



Artificial Intelligence Adoption and Business Performance among Informal Youth Entrepreneurs in Zambia

Clement Mwaanga*^{ID}, Edwin Moyo^{ID}
Mulungushi University, Zambia

Received : July 31, 2026

Revised : August 12, 2026

Accepted : October 16, 2026

Online : October 19, 2026

Abstract

Informal enterprises absorb most youth employment in Sub-Saharan Africa, yet it remains unclear whether artificial intelligence (AI) improves their performance or widens the digital divide. This study extends the Technology Acceptance Model (TAM) by linking perceived usefulness (PU) and perceived ease of use (PEOU) to AI adoption and to financial (FP), marketing (MP) and operational (OP) performance among informal youth entrepreneurs in Zambia. Survey data from owner-operators aged 18–35 were analysed with confirmatory factor analysis and covariance-based structural equation modelling, using a cluster bootstrap because the data file contained paired, near-identical records. PEOU, but not PU, predicted AI adoption. AI adoption was positively associated with all three performance dimensions, most strongly with operational performance. PEOU had significant indirect effects on performance through AI adoption; however, when we added direct paths from PEOU to performance, these indirect effects were no longer significant, and PEOU was directly associated with marketing and operational performance. Measurement quality was modest, particularly for the AI adoption scale, and model fit was below conventional benchmarks, so the findings should be read as exploratory. In informal, resource-constrained settings, usability, rather than perceived usefulness, appears to be the gateway to AI adoption, and AI's performance benefits are associated with how easily entrepreneurs can use it.

Keywords: *Artificial Intelligence, Informal Youth Entrepreneurs, Technology Acceptance Model, Business Performance, Digital Transformation, Zambia*

INTRODUCTION

In Zambia, most young workers earn their living in enterprises that have never registered with a tax authority, filed a formal business plan or obtained institutional credit ([International Labour Organisation \[ILO\], 2023](#); [Zambia Statistics Agency, 2023](#)). These entrepreneurs may be among the hardest for national digital-transformation strategies to reach, because many digital-inclusion channels rely on formal registration and credit systems from which informal operators are largely absent ([Begazo et al., 2023](#)). Artificial intelligence (AI) is quickly changing how businesses of all sizes compete, learn and sustain performance. As a family of technologies that can perceive, reason, and automate tasks that traditionally require human cognition, AI offers benefits beyond simple automation, extending into strategic decision-making ([Shepherd & Majchrzak, 2022](#); [Fossen et al., 2024](#)). In entrepreneurship theory, AI is viewed as an external enabler that supports opportunity recognition, market sensing, customer engagement and operational workflows ([Cristofaro & Bañón-Gomis, 2026](#); [OECD, 2025a](#)). Research on digital technology adoption in small and medium-sized enterprises (SMEs) similarly links advanced digital tools, including machine learning and generative AI, to lower costs, faster customer response, higher sales and more customised services ([Fossen et al., 2024](#); [UNCTAD, 2025](#)).

However, this literature has largely examined formal SMEs in high-income contexts or structured enterprises with systematic business processes, leaving a gap in understanding how

Copyright Holder:

© Mwaanga & Moyo. (2026)

Corresponding author's email: clementmwaanga98@gmail.com

This Article is Licensed Under:



these mechanisms operate in informal, resource-constrained settings (Shepherd & Majchrzak, 2022; Cristofaro & Bañón-Gomis, 2026). Most existing research examines AI adoption in formal or registered SMEs, where organisational routines, workforce skills and governance systems support technology integration (Alisyahbana et al., 2025; OECD, 2025a; UNCTAD, 2025). Informal enterprises, characterised by low registration rates, limited access to finance and inconsistent management practices, face distinct constraints that may hinder AI adoption (Begazo et al., 2023; Nsokolo et al., 2025). Research on digital technology in informal micro-businesses in Zambia and the wider region shows that basic tools such as mobile money, social media and simple apps are widely used for transactions and marketing, whereas AI-specific tools such as generative text or image models and automated analytics remain largely unexplored (Aryeh-Adjei et al., 2025; Sikalumbi et al., 2025). Evidence is also lacking on whether AI adoption in these contexts translates into tangible performance outcomes, because adoption alone does not guarantee effective use or value capture (Fossen et al., 2024; OECD, 2025a).

Understanding AI adoption among informal youth entrepreneurs matters for three reasons. First, young people make up the majority of Zambia's population; youth unemployment and underemployment remain high, and informal enterprises provide most youth employment (ILO, 2023; Zambia Statistics Agency, 2023); therefore, productivity in this segment affects employment and poverty reduction. Second, Zambia's National Digital Transformation Strategy 2023–2027 emphasises digital inclusion and the adoption of advanced technologies. However, evidence on how such strategies reach micro and informal enterprises is limited (Ministry of Technology and Science, Zambia, 2023). Third, development agencies increasingly promote AI as a lever for enterprise performance while cautioning that, without complementary skills, infrastructure and governance arrangements, technology adoption can widen rather than close existing inequalities (OECD, 2025b; UNCTAD, 2025).

The study contributes in three ways. Theoretically, it extends TAM by situating it within the informal economy, where formal procedures, organisational structures and predictable routines are weak or absent (Alisyahbana et al., 2025; Fossen et al., 2024), and by linking AI adoption to performance outcomes rather than to intentions alone. Practically, it offers evidence for entrepreneurship-support organisations, educators and policymakers on how to support AI use among informal youth ventures (OECD, 2025b; UNCTAD, 2025). For policy, it provides Zambian evidence relevant to implementing the National Digital Transformation Strategy.

Accordingly, the study has three objectives: (1) to examine whether perceived usefulness and perceived ease of use predict AI adoption among informal youth entrepreneurs in Zambia; (2) to assess the relationships between AI adoption and financial, marketing and operational performance; and (3) to test whether AI adoption mediates the relationships between perceived usefulness, perceived ease of use and each performance dimension.

LITERATURE REVIEW

Technology Acceptance Model

AI adoption by informal youth entrepreneurs remains under-theorised, particularly in Sub-Saharan Africa, where owner-managed micro-enterprises dominate economic activity. Organisational-level frameworks such as the technology–organisation–environment (TOE) framework explain the contextual determinants of adoption, but the cognitive mechanisms behind individual-level acceptance require a complementary lens. In owner-operated enterprises, the adopter and the organisation are effectively the same person, which makes an individual-level model appropriate. The Technology Acceptance Model (TAM) offers a parsimonious and well-validated framework for explaining how beliefs about usefulness and ease of use shape intention and actual use (Davis, 1989; Venkatesh & Davis, 2000).

