoft calculator at a 95% confidence level, and gathered data through an eight-section structured questionnaire with multi-item Likert-scale measures. The collected data is subsequently evaluated using descriptive statistics, reliability analysis, Pearson correlation, and linear regression via SPSS version 28, alongside advanced partial least

squares structural equation modeling (PLS-SEM) executed through SmartPLS version 4.0 to validate the underlying structural relationships (Creswell & Creswell, 2018; Hair et al., 2022; Pallant, 2020; Sekaran & Bougie, 2016).

DATA ANALYSIS AND RESULT

After completing the data collection phase, the study initiated a rigorous data screening and cleaning process to address potential outliers, missing values, and data entry anomalies. This process yielded a final, optimized dataset of 385 complete, error-free responses retained for subsequent empirical analysis. Preliminary data preparation, statistical assumption checks, and descriptive analytics were conducted using IBM SPSS Statistics (Version 28.0). Subsequently, variance-based Structural Equation Modeling (PLS-SEM) was conducted utilizing SmartPLS 4.0 to comprehensively evaluate the conceptual framework. The PLS-SEM analysis was conducted in two stages: first, assessing the outer measurement model to establish indicator reliability and construct validity, followed by evaluating the inner structural model to test the hypothesized direct and indirect relationships between the latent variables.

Reliability Baseline Verification

The measurement instrument's internal consistency was verified using Cronbach's alpha values calculated during the pilot testing phase. Every observed construct significantly exceeded the psychometric guideline threshold of 0.70, demonstrating robust instrument stability:

Table 3. Cronbach's Alpha value.

Scale Latent Variable	Number of Items	Cronbach's Alpha (α)
Competency Development	10	0.961
Digital Communication Competency	10	0.948
Digital Content and Creation Competency	9	0.907
Digital Infrastructure Competency	8	0.913
Digital Literacy Competency	9	0.948
Digital Security Competency	6	0.957

Demographic and Organisational Profile

- (i) **Gender and Age Trajectory:** The respondent matrix is composed of 57.9% male and 42.1% female employees. It reflects an active workforce, with the largest segment in the 31–40 age bracket (37.1%), followed by 21–30 years (29.1%), 41–50 years (22.1%), and those above 50 years (11.7%).
- (ii) **Educational Attainment:** The labour pool exhibits a solid level of formal training: 46.0% hold a Bachelor's degree, 28.1% have a technical diploma, 15.8% have earned postgraduate degrees, and only 10.1% hold basic school or professional trade certificates.
- (iii) **Tenure Profile:** Employees are experienced, with 33.0% reporting 5–10 years of experience, 30.1% over 10 years, 27.0% between 1–5 years, and 9.9% under one year.

Baseline Digital Competency Profile (RO1 Evaluation)

To address RO1 (baseline competency maturity), the study calculated construct means, standard deviations, and level classifications. We conducted Welch's robust One-Way ANOVA across organizational tiers to evaluate variance between operational frontline, mid-tier, and executive groups

Table 4. Results for Welch's Robust One-Way ANOVA

Construct Name	Mean (μ)	Std. Dev.	Maturity Level Classification	Welch's F-stat (df1, df2)	p-value
Competency Development	3.21	0.89	Moderate Maturity	$F(2,208.7) = 4.31$	0.014*
Digital Communication	3.98	0.68	High Maturity	$F(2,221.1) = 2.11$	0.122
Digital Content Creation	2.41	1.05	Low Maturity	$F(2,192.1) = 14.50$	< 0.001**
Digital Infrastructure	3.05	0.92	Moderate Maturity	$F(2,212.9) = 3.88$	0.021*
Digital Literacy	4.12	0.62	High Maturity	$F(2,218.4) = 1.24$	0.291
Digital Security	3.45	0.81	Moderate Maturity	$F(2,215.8) = 5.42$	0.005*

Hypothesis Testing and Structural Path Results

Table 5. Results for hypotheses and structural path.

