International Journal of Advanced and Applied Sciences, 13(4) 2026, Pages: 231-239

Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: https://www.science-gate.com/IJAAS.html

The impact of digital technology on MSME performance: A Rasch Jakpreneur study in Indonesia

Suyono Thamrin [1,*], Tuty Sariwulan [2], M. Calvin Capnary [3], Yaya Jakaria [3]

[1]*Faculty of Defense Management, Defense University, Bogor, Indonesia*
[2]*Faculty of Economics and Business, State University of Jakarta, Jakarta, Indonesia*
[3]*Faculty of Management and Business, Binus University, Jakarta, Indonesia*

ARTICLE INFO

Article history:
Received 9 September 2025
Received in revised form
15 January 2026
Accepted 26 April 2026

Keywords:
Digital technology use
Business performance
MSMEs
Rasch measurement
Jakarta MSMEs

ABSTRACT

The aim of this study is to examine the relationship between digital technology use and business performance among micro, small, and medium enterprises (MSMEs) participating in the Jakpreneur program in Jakarta (n = 200). A 30-item instrument was calibrated using the Rasch model and demonstrated high measurement precision, with strong person reliability (0.94) and item reliability (0.95). The person–item map revealed under-targeting at higher ability levels, indicating a ceiling effect and the need for more difficult items. Ordinary least squares regression analysis showed that digital technology use has a strong and statistically significant effect on business performance (B = 0.741, SE = 0.030, β = 0.866, t(198) = 24.424, $p < 0.001$), explaining 75.1% of the variance in performance (R^2 = 0.751; adjusted R^2 = 0.750). These findings highlight the importance of strengthening digital capabilities, from basic to advanced levels, in performance improvement strategies for urban MSMEs. Methodologically, expanding the item bank with higher-difficulty items is necessary to improve measurement targeting and maintain validity as respondents' competencies increase. The main limitations of this study are its cross-sectional design and purposive sampling; future research should adopt longitudinal designs and include differential item functioning analyses across sectors and income groups.

1. Introduction

The acceleration of digital transformation in the past decade has changed the way micro, small, and medium enterprises (MSMEs; locally called MSMEs) create value, access markets, and manage operations (Matarazzo et al., 2021). In a competitive urban environment like DKI Jakarta, the use of technology—from point-of-sale systems, marketplace platforms, digital payments, to customer analytics—is no longer a complement, but a determinant of competitive advantage. Various cutting-edge studies confirm that digital capabilities and orientation are closely associated with business performance, sales growth, innovation, and business model resilience (Hokmabadi et al., 2024; Putritamara et al., 2023). In the context of SMEs, digital transformation has been proven to strengthen the ability to respond to crises and drive competitiveness through business model design, e-commerce adoption, and data utilization (Hokmabadi et al., 2024; Klein and Todesco, 2021). In Indonesia, empirical evidence shows that the adoption of digital technology is increasingly widespread among micro and small business actors, with links to financial performance and inclusion.

Digital technology adoption and performance improvement among MSMEs can be theoretically grounded in the Dynamic Capabilities framework, which emphasizes a firm's ability to continuously sense market opportunities, seize them through strategic action, and reconfigure resources to maintain competitive advantage in dynamic environments. Digital capabilities enhance the sensing function by enabling firms to leverage data analytics for real-time consumer insights, strengthen seizing through operational automation and the utilization of digital platforms, and support resource reconfiguration through integration across systems and business processes. Empirical studies have shown that well-developed digital capabilities are

* Corresponding Author.
Email Address: suyonothamrin.untan@gmail.com (S. Thamrin)
https://doi.org/10.21833/ijaas.2026.04.023
Corresponding author's ORCID profile:
https://orcid.org/0000-0002-8881-7677

positively associated with process efficiency, business model innovation, and financial outcomes in small business settings (Khin and Ho, 2019; Matarazzo et al., 2021). However, despite increasing digital adoption across Indonesian MSMEs, research explicitly linking Dynamic Capabilities with digitally driven performance at the microenterprise level remains limited, particularly in studies that apply modern measurement frameworks to ensure construct validity.

On the other hand, the literature on measuring competency and digital utilization in MSMEs still relies on conventional internal reliability and exploratory/confirmatory factor analysis, while Rasch-based metric evidence, which places respondents and items on the same logit scale to assess targeting, category function, and unidimensionality, is less commonly used. This gap is important because the item targeting error decreases the measurement precision in critical segments (e.g., the upper tail), which in turn affects the estimation of the relationship between digital utilization and performance. Rasch's application of person–item map inspection and fit diagnostics provides a strong metric foundation for accountable substantive inference.

This research closes the gap with two main contributions. First, at the methodological level, we validate the instruments of digital technology utilization and business performance through the Rasch Model and present evidence of targeting accuracy and model suitability at the respondent and item levels, so that the composite score used by the inferential analysis is based on a precisely measurable latent dimension. Second, at the substantive level, we test and quantify the relationship between the use of digital technology and business performance in a sample of MSMEs participating in the Jakpreneur program, a policy-relevant coaching ecosystem, so that the findings can be more directly operationalized in digital capability enhancement interventions (Ukko et al., 2019). a development ecosystem that is policy-relevant and representative of the dynamics of urban entrepreneurship in Indonesia.