TAM posits that perceived usefulness (PU), the belief that using a system enhances job performance, is the strongest predictor of technology adoption (Davis, 1989). Among informal youth entrepreneurs, PU reflects beliefs about whether AI tools improve sales conversion, customer engagement, operational efficiency and decision quality. Recent generative-AI studies confirm that performance-oriented beliefs remain central to adoption intentions (Sharma et al., 2025; Song et al., 2025). Perceived ease of use (PEOU) refers to the extent to which using a technology is free of effort (Davis, 1989), and TAM proposes that PEOU also shapes PU because easier technologies are more readily seen as useful. Where digital skills and infrastructure are limited, the ease of prompting, mobile compatibility and reliability of AI outputs become critical determinants of sustained use (Ibrahim et al., 2025; Zavodna et al., 2024).

Although TAM was developed to explain acceptance and use, PU is fundamentally performance-focused. If AI adoption is motivated by the belief that it improves business outcomes, it is logical to ask whether its use is in fact associated with better performance. This study therefore models PU and PEOU as antecedents of AI adoption and links adoption to performance outcomes, extending TAM into an under-explored informal-economy context.

Perceived Usefulness and AI Adoption

Contemporary research confirms that PU remains a central determinant of AI-adoption decisions. In studies of generative AI tools, PU predicts both behavioural intention and intensity of use, even when users face skill and infrastructure constraints (Sharma et al., 2025; Song et al., 2025). The effect of PU is not uniform across contexts, however: evidence from resource-constrained SME settings indicates that structural barriers such as connectivity, cost and digital literacy can prevent perceived benefits from translating into actual use (Zavodna et al., 2024), suggesting that the strength of the PU–adoption relationship depends on infrastructural and institutional context. For informal youth entrepreneurs facing resource shortages, time pressures and competitive markets, the perception that AI can improve performance is nonetheless likely to matter for the decision to adopt it.

H1: Perceived usefulness of AI is positively associated with AI adoption among informal youth entrepreneurs in Zambia.

Perceived Ease of Use and AI Adoption

In the AI domain, PEOU refers to whether users see AI tools as understandable, easy to learn, intuitive and simple to incorporate into daily tasks. Technologies that lower learning effort and operational barriers are more likely to be tried and integrated into routines. Recent studies confirm that ease-of-use perceptions influence generative-AI adoption among SMEs and young users, although the effect is often weaker than that of PU and varies by context (Bahaw et al., 2025; Ibrahim et al., 2025). Evidence from digitally engaged SME populations suggests that once users cross a threshold of basic digital literacy, ease of use ceases to predict adoption and infrastructural constraints become binding (Alisyahbana et al., 2025). In contrast, in informal settings where cost and connectivity dominate, PEOU may be attenuated regardless of how easy a tool is (Aryeh-Adjei et al., 2025). Most research has focused on formal firms and student populations (Mwaanga et al., 2022), providing limited insight into informal youth entrepreneurship. In Zambia, where informality dominates employment and digital-skills gaps persist, ease of use raises concerns about whether informal youth entrepreneurs can understand, access, trust, and apply AI under resource-limited conditions.

H2: Perceived ease of use is positively associated with AI adoption among informal youth entrepreneurs in Zambia.

AI Adoption and Business Performance

AI adoption is increasingly treated as a driver of business performance among SMEs and entrepreneurial ventures (Yesuf et al., 2025). Machine learning, predictive analytics and generative AI help entrepreneurs automate processes, analyse market data, improve customer engagement and make better decisions (Le Dinh et al., 2025). Studies generally find that AI adoption improves financial performance (FP) through productivity gains, cost reductions and increased revenue (Wamba-Taguimdje et al., 2020; Abrokwah-Larbi & Awuku-Larbi, 2024; Magableh et al., 2024), although financial gains may lag behind improvements in internal processes (OECD, 2025a).

AI adoption also affects marketing performance (MP). AI tools enable businesses to analyse customer data, personalise messages, produce promotional content and enhance customer engagement (Ledro et al., 2025; Zahara et al., 2023), improving segmentation and responsiveness to consumer needs (Beyari & Hashem, 2025). For entrepreneurs operating in social-media-driven markets, faster customer communication and more efficient promotion can raise customer satisfaction and loyalty (Afriyie et al., 2019). The literature further links AI adoption to operational performance (OP): automation, process optimisation, inventory management and decision support streamline daily operations and reduce time spent on repetitive tasks (Andayani et al., 2024; Cimino et al., 2025). Operational improvements are often the first observable benefit of AI, which is particularly valuable for small businesses whose owners manage several functions at once.

These benefits are not automatic. They depend on entrepreneurs' skills, resources and ability to embed AI in daily activities, and studies of SMEs in emerging and resource-constrained settings report null or even negative short-run effects where implementation disrupts workflows or costs outweigh gains (Boonmee et al., 2025; Sánchez et al., 2025). Because AI's effects may therefore differ across outcomes, this study tests them separately for the financial, marketing and operational dimensions.

H3: AI adoption is positively associated with financial performance among informal youth entrepreneurs.

H4: AI adoption is positively associated with marketing performance among informal youth entrepreneurs.

H5: AI adoption is positively associated with operational performance among informal youth entrepreneurs.

The Mediating Role of AI Adoption

Because TAM positions technology use as the behavioural channel through which beliefs about a technology affect outcomes, AI adoption is expected to transmit the effects of PU and PEOU to business performance. Beliefs alone cannot improve sales, marketing reach or efficiency unless they lead entrepreneurs to use AI in their businesses. In line with the third objective, the following hypothesis is proposed:

H6: AI adoption mediates the relationships between (a) perceived usefulness and (b) perceived ease of use and the financial, marketing and operational performance of informal youth entrepreneurs.

Figure 1 presents the conceptual framework. H6 is tested through the indirect paths implied by the model (PU/PEOU → AI adoption → performance).