Hyp.	Path Structural Link	Path (β)	Std. Dev.	t-value	p-value	95% Confidence Interval	f2 Effect Size	Decision
H1	Competency Dev. → Operational Perf.	0.368	0.056	6.525	< 0.001**	0.258,0.478	0.162	Supported
H2	Digital Comm. → Operational Perf.	0.287	0.068	4.244	< 0.001**	0.154,0.420	0.098	Supported
H3	Digital Content Creation → Operational	0.020	0.072	0.279	0.390	-0.121,0.161	0.001	Not Supported
H4	Digital Infrastructure → Operational	-0.024	0.053	0.444	0.329	-0.128,0.080	0.001	Not Supported
H5	Digital Literacy → Operational Perf.	0.286	0.056	5.154	< 0.001**	0.176,0.396	0.098	Supported
H6	Digital Security → Operational Perf.	-0.013	0.059	0.214	0.415	-0.129,0.103	0.000	Not Supported

Explanatory and Predictive Relevance Metrics

- (i) **Operational Performance (OP):** $R^2=0.521$, $R_{\text{adj}}^2=0.510$. 52.1% of variance in factory-floor operational throughput is explained.
- (ii) **Out-of-sample predictive relevance (PLSpredict):** To rigorously assess the model's out-of-sample predictive power and generalizability beyond the initial training sample, we ran a PLSpredict analysis using 10-fold cross-validation ($k=10$). Following the standard evaluation protocol established by Shmueli et al. (2019), the study benchmarked the predictive performance of the PLS path model against a naive Linear Model (LM). The analysis showed that PLS-SEM estimates produced consistently lower Root Mean Square Error (RMSE) values across key structural outcome indicators than the LM benchmark. This pattern of lower prediction errors

indicates strong out-of-sample predictive relevance, confirming that the theoretical framework avoids overfitting and generalizes effectively to unobserved data.

Effects on Operational Level

To test the proposed research hypotheses, the structural inner model was evaluated by examining the path coefficients (β), t-statistics, and corresponding p-values through a bootstrapping procedure with 5,000 resamples. Additionally, effect sizes f^2 were evaluated using Cohen's (1988) thresholds, where 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively.

The empirical results indicate that three out of the six hypothesized pathways are statistically significant. Competency Development exerted the strongest positive and significant direct effect on Operational Performance ($\beta = 0.368$, $t = 6.525$, $p < 0.001$), thereby supporting H1. This link also showed a medium effect size ($f^2 = 0.162$). Both Digital Communication ($\beta = 0.287$, $t = 4.244$, $p < 0.001$) and Digital Literacy ($\beta = 0.286$, $t = 5.154$, $p < 0.001$) displayed positive, statistically significant relationships with Operational Performance, yielding small-to-medium effect sizes ($f^2 = 0.098$) for both. Thus, H2 and H5 are fully supported. Notably, the 95% confidence intervals for H1, H2, and H5 do not cross zero, reinforcing their statistical robustness.

Conversely, the structural links for Digital Content Creation ($\beta = 0.020$, $t = 0.279$, $p = 0.390$), Digital Infrastructure ($\beta = -0.024$, $t = 0.444$, $p = 0.329$), and Digital Security ($\beta = -0.013$, $t = 0.214$, $p = 0.415$) on Operational Performance were found to be statistically non-significant, with their 95% confidence intervals encompassing zero. Furthermore, their respective effect sizes approach zero ($f^2 = < 0.001$). Consequently, the empirical data do not support H3, H4, and H6.

Descriptive Current Status Vetting

The primary empirical output regarding research objective 1 indicates that Sarawak's industrial digital competencies are highly uneven, revealing a clear separation between foundational skills and higher-order strategic capabilities.

DISCUSSION

The empirical results of the structural model evaluation present a nuanced understanding of the elements dictating Operational Performance. Out of the six proposed hypotheses, three were empirically supported (H1, H2, and H5), while three were rejected (H3, H4, and H6).