Departing from the theoretical foundation of dynamic capabilities and digital orientation, the conceptual framework of the research positions the use of digital technology as a direct driver of business performance through three main mechanisms: process efficiency (operational automation and system integration), market expansion (access to online channels and measurable promotions), and improvement of decision quality (utilization of data and performance metrics) (Deichmann et al., 2016; Escandon-Barbosa and Salas-Paramo, 2025). Thus, the research statement tested is that the use of digital technology is positively associated with the business performance of MSMEs. Operationally, Rasch's methodological contribution is integrated with OLS estimation on composite scores to ensure consistency between measurement quality and inference strength (Yaniar et al., 2021). In the empirical context of research, participants in the Jakpreneur program provide a unique opportunity to examine variations in digital utilization across sectors and business income levels in an ecosystem that is actively digitized. In addition, the results are of practical value to policy designers and program managers, as they provide a baseline of metrics that can be used to map training needs, measure progress, and design interventions targeted by capability segments (Deichmann et al., 2016; Escandon-Barbosa and Salas-Paramo, 2025). With this building, the next section describes the method, results of Rasch measurements, and inferential analysis, followed by a discussion, as well as its conclusions and implications.

2. Methods

The study used a survey-based cross-sectional design on Jakpreneur program participants in DKI Jakarta. Reporting follows the general guidelines of STROBE for observational studies and RULER for Rasch analysis reporting, to maintain transparency of measurement and inference procedures.

The target population is micro, small, and medium enterprises (MSMEs; locally called MSMEs) who are registered and active in the Jakpreneur program. Inclusion criteria: (i) running a business for at least 12 months, (ii) participating in coaching activities in the last 6 months, (iii) willing to fill out questionnaires and provide informed consent. The sampling technique is purposive with sectoral quotas to maintain the diversity of business domains.

The final sample size n = 200 is adequate for measurement and inferential purposes. For Rasch calibration of the rating scale with ±30 items, a ≥ size of 150–200 is commonly recommended so that the estimate of item difficulty is stable. For simple linear regression, a priori calculation with a moderate effect ($f^2 = 0.15$), $\alpha = 0.05$, and power 0.80 results in a requirement of about $n \approx 55$; therefore, n = 200 provides a high-power margin as well as better estimation accuracy for subgroup analysis.

The instrument consists of 30 Likert items with uniform response anchors. Two constructs were measured: the use of digital technology in business processes (predictors) and business performance (outcomes). The composite score is calculated per construct after checking the category function and suitability of the model. Conceptual definitions and indicators are provided in the appendix to keep the core narrative compact.

Data collection was carried out by trained enumerators through structured questionnaires. Quality control includes enumerator training, fill integrity checks, detection of abnormal response patterns, and data cleansing. Missing data is handled by a rule: if the proportion of missing per respondent is > 10%, then it is eliminated; if < 10%, a simple imputation is carried out per item in the same construct. The sensitivity of the results to imputation is examined. Calibration was carried out with the Rasch Model rating scale type due to the uniform response category. Estimation of item and person parameters is carried out with a maximum likelihood procedure with bias correction; Person measure values are reported in logits using WLE estimates, along with standard errors. The function of categories is examined through: (i) an increasing sequence of thresholds, (ii) a pattern of category probability, and (iii) monotonous average measures. The feasibility of items and persons was evaluated with Infit/Outfit MNSQ (general feasibility range 0.5–1.5) and ZSTD (|±2|), point–measure correlation, and graphical inspection of the item characteristic curve (Boone, 2016). Unidimensionality is evaluated through residual PCA: the variation is explained by the primary measure and the first eigen contrast. Local dependence is examined through residual correlations (e.g., criteria > 0.20 above average as a potential indication). A person-item map is used to assess scale targeting. An exploratory item function differential (DIF) test is planned in gender groups, sectors, and income levels, meaningful DIF findings will be considered for revision or item separation.

Comparison of the average performance between groups was carried out with ANOVA (Kim, 2017). Assumptions of residual normality and homogeneity of variance are examined; if the assumption is not met, ANOVA, Welch, and appropriate post-hoc procedures are used. The effect size is reported as eta-squared. The relationship between the use of digital technology and business performance was tested by OLS linear regression on composite scores. Reported non-standardized coefficients (B), standardized coefficients (β), standard errors, t-statistics, p-value, 95% confidence intervals, R^2, and R^2 adjusted. Model diagnostics include Q–Q plot inspection, residual versus predicted value, Breusch–Pagan test for heteroscedasticity, Durbin–Watson index for independence, and leverage and Cook distance inspection for influential observations.

3. Results and discussion

This subdivision describes the demographic profile and business characteristics of the research respondents, as many as n = 200 MSME actors participating in the Jakpreneur program in DKI Jakarta. Descriptions were conducted to assess the context of the sample, potential structural bias, and their relevance to the main findings. The focus of the summary includes gender composition, age, and education distribution, variety of business sectors, length of operation, and monthly income level. For transparency and ease of analysis, Table 1 presents the frequency and percentage distribution of each category of variables. This presentation forms the basis for further analysis to interpret the substantive and methodological implications of the sample structure.

The male composition of 83.0% (≈ ratio of 3.8:1) indicates gender inequality that has the potential to affect digital adoption patterns and business networks; The estimated 95% CI ≈ 77.8–88.2% confirms that this dominance is not a statistical coincidence. The age structure is skewed towards the mature group: the ≥31 age category reaches 76.0% (31–35 = 22.5%; 36–40 = 26.0%; > 41 = 27.5%), indicating longer business experience and the possibility of more stable operational practices. In education, high school/equivalent dominates (59.0%), while higher education (Diploma + S1) is 16.5%. Implicitly, digital capacity-building strategies should emphasize practice-based training before encouraging advanced competencies.