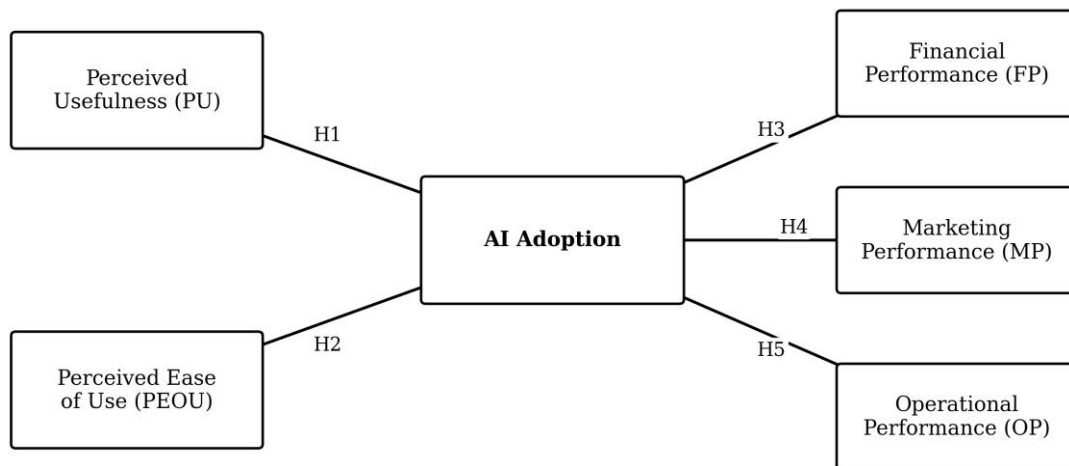


Figure 1. Conceptual framework and hypothesised relationships

RESEARCH METHOD

Study Setting and Sampling

The study focuses on informal youth entrepreneurs aged 18 to 35 years in Zambia. Because Zambia's informal sector lacks a comprehensive business register, no probability sampling frame was available. Hence, the study adopted a purposive, multi-site strategy targeting informal enterprises in urban and peri-urban trading areas. Eligible participants were owner-operators aged 18–35 who identified their enterprise as informal (unregistered or not fully tax-compliant, following the Zambia Statistics Agency's operational definition) and had been trading for at least three months. Trained enumerators approached entrepreneurs at their places of business, explained the study's purpose, the voluntary nature of participation, the confidentiality of responses, and the right to withdraw, and obtained written informed consent before administering the structured questionnaire on paper or a tablet. Of the 320 questionnaires administered, 300 were returned and usable (94% response rate).

All respondents completed every scale, including the 122 respondents (40.7%) who reported that they did not currently use AI tools; for these respondents, the AI adoption items capture the absence or low intensity of use, and the PU and PEOU items capture their expectations of AI tools. Data screening identified two further issues. First, 24 records contained at least one missing item response; these were excluded listwise, leaving 276 records for the measurement and structural models. Second, records 151–300 closely matched records 1–150: within each pair, the 31 item responses were identical or differed on no more than two items. Because such records cannot be treated as statistically independent, all inferential statistics were computed with a cluster bootstrap in which each matched pair was resampled together, so that standard errors and confidence intervals reflect approximately 150 independent responses rather than 300.

Measures

All constructs were measured with multi-item scales adapted from validated instruments and scored on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). PU and PEOU items were adapted from Davis (1989) and Venkatesh et al. (2003). AI adoption items were developed with reference to recent work on AI adoption in SMEs (Le Dinh et al., 2025; OECD, 2025a). Financial, marketing and operational performance were adapted from Wiklund and Shepherd (2005), Trainor et al. (2014), Venkatraman (1989) and Le Dinh et al. (2025). The questionnaire contained 26 items measuring six constructs; 24 were retained after measurement

refinement (Table 1).

Data Analysis

Descriptive statistics and data screening were conducted in SPSS. Confirmatory factor analysis (CFA) and covariance-based structural equation modelling (SEM) were conducted in Python using the semopy package (Igolkina & Meshcheryakov, 2020) with maximum-likelihood estimation. SEM was chosen over multiple regression because it estimates the measurement and structural models simultaneously, corrects for measurement error in latent constructs and allows direct and indirect effects to be tested within one framework. The analysis followed Anderson and Gerbing's (1988) two-step procedure: the measurement model was validated first, and the structural model was then estimated. In the structural model, PU and PEOU were allowed to covary, and the disturbances of the three performance constructs were allowed to covary because the performance dimensions are expected to share causes other than AI adoption.

Standardised coefficients are reported. Their standard errors, two-sided p-values and 95% bias-corrected (BC) confidence intervals were obtained from 5,000 cluster-bootstrap resamples, in which the 150 matched record pairs were resampled with replacement. Resamples yielding improper solutions (a standardised structural coefficient with an absolute value above 1) were discarded (187 of 5,000 for the hypothesised model). Indirect effects were computed as the products of their constituent standardised paths and judged significant when the BC interval excluded zero (Zhao et al., 2010). Variance explained (R^2) is reported for each endogenous construct. Heterotrait–monotrait (HTMT) ratios were calculated from the item correlation matrix following Henseler et al. (2015). Model fit was evaluated against conventional criteria (CFI and TLI ≥ 0.90 , RMSEA ≤ 0.08 , SRMR ≤ 0.08 ; Hu & Bentler, 1999; Kline, 2023).

Reliability and Validity

Indicator reliability was assessed through standardised factor loadings. Two AI adoption items, AI3 and AI4, loaded weakly or negatively (0.19 and -0.08 in a CFA with all five items) and were removed (Kline, 2023). Because both removed items captured analytical and decision-support uses of AI, the refined three-item scale represents adoption mainly in terms of frequency of use, marketing use and integration into daily operations. The remaining loadings ranged from 0.271 to 0.791 (Table 1). Twenty of the 24 loadings exceeded 0.60; PU4 (0.598), PEOU3 (0.588) and AI2 (0.578) fell just below this level, and AI5 loaded weakly (0.271). These items were retained for content validity because removing AI5 would leave a two-item adoption scale.

Cronbach's alpha and composite reliability (CR) exceeded 0.70 for PU, PEOU, FP, MP and OP ($\alpha = 0.752$ – 0.802 ; CR = 0.755–0.805) but not for AI adoption ($\alpha = 0.538$; CR = 0.545). Average variance extracted (AVE) reached 0.50 only for OP (0.509); it ranged from 0.437 to 0.471 for PU, PEOU, FP and MP and was 0.311 for AI adoption. Following Fornell and Larcker (1981), convergent validity is adequate when AVE is below 0.50, but CR exceeds 0.60, which holds for every construct except AI adoption. Discriminant validity was supported by HTMT ratios, all below 0.85 (maximum 0.801 for PU–PEOU; Henseler et al., 2015), but the Fornell–Larcker criterion was not met for four pairs, in which the latent correlation exceeded the square root of at least one AVE: PU–PEOU (0.790), FP–MP (0.767), PEOU–OP (0.678) and AI–OP (0.571) (Table 2). The AI adoption measure is therefore the weakest part of the model, and results involving it are interpreted with caution.

Table 1. Factor loadings, reliability and convergent validity

Construct / item	Loading	α / CR / AVE
Perceived usefulness (PU) (Davis, 1989; Venkatesh et		$\alpha = 0.788$; CR = 0.794;