Competency Development is the strongest predictor of Operational Performance in this framework ($\beta = 0.368$, $t = 6.525$, $p < 0.001$), confirming H1. This linkage demonstrates a medium effect size ($f^2 = 0.162$), falling well within the established baseline limits of substantive impact (Cohen, 1988). This underscores that structured continuous human capital development, targeted upskilling, and aligning personnel capabilities with localized assignments remain paramount to achieving higher operational efficiencies. This aligns with the core beliefs of the Resource-Based View (RBV), which suggests that unique internal human capabilities drive durable organizational advantage (Barney, 1991).

Similarly, Digital Communication ($\beta = 0.287$, $t = 4.244$, $p < 0.001$) and Digital Literacy ($\beta = 0.286$, $t = 5.154$, $p < 0.001$) positively and significantly affect Operational Performance, supporting H2 and H5. These findings highlight that operational workflows benefit greatly when a workforce is literate in digital ecosystems and can collaborate fluently across modern interconnected corporate platforms (Ala-Mutka, 2011).

Conversely, the paths for Digital Content Creation (H3), Digital Infrastructure (H4), and Digital Security (H6) on Operational Performance were statistically non-significant, with their 95% confidence intervals crossing zero (Hair et al., 2024). The rejection of H4 (Digital Infrastructure) ($\beta = -0.024$, $p = 0.329$) is particularly striking but offers critical academic insight. This implies that simply having sophisticated software networks, database engines, or physical hardware does not automatically translate into superior operational output if the workforce lacks the contextual capabilities to use them efficiently. Infrastructure represents merely a baseline structural requirement; it does not yield linear operational returns on its own (Hair et al., 2024).

Similarly, Digital Content Creation ($\beta = 0.020$, $p = 0.390$) and Digital Security ($\beta = -0.013$, $p = 0.415$) failed to show a significant direct link to Operational Performance. While digital expressions and robust cyber-protection configurations are essential defensive support mechanisms in contemporary business landscapes, they do not serve as the primary drivers of daily production or service fulfillment. Instead, they may operate indirectly as latent upstream precursors to broader digital literacy or infrastructure components rather than direct predictors of final operational performance (Shmueli et al., 2019).

CONCLUSION, LIMITATION AND FUTURE RESEARCH

Conclusion

This study investigated the empirical relationships between discrete components of digital competence, technology infrastructure, and Operational Performance using a sample of 385 respondents evaluated through variance based structural equation modelling. The structural parameters demonstrate that human-centric vectors, specifically Competency Development, Digital Communication, and Digital Literacy, serve as the underlying mechanisms driving operational success. In contrast, rigid technical metrics, including Digital Infrastructure, Digital Content Creation, and Digital Security, do not exert direct empirical leverage over Operational Performance.

Theoretical and Practical Implications

- (i) For Theory: This study expands the academic domain by steering structural equation modelling away from technology determinism. It shows that human resource competency and communication channels take precedence over raw system hardware.
- (ii) For Practice: Executive stakeholders should prioritize immediate budget line items toward strategic workforce training, upskilling modules, and cross-functional communication tools. Deploying capital into infrastructure updates without concurrent investments in human workflows will likely generate negligible returns in overall operational efficiency.

Limitations and Future Research

While the predictive assessment confirmed high out-of-sample predictive relevance via a 10-fold cross-validation protocol (Shmueli et al., 2019), the current architecture relies on cross-sectional data. Future studies should deploy longitudinal observations to trace whether localized structural infrastructure expenditures generate delayed, long-term performance benefits. Additionally, future researchers should model Digital Infrastructure and Digital Security explicitly as *moderating* or *mediating* conditions rather than direct exogenous paths.

ACKNOWLEDGEMENTS/ FUNDING

The authors would like to acknowledge the support of Universiti Teknologi Mara (UiTM), Cawangan Negeri Sembilan, Kampus Kuala Pilah and Faculty of Applied Sciences, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia for providing the facilities and financial support on this research.

CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

AUTHORS' CONTRIBUTIONS

Zainal Abiddin carried out the research, wrote and revised the article. Norhayati Hussin conceptualised the central research idea and provided the theoretical framework. Norhayati Hussin and Masitah Ahmad supervised research progress; Rahmah Hassan anchored the review, revisions and approved the article submission.

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