In terms of business sectors, the three largest categories—Culinary (21.5%), Fashion (14.0%), Services (14.0%)—comprised ±49.5% of the sample, reflecting moderate diversification. The confidence interval for Culinary is estimated at 15.8–27.2% (95% CI), so the sector's representation is quite stable. The length of business is dominated by 6–10 years (52.0%) and 11–15 years (28.0%), indicating that most established businesses. This context is consistent with the finding that the use of digital technology tends to be more valuable in organizations that already have SOPs and infrastructure. In line with that, ≈65.0% of respondents are at an income of ≥ IDR 25 million/month, which provides financial space for digital investments (e.g., devices, marketing platforms, POS, and analytics). The methodological implication is that follow-up analysis needs to control for gender variables and age/length of business (potential collinearity) and consider the effects of interactions between sectors × digital utilization. Sample structures like this become an important context when interpreting Rasch results and regressions in the next subsection (Briggs, 2019).

3.1. Validity and reliability

This section presents the results of validity and reliability tests with the Rasch Model to ensure that the measured construction meets the model's expectations, and the measurement results are consistent when the instrument is used under similar conditions. Statistical summaries at the respondent and item levels are shown sequentially in Table 2.

At the respondent level, a reliability coefficient of 0.94 with a separation of 3.82 indicates that the scale can distinguish at least four layers of respondents' abilities. The average ability of 2.96 logits (SD 1.59) placed the sample in the latent medium–high range. The same Infit and MNSQ Outfit values of 1.00, accompanied by ZSTD of 0.0 and −0.8, are right at or very close to the model reference (MNSQ ≈ 1 and |ZSTD| ≤ 2), so that the response pattern is consistent and supports the validity of the construct.

At the item level, the reliability of 0.95 and the separation of 4.50 confirm that the difficulty hierarchy is stable and can be replicated if the measurement is repeated. The mean difficulty of 0.00 logit with a standard deviation of 0.71

corresponds to the Rasch scaling convention and shows an adequate variation of difficulty across items. Infit values of 1.01 and Outfit 1.00 with ZSTD −0.6/−0.6 are within the general eligibility range (MNSQ 0.5–1.5; |ZSTD| ≤ 2), indicating that there is no substantial misfit at the item level. Overall, these results demonstrate high measurement precision, excellent reliability, and strong support for construct validity at both levels. Scale is reliable for advanced analysis, such as ANOVA and regression. The large separation findings also suggest the maintenance and expansion of greater difficulty item banks so that the scale coverage continues to be in line with the respondents' ability profile.

Table 1: Respondent characteristics (n = 200)

Demographics	Description	Respondents	Percentage (%)
Gender	Male	166	83.0
	Female	44	17.0
Age	< 25 years	20	10.0
	26 - 30 years	28	14.0
	31 - 35 years	45	22.5
	36 - 40 years	52	26.0
	> 41 years	55	27.5
Education	ES or equivalent	2	1.0
	Junior high school or equivalent	44	22.0
	Senior high school or equivalent	118	59.0
	Diploma 1/2/3	18	9.0
	Bachelor's degree-1	15	7.5
	Others	3	1.5
Type	Culinary	43	21.5
	Fashion	28	14.0
	Tech and the Internet	21	10.5
	Services	28	14.0
	Agribusiness	24	12.0
	Education and Training	14	7.0
	Crafts and Toys	24	12.0
	Snacks	12	6.0
	Others	6	3.0
Length	Less than five years	38	19.0
	6 - 10 years	104	52.0
	11 - 15 years	56	28.0
	More than 16 years	2	1.0
Income per month	Less than 10,000,000	24	12.0
	10,000,001 - 25,000,000	46	23.0
	25,000,001 - 40,000,000	45	22.5
	40,000,001 - 55,000,000	23	11.5
	55,000,001 - 70,000,000	25	12.5
	70,000,001 - 85,000,000	27	13.5
	About 85,000,000	10	5.0

Table 2: Validity reliability

Indicators	Value
A: Respondent/person level	
Reliability of the person	0.94
Separation person	3.82
Average ability (logit)	2.96
Ability standard deviation (SD)	1.59
Infit MNSQ	1.00
Outfit MNSQ	1.00
ZSTD infit	0.0
ZSTD outfit	−0.8
B: Item/item level	
Item reliability	0.95
Item separation	4.50
Average difficulty (logit)	0.00
Standard deviation of difficulty (SD)	0.71
Infit MNSQ	1.01
Outfit MNSQ	1.00
ZSTD infit	−0.6
ZSTD outfit	−0.6

3.2. Item person fit

The item-person fit in with the Rasch Model assesses the alignment between individual response patterns and item characteristics, according to the assumption of unidimensionality. The probability of an affirmative response is seen as a function of the difference between the person's ability and the difficulty of the item on the same logit scale. This check is important to ensure that each item truly reflects the same construct and that the respondent's behavior does not systematically deviate from the model's probabilistic expectations (Briggs, 2019). Table 3 presents the diagnostic statistics of the items in the order of measure generated by the Rasch software. The columns displayed include the difficulty measure (measure), standard error, Infit/Outfit match index in mean square units (MNSQ), along with the Z standard value (ZSTD), point-measure correlation (PTMEA), and the percentage of observed and expected exact matches. The original output image is retained as in the manuscript.