Construct / item	Loading	α / CR / AVE
al., 2003)		AVE = 0.437
PU1 Using AI improves my business productivity.	0.628	
PU2 Using AI helps me make better business decisions.	0.730	
PU3 AI enhances the efficiency of my business operations.	0.619	
PU4 AI improves customer service in my business.	0.598	
PU5 AI increases overall business performance.	0.720	
Perceived ease of use (PEOU) (Davis, 1989; Venkatesh et al., 2003)		α = 0.759; CR = 0.765; AVE = 0.450
PEOU1 Learning to use AI tools is easy for me.	0.677	
PEOU2 AI tools are easy to use.	0.730	
PEOU3 Interaction with AI tools is clear and understandable.	0.588	
PEOU4 It is easy for me to become skilled at using AI.	0.680	
AI adoption (AI)		α = 0.538; CR = 0.545; AVE = 0.311
AI1 I frequently use AI tools in my business.	0.725	
AI2 I use AI for marketing activities.	0.578	
AI5 AI is integrated into my daily business operations.	0.271	
Removed: AI3 ("AI helps me analyse business information") and AI4 ("AI supports decision-making in my business"), loadings 0.19 and -0.08.		
Financial performance (FP) (Venkatraman, 1989; Wiklund & Shepherd, 2005)		α = 0.752; CR = 0.755; AVE = 0.437
FP1 My business sales have increased.	0.634	
FP2 My business profitability has improved.	0.609	
FP3 My revenue growth has increased.	0.769	
FP4 My financial performance is better than that of my competitors.	0.620	
Marketing performance (MP) (Trainor et al., 2014)		α = 0.775; CR = 0.779; AVE = 0.471
MP1 Customer engagement in my business has improved.	0.618	
MP2 My marketing activities have become more effective.	0.701	
MP3 My customer base has increased.	0.791	
MP4 My business visibility has improved.	0.621	
Operational performance (OP) (Venkatraman, 1989; Le Dinh et al., 2025)		α = 0.802; CR = 0.805; AVE = 0.509
OP1 My business operations are more efficient.	0.621	
OP2 Tasks are completed faster in my business.	0.782	
OP3 Operational costs have reduced.	0.739	
OP4 My business productivity has improved.	0.702	

Note. Standardised loadings from the six-factor CFA (n = 276). Items scored 1 = strongly disagree to 5 = strongly agree. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Table 2. Discriminant validity: Fornell–Larcker criterion (below diagonal) and HTMT ratios (above diagonal)

	CR	AVE	PU	PEOU	AI	FP	MP	OP
PU	0.794	0.437	0.661					
PEOU	0.765	0.450	0.790	0.671				
AI	0.545	0.311	0.468	0.547	0.558			
FP	0.755	0.437	0.534	0.525	0.532	0.661		
MP	0.779	0.471	0.499	0.517	0.407	0.767	0.686	
OP	0.805	0.509	0.628	0.678	0.571	0.614	0.488	0.713

Note. Bold diagonal values are the square roots of AVE; values below the diagonal are latent correlations from the CFA; values above the diagonal are HTMT ratios.

Common Method Bias

Because all constructs were measured with self-reports from a single respondent per enterprise, common method bias (CMB) was addressed procedurally and statistically (Podsakoff et al., 2003). Procedurally, respondents were assured of anonymity and confidentiality, were told that there were no right or wrong answers, and answered the predictor items (PU, PEOU, AI adoption) and outcome items (business performance) in separate sections of the questionnaire. Statistically, three tests were conducted. First, in Harman's single-factor test, all 24 retained items were entered into one unrotated factor analysis; the first factor accounted for 31.3% of the total variance, below the 50% threshold. Second, a single-factor CFA fit substantially worse than the six-factor measurement model ($\Delta\chi^2(15) = 502.97$, $p < .001$). Third, full-collinearity variance inflation factors for the six constructs, computed from construct composite scores, ranged from 1.19 to 1.96, below the 3.3 threshold (Kock, 2015). Because Harman's test is weak on its own (Podsakoff et al., 2003), the three tests are considered jointly; together they indicate that CMB is unlikely to account for the results.

Additional Diagnostic Tests

Three further checks were conducted. First, the variance inflation factor for PU and PEOU in the AI adoption equation was 1.64, below the 3.3 and 5.0 thresholds (Hair et al., 2022; Kock, 2015); each performance equation has a single predictor, so collinearity does not arise there. Second, univariate skewness ranged from -1.36 to 0.79, and excess kurtosis from -0.70 to 3.09, below the levels that Kline (2023) treats as severe ($|\text{skewness}| > 3$; $|\text{kurtosis}| > 10$), but Mardia's multivariate kurtosis was 123.30 (critical ratio = 28.99), indicating multivariate non-normality. Because maximum-likelihood standard errors can be biased under non-normality, all inferences rely on bootstrap confidence intervals, which do not assume normality (Kline, 2023). Third, because 122 respondents did not use AI tools, the structural model was re-estimated for current AI users only (n = 168 complete records); the results are reported with the hypothesis tests.

FINDINGS AND DISCUSSION

Respondent Profile

Table 3 summarises the 300 records. Most respondents were aged 30–35 years (40.7%), and 62.0% were male, consistent with broader patterns of informal entrepreneurship, where male participation is higher (ILO, 2023). Overall, 59.3% reported using AI tools and 40.7% did not, indicating a pronounced divide between users and non-users. Most respondents held a diploma or degree (72.3%), suggesting a relatively educated entrepreneurial base. Businesses were concentrated in services (27.3%) and retail (26.7%), followed by digital businesses (21.3%) and agriculture (17.0%).

Table 3. Characteristics of the respondents (N = 300)

Characteristic	Category	N	%
Age	18–24	78	26.0
	25–29	100	33.3
	30–35	122	40.7
Gender	Male	186	62.0
	Female	114	38.0
Uses AI tools	Yes	178	59.3
	No	122	40.7
Years in business	1 year or less	130	43.3
	1–3 years	170	56.7
Education	Primary	28	9.3
	Secondary	55	18.3
	Diploma	112	37.3
	Degree	105	35.0
Type of business	Retail	80	26.7
	Digital	64	21.3
	Services	82	27.3
	Agriculture	51	17.0
	Other	23	7.7

Measurement Model

The six-factor measurement model showed mixed fit: $\chi^2(237) = 659.92$, $\chi^2/\text{df} = 2.78$, CFI = 0.830, TLI = 0.802, RMSEA = 0.081 (90% CI [0.073, 0.088]), SRMR = 0.061. The χ^2/df ratio and SRMR met conventional criteria, and RMSEA was marginal, but CFI and TLI fell below 0.90 (Hu & Bentler, 1999; Marsh et al., 2004). Together with the reliability and validity results above, this indicates that the measurement model is adequate for exploratory purposes but not strong, with the AI adoption scale as the main weakness.

Hypothesis Testing

The structural model showed similar fit: $\chi^2(243) = 689.72$, $\chi^2/\text{df} = 2.84$, CFI = 0.821, TLI = 0.796, RMSEA = 0.082 (90% CI [0.075, 0.089]), SRMR = 0.063. The χ^2/df ratio and SRMR met conventional criteria, RMSEA was marginal, and CFI and TLI fell below 0.90, so the structural

estimates are interpreted with caution. Table 4 reports the direct effects, Table 5 the variance explained and Table 6 the indirect effects.