The average Infit MNSQ was recorded at 1.01 (SD 0.37), and the Outfit MNSQ was 1.00 (SD 0.38), very close to the reference of 1.00 and was in the range of 0.5–1.5, which is commonly used for productive measurement. The average ZSTD scores for Infit and Outfit were −0.64 and −0.65, respectively, both well within the ±2.0 eligibility threshold. In general, this indicates the absence of systemic misfits at the item level. Nevertheless, some items show a tendency to overfit or underfit; These items need to be reviewed through the editorial reading of the item, examination of the category function, and possible ambiguity of the context. The point–measure correlation range of 0.41–0.74 was entirely positive, thus supporting the validity of the construct because the item moved in the direction of the latent trait being measured. The percentage of exact matches observed was in the range of 63.0–74.5 percent, with an expectation of 66–76 percent, indicating the accuracy of the model's predictions was adequate.

Table 3: Item statistics: Measure order

Entry	Total score	Count	Measure	SE	Infit MNSQ	Infit ZSTD	Outfit MNSQ	Outfit ZSTD	PTMEA corr	Exp corr	OBS%	EXP%	Item
2	550	200	2.04	0.15	1.35	2.86	1.40	3.05	0.49	0.63	67.5	73.4	X2
3	567	200	1.65	0.15	1.87	5.76	1.85	5.55	0.48	0.63	66.5	75.6	X1
1	577	200	1.42	0.15	1.66	4.52	1.66	4.44	0.53	0.63	70.5	76.0	X1
13	591	200	1.13	0.15	1.23	3.17	1.31	3.86	0.62	0.53	53.5	75.5	X13
8	622	200	0.40	0.15	0.59	-4.83	0.56	-4.97	0.79	0.62	80.5	70.5	X8
20	623	200	0.38	0.15	0.70	-2.81	0.75	-2.73	0.68	0.62	74.0	69.6	X20
11	624	200	0.36	0.15	0.84	-1.74	0.82	-1.86	0.68	0.62	73.0	70.1	X11
22	635	200	0.17	0.15	0.93	-0.78	0.96	-0.43	0.65	0.61	70.5	68.2	X22
23	636	200	0.10	0.14	0.98	-0.23	0.98	-0.19	0.59	0.61	67.0	66.7	X23
7	640	200	0.04	0.14	1.13	2.39	1.31	2.81	0.74	0.61	71.0	66.4	X7
21	640	200	0.04	0.14	1.73	3.59	1.69	3.80	0.52	0.61	74.5	66.4	X21
30	644	200	-0.06	0.15	1.28	-6.28	0.87	-1.47	0.69	0.61	73.0	65.9	X30
10	645	200	-0.10	0.14	0.77	-3.04	0.75	-3.32	0.54	0.60	75.5	65.3	X10
17	646	200	-0.12	0.14	0.78	-3.12	0.83	-2.73	0.72	0.60	75.0	65.5	X17
6	650	200	-0.19	0.14	0.85	-1.91	0.85	-1.73	0.67	0.60	70.5	64.9	X6
28	650	200	-0.19	0.14	0.86	-1.87	0.83	-1.98	0.61	0.60	67.5	65.1	X28
29	650	200	-0.19	0.14	0.86	-1.87	0.83	-1.98	0.41	0.60	67.5	64.8	X29
27	655	200	-0.25	0.14	0.94	-1.29	0.90	-1.25	0.60	0.60	65.0	63.5	X27
5	662	200	-0.43	0.14	0.91	-2.31	0.90	-2.25	0.66	0.59	60.0	63.3	X5
26	662	200	-0.43	0.14	0.81	-3.12	0.92	-1.21	0.63	0.59	59.0	62.4	X26
12	663	200	-0.45	0.14	0.94	-2.05	0.87	-1.98	0.78	0.59	59.0	63.0	X12
18	666	200	-0.47	0.14	0.95	-1.80	0.92	-1.06	0.67	0.59	55.0	62.6	X18
14	670	200	-0.55	0.14	0.92	-2.38	0.82	-2.32	0.78	0.59	60.0	63.4	X14
23	676	200	-0.68	0.14	0.82	-3.58	0.84	-3.19	0.58	0.59	73.5	63.2	X24
24	683	200	-0.82	0.14	0.93	-2.28	0.84	-1.97	0.59	0.59	73.5	63.4	X24
19	686	200	-0.87	0.15	0.77	-3.69	0.79	-3.37	0.59	0.59	76.0	63.5	X19
16	686	200	-0.93	0.15	1.62	7.64	1.57	5.68	0.04	0.59	50.5	63.9	X16
Mean	641.8	200.0	0.00	0.15	1.01	-0.64	1.00	-0.65	0.68	0.66	68.6	66.7	—
SD	32.9	0.0	0.71	0.00	0.37	3.19	0.38	2.97	—	—	6.7	4.0	—

On the person side, the dataset contains 200 respondents who answered 30 items. The estimated average ability is 2.96 logit (SD 1.59). The average value of Infit and MNSQ Outfit was 1.00 with a standard deviation of 0.34 and 0.36, respectively; The average ZSTD for Infit and Outfit is around −0.05 and −0.03. All these indicators are aligned with the theoretical ideal of the Rasch model, so that the response pattern of most respondents is consistent with the model's expectations. However, there were a small number of respondents with MNSQ above the threshold of 1.5 or showing too low overfit, which could reflect patterned responses or weak cognitive engagement. This case should be marked for qualitative review. Overall, the item–person fit findings support the unidimensionality and validity of the instrument construct (Darrow and Behrend, 2017; Flake et al., 2017). Most items and respondents were within the feasibility range, while the anomalies identified were local and did not interfere with the model's global suitability. The next section presents a person-item mapping (Wright map) to visually assess scale targeting.