Table 4. Structural model results: direct effects (hypothesised model)

Hypothesis	Path	β	SE	95% BC CI	p	Decision
H1	PU $\rightarrow$ AI	0.290	0.216	[-0.203, 0.665]	.161	Not supported
H2	PEOU $\rightarrow$ AI	0.557	0.197	[0.125, 0.913]	.015	Supported
H3	AI $\rightarrow$ FP	0.697	0.148	[0.330, 0.917]	.002	Supported
H4	AI $\rightarrow$ MP	0.622	0.173	[0.140, 0.866]	.014	Supported
H5	AI $\rightarrow$ OP	0.823	0.160	[0.482, 1.000]	.003	Supported

Note. β = standardised coefficient; SE, p and BC CI from 5,000 cluster-bootstrap resamples (matched record pairs resampled together; 187 improper solutions discarded). n = 276.

PEOU was positively associated with AI adoption ($\beta = 0.557$, 95% BC CI [0.125, 0.913]), whereas PU was not ($\beta = 0.290$, [-0.203, 0.665]); H2 is supported, and H1 is not. AI adoption was positively associated with financial performance ($\beta = 0.697$, [0.330, 0.917]), marketing performance ($\beta = 0.622$, [0.140, 0.866]) and operational performance ($\beta = 0.823$, [0.482, 1.000]), supporting H3, H4 and H5 (Figure 2). The upper limit of the interval for operational performance reaches 1.000, suggesting this estimate lies close to the boundary of an admissible solution and should not be over-interpreted. Together, PU and PEOU explain 65.0% of the variance in AI adoption, and AI adoption explains 48.6%, 38.7% and 67.7% of the variance in FP, MP and OP, respectively (Table 5). Because PU and PEOU are strongly correlated ($r = 0.790$), their separate contributions should be read with caution: PU adds little unique explanation once PEOU is controlled.

Table 5. Variance explained in the endogenous constructs

Endogenous construct	Predictor(s)	R ²
AI adoption	PU, PEOU	0.650
FP	AI adoption	0.486
MP	AI adoption	0.387
OP	AI adoption	0.677

PEOU had significant indirect effects through AI adoption on financial (indirect $\beta = 0.388$, 95% BC CI [0.104, 0.716]), marketing (0.346, [0.058, 0.687]) and operational performance (0.458, [0.106, 0.782]), whereas none of the indirect effects of PU was significant (Table 6). Therefore, the hypothesised model supports H6b but not H6a.

Table 6. Indirect effects through AI adoption (H6)

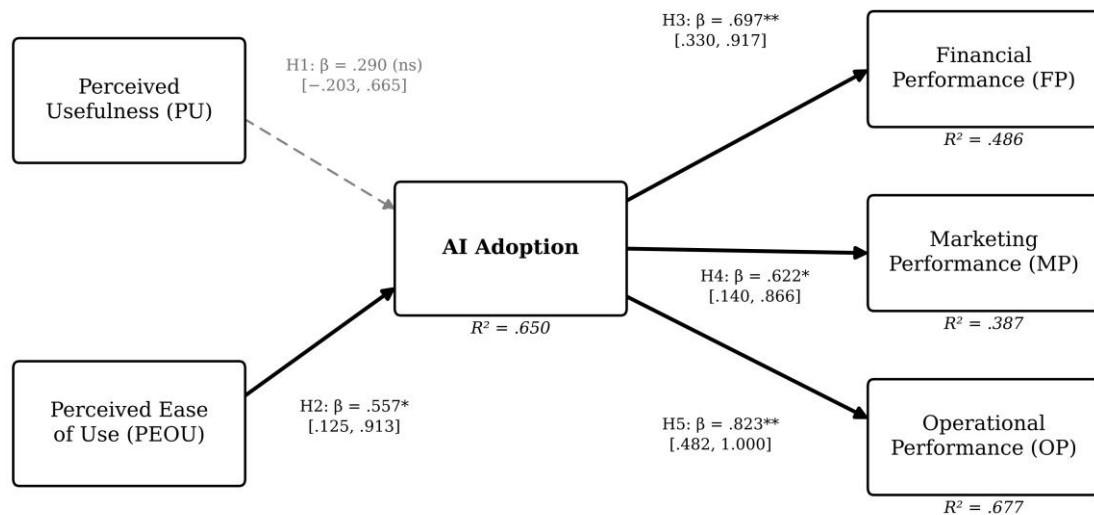
Indirect path	Indirect β	SE	95% BC CI	Result
PEOU $\rightarrow$ AI $\rightarrow$ FP	0.388	0.154	[0.104, 0.716]	Significant
PEOU $\rightarrow$ AI $\rightarrow$ MP	0.346	0.157	[0.058, 0.687]	Significant
PEOU $\rightarrow$ AI $\rightarrow$ OP	0.458	0.171	[0.106, 0.782]	Significant
PU $\rightarrow$ AI $\rightarrow$ FP	0.202	0.140	[-0.070, 0.485]	Not significant
PU $\rightarrow$ AI $\rightarrow$ MP	0.180	0.130	[-0.034, 0.492]	Not significant

Indirect path	Indirect β	SE	95% BC CI	Result
PU $\rightarrow$ AI $\rightarrow$ OP	0.239	0.158	[-0.057, 0.568]	Not significant

Note. Indirect β is the product of the constituent standardised paths in Table 4. An effect is significant when the 95% bias-corrected cluster-bootstrap CI excludes zero.

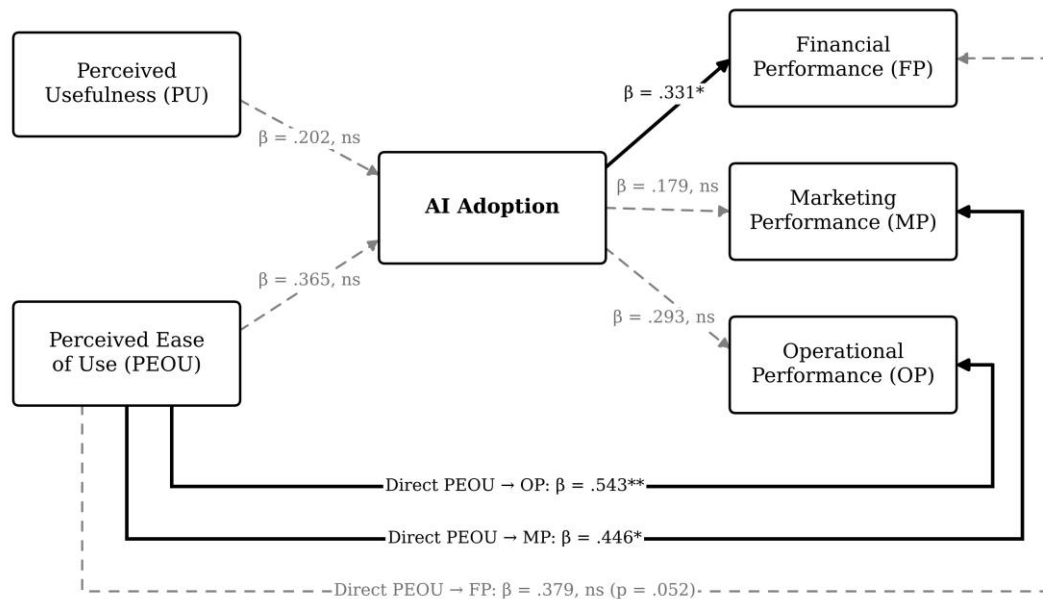
Because the hypothesised model contains no direct paths from PEOU to performance, it cannot show whether this mediation is partial or full (Zhao et al., 2010). A supplementary model that added direct paths from PEOU to FP, MP and OP fitted significantly better ($\Delta\chi^2(3) = 25.18, p < .001$; CFI = 0.830, TLI = 0.804, RMSEA = 0.080, SRMR = 0.062). In this model, PEOU had significant direct effects on marketing ($\beta = 0.446, [0.024, 0.801]$) and operational performance ($\beta = 0.543, [0.187, 0.799]$) and a direct effect on financial performance whose interval narrowly included zero ($\beta = 0.379, [-0.110, 0.676]$). Its indirect effects through AI adoption were no longer significant (FP: 0.121, [-0.018, 0.513]; MP: 0.065, [-0.035, 0.367]; OP: 0.107, [-0.005, 0.455]), and only the AI adoption $\rightarrow$ FP path remained significant ($\beta = 0.331, [0.021, 0.821]$). The total effects of PEOU on performance remained significant (FP: 0.499, [0.109, 0.765]; MP: 0.512, [0.169, 0.817]; OP: 0.650, [0.370, 0.875]). Figure 3 shows this model; 15.5% of its bootstrap resamples produced improper solutions, further indicating instability linked to the weak AI adoption measure. The evidence for H6b is therefore not robust: the association between ease of use and performance appears to be largely direct rather than channelled through AI adoption.