3.3. Wright map

The Wright Map, or person-item map, visualizes the distribution of respondent abilities and the difficulty of the item at the same logit scale (Boone, 2016; Hilaliyah et al., 2019). The vertical axis represents the Rasch scale, while the left side shows the distribution of respondents and the right side shows the position of the item (marked with an X). These maps help assess scale targeting accuracy, measurement accuracy, and potential floor or ceiling effects. Fig. 1 shows a scale range from about −3 to +7 logits. The notation on the left side shows the density of the respondents (each symbol represents several individuals), while the right side shows the location of each item according to the level of difficulty. The original image is preserved as the software output.

The Wright Map, or person–item map, visualizes the relative positioning of respondents' latent abilities and item difficulty estimates along the same Rasch logit scale (Carpenter, 2018). The vertical axis represents the Rasch scale, with the left panel displaying the distribution of person abilities and the right panel showing the calibrated location of each item. The map provides a clear indication of scale, targeting accuracy, and allows identification of potential ceiling or floor effects. As shown in Fig. 1, most respondents cluster between +2 and +4 logits, indicating medium-to-high digital capability levels. Meanwhile, item difficulties are highly concentrated around 0 logits, revealing a noticeable gap between item challenge and respondent ability. This misalignment suggests that the current scale provides limited information for distinguishing respondents with advanced digital capabilities. The

Wright Map, therefore, highlights the need for future refinement of item difficulty to improve measurement precision at the upper end of the trait continuum. Additionally, the narrow spread of item locations indicates that most items may be assessing relatively basic competencies rather than capturing the full spectrum of digital performance relevant to urban MSMEs.

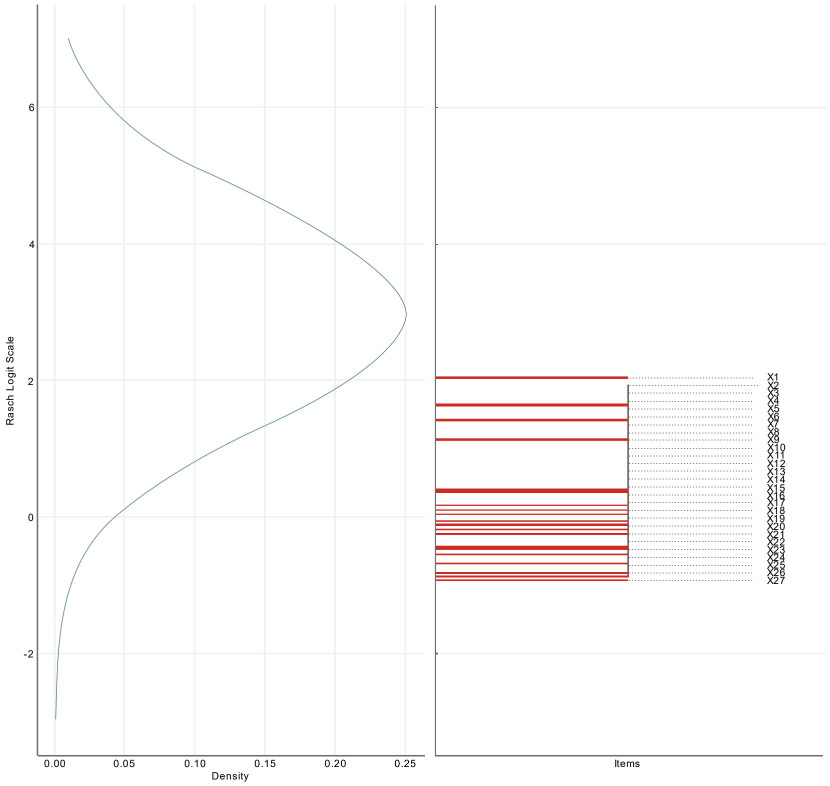

Fig. 1: Wright map (Rasch model) presenting person abilities (left) and item difficulties (right) on a shared logit scale. The predominance of respondents above item locations reflects poor item targeting and a ceiling effect

3.4. Group comparison

Fixed effects variance analysis was applied to evaluate the difference in average business performance scores across strata of respondent characteristics—education, type of business, length of business, and income. Inference rests not only on statistical significance, but also on the measure of the eta-squared effect (η^2) as an estimate of the proportion of total variance explained by the factor. The interpretation guidelines used follow the general convention: $\eta^2 \approx 0.01$ (small), ≈ 0.06 (medium), ≈ 0.14 (large). A summary of the results is shown in Table 4.