Finally, when the hypothesised model was re-estimated for current AI users only ($n = 168$), the PEOU $\rightarrow$ AI adoption path remained significant ($\beta = 0.787, [0.439, 1.000]$). PU remained non-significant ($\beta = 0.271, [-0.637, 0.704]$), but the paths from AI adoption to FP ($\beta = 0.255$), MP ($\beta = 0.376$) and OP ($\beta = 0.617$) had confidence intervals that included zero. The performance associations in the full sample therefore depend partly on the contrast between users and non-users of AI.



Note. Standardised coefficients; 95% bias-corrected bootstrap confidence intervals in brackets. * $p < .05$, ** $p < .01$; ns = not significant. Solid lines = supported hypotheses; dashed line = not supported.

Figure 2. Structural model results for the hypothesised model



Note. Solid lines = significant (95% bias-corrected bootstrap CI excludes zero); dashed lines = not significant. * $p < .05$, ** $p < .01$. Model fit: $\chi^2(240) = 664.54$, CFI = .830, TLI = .804, RMSEA = .080, SRMR = .062. Indirect effects of PEOU through AI adoption were not significant.

Figure 3. Supplementary model with direct paths from PEOU to performance

Discussion

The finding that PEOU, but not PU, predicts AI adoption departs from classical TAM studies, in which PU is typically the dominant predictor (Ibrahim et al., 2025; Sharma et al., 2025). The departure aligns with research showing that simplicity and accessibility can outweigh perceived performance benefits among resource-constrained and non-expert users (Alisyahbana et al., 2025; Zavodna et al., 2024). PEOU appears to act as a threshold factor that reduces cognitive burden and builds confidence before users can evaluate usefulness, particularly among those encountering AI for the first time (Ibrahim et al., 2025). Informal youth entrepreneurs typically lack structured training, technical support, and time to learn complex systems, so they favour tools they can use immediately. Notably, PEOU dominated PU despite the relatively high educational attainment of this sample, suggesting that contextual constraints rather than cognitive ability may shape adoption. Two further explanations should be considered. PU and PEOU are highly correlated in these data, and TAM's PEOU → PU path was not modelled, so part of PU's contribution may be absorbed by PEOU; the non-significant PU coefficient indicates that PU adds little unique explanation once PEOU is controlled, not that usefulness is irrelevant. In addition, perceived risks such as fear of costly mistakes with an unfamiliar tool may suppress adoption despite recognised usefulness, although perceived risk was not measured here (Zavodna et al., 2024).

In the hypothesised model, AI adoption was positively associated with all three performance dimensions, and most strongly with operational performance. This pattern aligns with the view that operational improvements are often the first observable benefit of AI, as automation and improved information processing reduce the time owner-operators spend on repetitive tasks (Andayani et al., 2024; Cimino et al., 2025). The associations with financial and marketing performance align with evidence that AI use supports pricing, customer communication, and promotional content that increase revenue and visibility (Abrokwah-Larbi & Awuku-Larbi, 2024;

[Le Dinh et al., 2025](#); [Magableh et al., 2024](#)). These associations should not be read causally. The data are cross-sectional, so better-performing enterprises may be better able to adopt AI, and the associations weakened markedly when we analysed only AI users, suggesting they reflect differences between users and non-users rather than gains that increase with intensity of use.

The mediation results show that the role of AI adoption as a channel from ease of use to performance is sensitive to model specification. When PEOU could affect performance directly, the indirect effects disappeared, and PEOU remained directly associated with marketing and operational performance. One interpretation is that ease of use reflects a broader digital capability (comfort with smartphones, apps and online platforms) that supports marketing and operations whether or not AI tools are used. This extends research framing digital technologies as capability enablers in resource-constrained environments ([Dwivedi et al., 2023](#); [Nambisan et al., 2019](#)) and suggests that, in informal settings, the ability to use technology may matter more than adopting any single tool.

Theoretical Implications

First, the study shows that the relative importance of TAM's core constructs is context-dependent. Contrary to the assumption that PU is the primary determinant of adoption ([Venkatesh et al., 2003](#)), PEOU was the only significant predictor of AI adoption among informal youth entrepreneurs, supporting more contextualised adoption models that incorporate environmental and socioeconomic constraints ([Alisyahbana et al., 2025](#)). Second, the study adds evidence from the informal sector to the still-limited literature on AI and entrepreneurship in developing economies ([Fossen et al., 2024](#); [Le Dinh et al., 2025](#)). Third, the mediation analysis cautions against treating technology adoption as the automatic mechanism linking TAM beliefs to outcomes: ease of use was largely associated with performance directly, suggesting that TAM-based performance models should account for the broader capabilities ease-of-use beliefs may capture. Finally, the study shows that young informal entrepreneurs are already engaging with AI, supporting arguments that informal enterprises can be digitally adaptive ([Begazo et al., 2023](#)).

Policy and Practical Implications

Because ease of use is the clearest determinant of AI adoption, technology developers, trainers and policymakers should treat simplicity as a design requirement rather than a secondary feature. AI solutions for informal entrepreneurs should minimise technical complexity and focus on practical applications such as automated messaging, pricing support and basic record-keeping, designed for mobile devices and low-bandwidth conditions. Training programmes should emphasise hands-on use and build general digital confidence, since ease of use was associated with performance even beyond AI adoption itself. Policymakers can support adoption by expanding affordable internet access, supporting innovation hubs and incubation centres, and providing incentives for digital tools, which are critical for bridging the digital divide within the informal sector ([Begazo et al., 2023](#); [UNCTAD, 2025](#)).