The findings show that the largest substantive contribution came from the type of business and income ($p < 0.01$; $\eta^2 \approx 0.10$). In other words, about ten percent of the variance in performance in this sample can be linearly associated with differences in sector structure and financial capacity. The effects of education ($\eta^2 = 0.070$; $p = 0.014$) were moderate; When read together with the demographic profile, this suggests that formal knowledge capital plays a role but is not dominant compared to structural determinants. In contrast, the length of effort did not show a significant mean difference ($p = 0.377$; $\eta^2 = 0.016$), indicating that the accumulation of chronological experience without strengthening digital and commercial strategies was not sufficient to produce performance differentiation. This pattern is consistent with the results of people-item mapping that positions most actors in the medium-high ability range: when basic competencies are relatively homogeneous, performance variations are driven more by market context (type of business) and resource carrying capacity (income) than by the age of the business itself. The policy implications that can be drawn are the need for intervention design that is segmented by sector—for example, differentiation of domain-specific digital competencies—as well as strengthening access to capital and cash flow so that technology adoption translates directly into performance indicators.

3.5. Linear regression: Utilization of digital technology in business performance

The estimated model is expressed as $y_i = \alpha + \beta x_i + \varepsilon_i$, with y representing the business performance score and x the digital technology utilization score. Estimates were made using ordinary least squares on composite scores obtained from Rasch-calibrated instruments. Table 5 summarizes the main parameters of OLS results, including unstandardized and standardized coefficients, test statistics, estimation uncertainty, and model fit measures.

Table 4: Summary of ANOVA results between groups

Factor	Number of groups (k)	df (between)	df (whitin)	F	p	η^2	Brief interpretation
Education	6	5	194	2.923	0.014	0.070	Average differences by level; small–medium effects
Type of business	9	8	191	2.700	0.008	0.102	Differences across business typologies: intermediate effects
Length of effort	4	3	196	1.038	0.377	0.016	There is no meaningful difference; The effect is very small
Income	7	6	193	3.603	0.002	0.101	Average difference by income level; intermediate effects

Table 5: Summary of regression results (OLS)

Predictor	B	ONE	β	t(df)	p	CI 95% (B)	R^2	R^2 customized	n
Utilization of digital technology	0.741	0.030	0.866	24.424 (198)	< 0.001	[0.682; 0.800]	0.751	0.750	200

The estimate yielded a standardized β of 0.866 and an unstandardized coefficient of B = 0.741 with an SE of 0.030; The test t(198) = 24.424 yields $p < 0.001$. The 95% confidence interval for B was at [0.682; 0.800]. The intercept was insignificant (B = −1.035; p = 0.545), in line with the concentration of the data, so that the main interpretation focused on the regression slope. The value of $R^2 = 0.751$ (adjusted $R^2 = 0.750$) indicates that about 75 percent of the variation in business performance in the sample can be explained linearly by variations in the use of digital technology. Conversion to effect size $f^2 = R^2/(1 - R^2)$ gives $f^2 \approx 3.02$, which is well above the convention of large effects, thus corroborating the practical significance of the findings.

Graphical examination of residues (Q–Q plots and residual versus predicted values) showed no systematic deviation from normality or linearity, and no significant heteroscedastic patterns appeared. Because the model is a single predictor, the issue of multicollinearity is irrelevant; Screening of the influence of high-impact observations is done visually through Cook leverage and spacing to ensure that no single observation dominates the estimate. The statistical magnitude of t implies that the inferential conclusions remain stable even if the standard deviation is robustly corrected (e.g., HC3). An increase of one unit in the digital technology utilization index is associated with an increase of around 0.74 units in the business performance index. These results are consistent with the findings of Rasch and Wright Map: when digital competencies are in the mid-high range, the adoption of more advanced practices (process automation, marketplace and POS integration, customer analytics) has the potential to deliver measurable performance gains (Boone, 2016; Kastelli et al., 2024). Thus, strengthening digital capacity in these domains is an empirically justified intervention.

3.6. Discussion

The results of Rasch's measurement confirm that the instrument is reliable and valid for assessing the use of digital literacy/technology and the business performance of MSME actors. The high reliability of people and items ensures that the estimation of ability and difficulty is stable, so that the inferential findings derived from the composite score have a strong metric foundation. Visualization via the Wright map shows under-targeting at the upper capability range pattern that in the Rasch literature is commonly associated with potential ceiling effects and decreased precision at the distribution tail. Implicitly, expanding the item bank with advanced items (e.g., marketing automation, data-driven sales analytics, POS–marketplace integration, privacy/cyber management) will increase measurement sensitivity for highly skilled respondents. These results indicate a strong positive association rather than a deterministic causal effect, since the cross-sectional nature of the study does not allow temporal ordering or control of unobserved confounders. Therefore, the interpretation remains correlational and should be understood as a statistical relationship between digital technology use and MSME performance in this specific context.

In addition to the general strengths of the instrument, the Wright Map results reveal a substantive ceiling effect, where a considerable proportion of respondents are located at the upper end of the scale while item difficulty remains concentrated near the mean. This under-targeting reduces measurement precision for highly capable respondents and raises the possibility that performance variance in the upper tier is underestimated. Consequently, the observed strong association between digital utilization and business performance may partly reflect restricted variability among more advanced digital users, rather than purely substantive performance differentiation. Addressing this measurement limitation is essential for future research aiming to evaluate performance tiers more rigorously, especially as digital maturity among urban MSMEs continues to advance.