CONCLUSIONS

This study examined factors associated with AI adoption and whether adoption is associated with business performance among informal youth entrepreneurs in Zambia, addressing an evidence gap left by research focused on formal SMEs in high-income countries. In answer to the first objective, PEOU, not PU, predicted AI adoption, indicating that usability is the gateway to AI adoption in this informal context. For the second objective, AI adoption was positively associated with financial, marketing, and operational performance, strongest with operational performance, although these associations weakened when we analysed only AI users. In answer to the third

objective, AI adoption carried significant indirect effects of PEOU on performance in the hypothesised model. However, these did not survive the addition of direct paths, which showed PEOU to be directly associated with marketing and operational performance. The study advances the field by situating TAM in the informal economy and showing that, for informal youth entrepreneurs, ease of use matters more for adoption than perceived usefulness. Given the modest measurement quality and model fit, these conclusions should be treated as exploratory.

LIMITATIONS AND FURTHER RESEARCH

Several limitations qualify these findings. First, the cross-sectional design limits causal inference: SEM tests theoretically grounded associations but cannot establish direction or capture the gradual, iterative nature of AI adoption (Boonmee et al., 2025). Longitudinal studies are needed to examine how adoption and its performance effects evolve as entrepreneurs gain experience. Second, the purposive sample limits generalisability to formal SMEs and to other countries with different institutional support and technological readiness; comparative studies across countries and sectors are recommended (OECD, 2025a).

Third, the data file contained paired, near-identical records and 24 records with missing responses. Although cluster bootstrapping prevents paired records from inflating precision, the effective sample is about 150, which limits statistical power and contributed to unstable estimates in the supplementary model; future studies should verify data entry against source questionnaires and use larger independent samples. Fourth, measurement quality was modest: AVE fell below 0.50 for five constructs, discriminant validity was weak under the Fornell–Larcker criterion for four construct pairs, notably PU–PEOU and FP–MP, model fit was below conventional benchmarks, and the three-item AI adoption scale had low reliability. Future research should develop and pretest AI adoption measures for informal settings that capture distinct types of use (communication, marketing, analytics and operations).

Fifth, the study relies on self-reported data. Although statistical tests indicated that common method bias is unlikely to explain the results, self-reported performance may not fully capture actual outcomes, particularly given informal record-keeping; future studies should use objective data such as mobile-money transaction records where feasible (Sánchez et al., 2025). Sixth, the model includes only TAM variables and omits organisational readiness, environmental pressures and institutional support; integrating TOE, the resource-based view and dynamic-capabilities perspectives, and modelling TAM's PEOU → PU path, would provide a fuller account (Dwivedi et al., 2023; Sánchez et al., 2025). Finally, sector-specific studies in agriculture, retail and services are needed, because readiness, adoption challenges and performance outcomes are likely to differ across sectors.

Acknowledgement

The authors used Claude, an AI assistant developed by Anthropic, to support this manuscript's revision, including arranging the references, while Grammarly was used to edit the language. The authors conducted data analysis, reviewed all outputs and take full responsibility for the content of the article.

REFERENCES

- Abrokwhah-Larbi, K., & Awuku-Larbi, Y. (2024). The impact of artificial intelligence in marketing on the performance of business organisations: Evidence from SMEs in an emerging economy. *Journal of Entrepreneurship in Emerging Economies*, 16(4), 1090–1117. <https://doi.org/10.1108/JEEE-07-2022-0207>
- Afriyie, S., Du, J., & Musah, A.-A. I. (2019). Innovation and marketing performance of SME in an

- emerging economy: The moderating effect of transformational leadership. *Journal of Global Entrepreneurship Research*, 9, Article 40. <https://doi.org/10.1186/s40497-019-0165-3>
- Alisyahbana, A. N. Q. A., Syakur, R. M., Isma, A., Fakhri, M. M., & Dewantara, H. (2025). Inclusive competitiveness through AI use in informal SMEs: Evidence from an extended TAM–TOE model. *Journal of Economic Education and Entrepreneurship Studies*, 6(4), 423–436. <https://journal.feb-unm.com/index.php/JE3S/article/view/2>
- Andayani, D., Indiyati, D., Sari, M. M., Yao, G., & Williams, J. (2024). Leveraging AI-powered automation for enhanced operational efficiency in small and medium enterprises (SMEs). *APTISI Transactions on Management*, 8(3), 250–258. <https://doi.org/10.33050/atm.v8i3.2363>
- Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103(3), 411–423. <https://doi.org/10.1037/0033-2909.103.3.411>
- Aryeh-Adjei, A. A., Adu, K. K., Adu-Marfo, A. O., & Awuku, G. (2025). Digital technology use and adoption in informal entrepreneurship: Evidence from Okere District, Ghana. *Journal of Innovation and Entrepreneurship*, 14(1), Article 144. <https://doi.org/10.1186/s13731-025-00611-8>
- Bahaw, P., Forgenie, D., Sadiq, G., & Sookhai, S. (2025). Generative AI for business sustainability: Examining usability, usefulness, and triple bottom line impacts in small and medium enterprises. *Sustainable Futures*, 10, Article 100815. <https://doi.org/10.1016/j.sftr.2025.100815>
- Begazo, T., Blimpo, M. P., & Dutz, M. A. (2023). *Digital Africa: Technological transformation for jobs*. World Bank. <https://doi.org/10.1596/978-1-4648-1737-3>
- Beyari, H., & Hashem, T. (2025). The role of artificial intelligence in personalizing social media marketing strategies for enhanced customer experience. *Behavioral Sciences*, 15(5), Article 700. <https://doi.org/10.3390/bs15050700>
- Boonmee, C., Mangkalakeeree, J., & Jeong, Y. (2025). Towards sustainable digital transformation: AI adoption barriers and enablers among SMEs in Northern Thailand. *Sustainable Futures*, 10, Article 101169. <https://doi.org/10.1016/j.sftr.2025.101169>
- Cimino, A., Corvello, V., Troise, C., Thomas, A., & Tani, M. (2025). Artificial intelligence adoption for sustainable growth in SMEs: An extended dynamic capability framework. *Corporate Social Responsibility and Environmental Management*, 32(5), 6120–6138. <https://doi.org/10.1002/csr.70019>
- Cristofaro, M., & Bañón-Gomis, A. J. (2026). Dancing with the algorithm: A framework to navigate knowledge and autonomy in AI-assisted managerial decisions. *Journal of Knowledge Management*, 30(11). <https://doi.org/10.1108/JKM-06-2025-0870>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). Opinion paper: “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, Article 102642. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>