The regression findings show a strong and significant association between the use of digital technology and business performance. These results are in line with the latest empirical studies that link digital capabilities/strategies with the performance of entrepreneurship and SMEs, including in Indonesia (Khin and Ho, 2019). Substantively, digital capabilities strengthen operational efficiencies (automation of record-keeping, inventory, and payments), expand the market through online channels and measurable promotions, and improve the quality of data-driven decision-making, a mechanism consistent with $R^2 \approx 0.75$ in our model.

From a policy and program perspective, these results support a gradual mentoring strategy: (1) strengthening the foundations (security literacy, basic technical competencies, digital communication); (2) acceleration of intermediate capabilities (content production, online store management, payment integration); and (3) advanced reinforcement (marketing automation, customer analytics, application interface integration) for high-skilled actors. The findings in the Indonesian context also underscore the importance of the link between digital strategies and the intensity of market competition, which contributes to the performance of MSMEs (Abdillah et al., 2023).

The cross-sectional design does not allow for purely causal inference; purposive sampling of program participants can limit generalization; Indication of ceiling effect lowers precision in certain segments. Further research should include a longitudinal design, conduct cross-sector/revenue/location DIF analysis, and refine instrument targeting at the upper tail—recommendations that align with current Rasch interpretation and practice guidelines (Putz et al., 2020). Thus, expanding and deepening the use of digital technology is a promising policy lever to improve the performance of MSME businesses. Methodologically, updating the instrument (adding difficult items) will improve targeting and maintain the validity of the measurement when the digital competence of the actors continues to increase.

The interpretability of the findings should be considered within the characteristics of the sampled population. The purposive sampling procedure exclusively targeted MSMEs enrolled in the Jakpreneur program in Jakarta, which represents a structured urban entrepreneurship development ecosystem rather than the broader MSME landscape in Indonesia. The sample profile was highly skewed toward male-owned businesses (83 percent), and most respondents operated in relatively established and moderately high-income segments. These characteristics likely contribute to higher readiness in digital adoption and may inflate the magnitude of the observed association between digital technology utilization and business performance. Therefore, the conclusions drawn from this study should be interpreted specifically within the context of urban MSMEs receiving systematic governmental support for digital capability upgrading, rather than being generalized to rural or unsupported MSME populations that face distinct resource constraints and market dynamics.

4. Conclusions

This study presents a consistent synthesis of metric and substantive evidence. On the metric side, the 30-item instrument calibrated with the Rasch Model showed high reliability at the respondent (0.94; separation 3.82) and item (0.95; separation 4.50) levels, the average fit index that was in line with the model reference (Infit/Outfit ≈ 1.00; $|ZSTD| \le 2$), as well as positive point-measure correlation for all items (≈0.41–0.74); An average ability of 2.96 logit against an average difficulty of 0.00 logit indicates the highest precision around the mid-range, while the person-item map indicates under targeting in the upper tail. On the substantive side, the most pronounced differences in performance between groups occurred in the type of business and income ($\eta^2 \approx 0.10$; $p < 0.01$), followed by education with a moderate effect ($\eta^2 \approx 0.07$), while the length of the business did not differentiate performance. A simple linear regression model confirms a strong and significant association between the use of digital technology and business performance (B = 0.741; SE = 0.030; β = 0,866; t(198) = 24,424; $p < 0.001$; R^2 = 0.751; 95% CI B = [0.682; 0.800]), so that overall the findings support the validity of the instrument construct and the strategic relevance of digital capabilities for the performance of urban MSMEs.

The implication is that digital capacity building needs to be designed in stages and sector-oriented, including basic practices (security, communication), intermediate capabilities (online stores, payment integration, content management), to advanced competencies (process automation, intersystem integration, customer analytics) so that the impact on performance is realized and measured; Assistance policies must be combined with capital support and digital infrastructure. Key limitations—cross-sectoral design, sampling of intended program participants, and lack of targeting indications—limit generalization and precision to high-capability segments. Further research is recommended using longitudinal or panel designs, testing measurement invariants via cross-sector DIF and income strata, enriching item banks with +3 to +6 logit difficulty, and performing yield robustness tests (e.g., standard strong HC3 errors, quantum regression, and leverage/Cook distance checks). Although the study offers strong empirical evidence, the generalizations remain limited to urban MSMEs involved in structured coaching programs. MSMEs operating in rural or informal contexts can show different digital capability profiles and performance dynamics. This approach will strengthen causal inference, expand the scope of measurement, and improve the policy usability of the findings obtained. Given the intended sample and the structured nature of the Jakpreneur program, these findings should be generalized specifically to urban MSMEs involved in formal coaching and digital support initiatives. A more diverse and less digitally supported MSME population can exhibit different patterns of behavior, resource constraints, and performance outcomes, which can lead to simpler or heterogeneous effect measures.

List of abbreviations

B	Unstandardized regression coefficient
CI	Confidence interval
df	Degrees of freedom
DIF	Differential item functioning

IRB	Institutional review board
Infit	Information-weighted fit statistic
Logit	Log-odds unit of measurement in the Rasch model
MNSQ	Mean square
MSMEs	Micro, small, and medium enterprises
OLS	Ordinary least squares
Outfit	Outlier-sensitive fit statistic
PCA	Principal component analysis
POS	Point of sale
PTMEA Corr	Point-measure correlation
Q–Q plot	Quantile–quantile plot
RSM	Rating scale model
RULER	Reporting standards for Rasch analysis (Rasch reporting guideline)
R^2	Coefficient of determination
SD	Standard deviation
SE	Standard error
SEM	Standard error of measurement
SOPs	Standard operating procedures
STROBE	Strengthening the reporting of observational studies in epidemiology
SVG	Scalable vector graphics
WLE	Weighted likelihood estimate
ZSTD	Standardized z-value of the fit statistic
f^2	Effect size for regression
β	Standardized regression coefficient
η^2	Eta-squared (effect size measure)

Compliance with ethical standards

Ethical considerations

The study involved voluntary participation with informed consent, anonymity, and confidentiality ensured. No personal identifiers were collected, and the research posed minimal risk to participants.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Abdillah A, Widianingsih I, Buchari RA, and Nurasa H (2023). Implications of urban farming on urban resilience in Indonesia: Systematic literature review and research identification. Cogent Food & Agriculture, 9(1): 2216484. https://doi.org/10.1080/23311932.2023.2216484

Boone WJ (2016). Rasch analysis for instrument development: Why, when, and how? CBE—Life Sciences Education, 15(4): rm4. https://doi.org/10.1187/cbe.16-04-0148 **PMid:27856555 PMCid:PMC5132390**

Briggs DC (2019). Interpreting and visualizing the unit of measurement in the Rasch model. Measurement, 146: 961-971. https://doi.org/10.1016/j.measurement.2019.07.035

Carpenter S (2018). Ten steps in scale development and reporting: A guide for researchers. Communication Methods and Measures, 12(1): 25-44. https://doi.org/10.1080/19312458.2017.1396583

Darrow JB and Behrend TS (2017). Person-environment fit is a formative construct. Journal of Vocational Behavior, 103: 117-131. https://doi.org/10.1016/j.jvb.2017.08.007

Deichmann U, Goyal A, and Mishra D (2016). Will digital technologies transform agriculture in developing countries? Agricultural Economics, 47(S1): 21-33. https://doi.org/10.1111/agec.12300 **PMCid:PMC9342736**

Escandon-Barbosa D and Salas-Paramo J (2025). Driving success: Leveraging strategic decision-making and digital technology for sustainable performance. Journal of Open Innovation: Technology, Market, and Complexity, 11(2): 100536. https://doi.org/10.1016/j.joitmc.2025.100536

Flake JK, Pek J, and Hehman E (2017). Construct validation in social and personality research: Current practice and recommendations. Social Psychological and Personality Science, 8(4): 370-378. https://doi.org/10.1177/1948550617693063

Hilaliyah H, Agustin Y, Setiawati S, Hapsari SN, Rangka IB, and Ratodi M (2019). Wright-map to investigate the actual abilities on math test of elementary students. Journal of Physics: Conference Series, 1318: 012067. https://doi.org/10.1088/1742-6596/1318/1/012067

Hokmabadi H, Rezvani SM, and de Matos CA (2024). Business resilience for small and medium enterprises and startups by digital transformation and the role of marketing capabilities—A systematic review. Systems, 12(6): 220. https://doi.org/10.3390/systems12060220

Kastelli I, Dimas P, Stamopoulos D, and Tsakanikas A (2024). Linking digital capacity to innovation performance: The mediating role of absorptive capacity. Journal of the Knowledge Economy, 15: 238-272. https://doi.org/10.1007/s13132-022-01092-w **PMid:40479428 PMCid:PMC9589644**

Khin S and Ho TC (2019). Digital technology, digital capability and organizational performance: A mediating role of digital innovation. International Journal of Innovation Science, 11(2): 177-195. https://doi.org/10.1108/IJIS-08-2018-0083

Kim TK (2017). Understanding one-way ANOVA using conceptual figures. Korean Journal of Anesthesiology, 70(1): 22-26. https://doi.org/10.4097/kjae.2017.70.1.22 **PMid:28184262 PMCid:PMC5296382**

Klein VB and Todesco JL (2021). COVID-19 crisis and SMEs responses: The role of digital transformation. Knowledge and Process Management, 28(2): 117-133. https://doi.org/10.1002/kpm.1660 **PMCid:PMC8206955**

Matarazzo M, Penco L, Profumo G, and Quaglia R (2021). Digital transformation and customer value creation in made in Italy SMEs: A dynamic capabilities perspective. Journal of Business Research, 123: 642-656. https://doi.org/10.1016/j.jbusres.2020.10.033

Putritamara JA, Hartono B, Toiba H, Utami HN, Rahman MS, and Masyithoh D (2023). Do dynamic capabilities and digital transformation improve business resilience during the COVID-19 pandemic? Insights from beekeeping MSMEs in Indonesia. Sustainability, 15(3): 1760. https://doi.org/10.3390/su15031760

Putz LM, Hofbauer F, and Treiblmaier H (2020). Can gamification help to improve education? Findings from a longitudinal study. Computers in Human Behavior, 110: 106392. https://doi.org/10.1016/j.chb.2020.106392

Ukko J, Nasiri M, Saunila M, and Rantala T (2019). Sustainability strategy as a moderator in the relationship between digital business strategy and financial performance. Journal of Cleaner Production, 236: 117626. https://doi.org/10.1016/j.jclepro.2019.117626

Yaniar N, Sasono AD, Sukoco A, and Rosyid A (2021). Financial technology and digital marketing on MSMEs and their impact on financial performance and business sustainability. International Journal of Entrepreneurship and Business Development, 4(6): 828-838. https://doi.org/10.29138/ijebd.v4i6.1546