- Fossen, F. M., McLemore, T., & Sorgner, A. (2024). Artificial intelligence and entrepreneurship. *Foundations and Trends in Entrepreneurship*, 20(8), 781–904. <https://doi.org/10.1561/0300000130>
- Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>
- Ibrahim, F., Münscher, J.-C., Daseking, M., & Telle, N.-T. (2025). The technology acceptance model and adopter type analysis in the context of artificial intelligence. *Frontiers in Artificial Intelligence*, 7, Article 1496518. <https://doi.org/10.3389/frai.2024.1496518>
- Igolkina, A. A., & Meshcheryakov, G. (2020). semopy: A Python package for structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 27(6), 952–963. <https://doi.org/10.1080/10705511.2019.1704289>
- International Labour Organization. (2023). *Women and men in the informal economy: A statistical update*. <https://researchrepository.ilo.org/esploro/outputs/report/Women-and-men-in-the-informal/995264809802676>
- Kline, R. B. (2023). *Principles and practice of structural equation modeling* (5th ed.). Guilford Press.
- Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1–10. <https://doi.org/10.4018/ijec.2015100101>
- Le Dinh, T., Vu, M.-C., & Tran, G. T. C. (2025). Artificial intelligence in SMEs: Enhancing business functions through technologies and applications. *Information*, 16(5), Article 415. <https://doi.org/10.3390/info16050415>
- Ledro, C., Nosella, A., Vinelli, A., Dalla Pozza, I., & Souverain, T. (2025). Artificial intelligence in customer relationship management: A systematic framework for a successful integration. *Journal of Business Research*, 199, Article 115531. <https://doi.org/10.1016/j.jbusres.2025.115531>
- Magableh, I. K., Mahrouq, M. H., Ta'Amnha, M. A., & Riyadh, H. A. (2024). The role of marketing artificial intelligence in enhancing sustainable financial performance of medium-sized enterprises through customer engagement and data-driven decision-making. *Sustainability*, 16(24), Article 11279. <https://doi.org/10.3390/su162411279>
- Marsh, H. W., Hau, K.-T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. *Structural Equation Modeling: A Multidisciplinary Journal*, 11(3), 320–341. https://doi.org/10.1207/s15328007sem1103_2
- Ministry of Technology and Science, Zambia. (2023). *National digital transformation strategy 2023–2027*. Government of the Republic of Zambia.
- Mwaanga, C., Van Zyl, C., & Shambare, R. (2022). Environmental factors and the formation of students' entrepreneurial intentions: Perspectives from Zambia. *African Journal of Educational Management, Teaching and Entrepreneurship Studies*, 7(2), 20–38.
- Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, 48(8), Article 103773. <https://doi.org/10.1016/j.respol.2019.03.018>
- Nsokolo, D. S., Simo-Kengne, B. D., & Chama-Chiliba, C. M. (2025). Entrepreneurial returns to

- education in Zambia: Formal education versus vocational training. *Journal of Entrepreneurship in Emerging Economies*, 17(7), 280–301. <https://doi.org/10.1108/JEEE-02-2025-0069>
- OECD. (2025a). *The adoption of artificial intelligence in firms: New evidence for policymaking*. OECD Publishing. <https://doi.org/10.1787/f9ef33c3-en>
- OECD. (2025b). *Generative AI and the SME workforce*. OECD Publishing. <https://doi.org/10.1787/2d08b99d-en>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Sánchez, E., Calderón, R., & Herrera, F. (2025). Artificial intelligence adoption in SMEs: Survey based on TOE–DOI framework, primary methodology and challenges. *Applied Sciences*, 15(12), Article 6465. <https://doi.org/10.3390/app15126465>
- Sharma, A., Goel, A., & Taneja, U. (2025). AI adoption and digital entrepreneurial intentions: A theory of planned behaviour and technology acceptance model approach. *Technology in Society*, 84, Article 103137. <https://doi.org/10.1016/j.techsoc.2025.103137>
- Shepherd, D. A., & Majchrzak, A. (2022). Machines augmenting entrepreneurs: Opportunities (and threats) at the nexus of artificial intelligence and entrepreneurship. *Journal of Business Venturing*, 37(4), Article 106227. <https://doi.org/10.1016/j.jbusvent.2022.106227>
- Sikalumbi, D. A., Bbune, C., Chikwanda, J. M., Kamwengo, G. L., Mudenda, G., & Sishumba, J. (2025). Shifting gears: From informal economies to digital enterprises in Zambia. In D. A. Sikalumbi, B. Mweemba, & E. K. Bbenkele (Eds.), *Digital transformation in emerging economies* (pp. 227–246). ZCAS University Press.
- Song, Y., Qiu, X., & Liu, J. (2025). The impact of artificial intelligence adoption on organisational decision-making: An empirical study based on the technology acceptance model in business management. *Systems*, 13(8), Article 683. <https://doi.org/10.3390/systems13080683>
- Trainor, K. J., Andzulis, J., Rapp, A., & Agnihotri, R. (2014). Social media technology usage and customer relationship performance: A capabilities-based examination of social CRM. *Journal of Business Research*, 67(6), 1201–1208. <https://doi.org/10.1016/j.jbusres.2013.05.002>
- UNCTAD. (2025). *Technology and innovation report 2025: Inclusive artificial intelligence for development*. United Nations. https://unctad.org/system/files/official-document/tir2025_en.pdf
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Venkatraman, N. (1989). Strategic orientation of business enterprises: The construct, dimensionality, and measurement. *Management Science*, 35(8), 942–962. <https://doi.org/10.1287/mnsc.35.8.942>
- Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, 26(7), 1893–1924. <https://doi.org/10.1108/BPMJ-10-2019-0411>
- Wiklund, J., & Shepherd, D. (2005). Entrepreneurial orientation and small business performance: A configurational approach. *Journal of Business Venturing*, 20(1), 71–91. <https://doi.org/10.1016/j.jbusvent.2004.01.001>

- Yesuf, Y., Fields, Z., Jain, A., & Kassa, E. (2025). Artificial intelligence adoption as a driver of innovation and competitiveness in SMEs: A bibliometric and systematic review. *F1000Research*, 14, Article 1187. <https://doi.org/10.12688/f1000research.171494.1>
- Zahara, Z., Ikhsan, S. I. N., & Farid. (2023). Entrepreneurial marketing and marketing performance through digital marketing capabilities of SMEs in post-pandemic recovery. *Cogent Business & Management*, 10(2), Article 2204592. <https://doi.org/10.1080/23311975.2023.2204592>
- Zambia Statistics Agency. (2023). *2022 labour force survey report*.
- Zavodna, L. S., Überwimmer, M., & Frankus, E. (2024). Barriers to the implementation of artificial intelligence in small and medium-sized enterprises: Pilot study. *Journal of Economics and Management*, 46, 331–352. <https://doi.org/10.22367/jem.2024.46.13>
- Zhao, X., Lynch, J. G., Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, 37(2), 197–206. <https://doi.org/10.1086/651257>