

Barriers to Artificial Intelligence and Machine Learning Adoption among Women Entrepreneurs: Evidence from Zimbabwe

Tawana MOYO*   and Kudakwashe ZVITAMBO**  

*Faculty of Commerce, Catholic University of Zimbabwe, Zimbabwe

**Faculty of Business Sciences, Midlands State University, Zimbabwe

Abstract

Cite: Moyo, T & Zvitambo, K. (2025).
Barriers to Artificial Intelligence and Machine
Learning Adoption among Women
Entrepreneurs: Evidence from Zimbabwe.
*Journal of Emerging Technologies for
Society*, Volume 1, 1(1), 79-86.
<https://doi.org/10.57017/jets.v1.iss1.05>

This study examines barriers to artificial intelligence (AI) and machine learning (ML) adoption among women entrepreneurs in Zimbabwe. Drawing on an integrated Technology–Organization–Environment (TOE) and Diffusion of Innovation (DOI) framework, the research employs a quantitative cross-sectional survey of 384 women entrepreneurs across urban and rural locations and multiple business sectors. Questionnaire data were analysed using descriptive statistics and multiple regression.

The findings reveal significant negative associations between AI/ML adoption and three barrier domains: technological and digital skills limitations, financial constraints, and socio-cultural and institutional barriers. Financial constraints emerged as the strongest predictor ($\beta = -0.389$, $p < .001$), while the regression model explained 71.8% of the variation in adoption. Advanced applications, particularly predictive analytics and business-intelligence tools, exhibited relatively low adoption levels. The study highlights the interconnected nature of financial, technological and institutional barriers and underscores the importance of affordable financing, targeted AI skills development and supportive digital infrastructure. By integrating TOE and DOI perspectives, it contributes context-specific evidence to understanding AI/ML adoption among

women entrepreneurs in resource-constrained economies.

Article info:

Received: 10 July, 2026;

Revised: 31 July, 2026;

Accepted: 22 August, 2026;

Published: 30 August, 2026.

Copyright: © The Author(s) 2026. This article is distributed under the terms and conditions of the license [Creative Commons Attribution \(CC BY\) license](#).

Keywords: artificial intelligence, machine learning, women entrepreneurs, technology adoption, financial constraints.

1. Introduction

Artificial intelligence (AI) and machine learning (ML) are reshaping business decision-making, customer engagement and operating efficiency. For small firms, these tools can support marketing automation, forecasting, inventory management and data-informed decisions. Yet the benefits are not distributed evenly. Smaller enterprises in resource-constrained economies often face weak digital infrastructure, limited technical capacity and financing gaps, while women entrepreneurs may encounter additional restrictions in access to assets, training and professional networks (Badghish and Soomro, 2024; Mashapure et al., 2025).

The Zimbabwean setting makes this question especially important. Women-owned enterprises contribute to livelihoods, employment and economic resilience, but many operate with narrow financial margins and unreliable access to electricity, connectivity and specialised technical services. Research in Mashonaland West documents infrastructure, skills, security, trust and financial-inclusion constraints

affecting women's participation in digital entrepreneurship (Mashapure et al., 2025). These conditions may be even more consequential for AI and ML because adoption can require data, suitable devices, paid software, training and continuing support.

Existing work has examined SME digitalisation and general AI adoption, but direct empirical evidence on the combined technological, financial and socio-institutional barriers facing women entrepreneurs in Zimbabwe remains limited. In particular, prior Zimbabwean evidence is predominantly concerned with the wider digital gender gap rather than the factors that predict AI/ML adoption. This study addresses that gap by testing three barrier domains in one quantitative model and by identifying their relative strength. It asks: How do technological and digital skills barriers, financial constraints, and socio-cultural and institutional barriers affect AI/ML adoption among women entrepreneurs in Zimbabwe? The study contributes context-specific evidence, integrates TOE and DOI at the level of testable relationships, and identifies where practical and policy intervention is likely to have the greatest effect. Recent systematic reviews identify recurring capability, infrastructure, resource and organisational barriers to AI adoption among SMEs, but these findings cannot substitute for Zimbabwe-specific evidence (Oldemeyer et al., 2025; Sagala and Ōri, 2024; Landini and Machado, 2026).

2. Literature Review and Theoretical Framework

AI refers broadly to computer systems that perform tasks associated with human intelligence, while ML is a subset through which systems learn patterns from data. Entrepreneurial applications include customer support, marketing, financial management, predictive analytics and business intelligence. Adoption in this study means the extent to which women entrepreneurs use such applications in routine business operations. Although some tools reduce the entry cost of digital automation, meaningful adoption still depends on skills, complementary infrastructure and the capacity to evaluate and sustain the technology (Dwivedi et al., 2023; OECD/BCG/INSEAD, 2025). This is consistent with evidence synthesising AI implementation challenges among SMEs (Oldemeyer et al., 2025; Hamid and Artha, 2026).

Women entrepreneurs may experience the ordinary constraints of small firms together with gendered limitations in access to finance, productive assets, time, training and networks. In Zimbabwe, Mashapure et al. (2025) found that women entrepreneurs faced limited technology training and infrastructure, security and trust concerns, discriminatory customary and statutory conditions, and weak financial inclusion. This evidence establishes the importance of the digital gender gap, but does not quantify how distinct barrier domains relate specifically to AI/ML adoption.

The TOE framework explains organisational innovation adoption through technological, organisational and environmental contexts (Tornatzky and Fleischer, 1990). In this study, technological conditions include AI knowledge, complexity, skills and support; organisational conditions include the financial and human resources available within women-owned enterprises; and environmental conditions include infrastructure, government support and wider socio-cultural influences. TOE is therefore useful for locating the constraints that surround an adoption decision rather than treating adoption as an individual preference alone.

DOI theory explains how an innovation spreads through a social system and highlights perceived relative advantage, compatibility, complexity, trialability and observability (Rogers, 2003). For women entrepreneurs, AI tools may diffuse slowly when they appear complex, cannot be tried affordably, are poorly aligned with existing practices, or have few visible local examples. DOI therefore adds an innovation-perception and social-diffusion lens to the contextual conditions captured by TOE.

The two perspectives are complementary. TOE identifies where barriers arise: within the technology, the enterprise and the external environment. DOI explains how those barriers shape perceptions and the pace of diffusion. Limited skills can increase perceived complexity; limited finance can restrict trialability and the acquisition of compatible tools; and weak infrastructure, policy support and peer networks can reduce observability and social learning. The integrated framework therefore predicts that stronger barriers in each domain will be associated with lower adoption.

Hypotheses

H1: Technological and digital skills barriers have a significant negative influence on AI/ML adoption among women entrepreneurs in Zimbabwe.

H2: Financial constraints have a significant negative influence on AI/ML adoption among women entrepreneurs in Zimbabwe.

H3: Socio-cultural and institutional barriers have a significant negative influence on AI/ML adoption among women entrepreneurs in Zimbabwe.

3. Research Results

Technological and Digital Skills Barriers

Respondents generally agreed that technological and skills constraints impeded adoption ($M=4.15$, $SD=0.82$; Table 1). Lack of AI/ML knowledge was the highest-rated item ($M=4.31$), followed by limited access to AI-related training ($M=4.25$) and lack of technical support ($M=4.19$).

Table 1: Technological and Digital Skills Barriers (n = 384)

Statement	Mean	Std. Dev
I lack adequate knowledge of AI and Machine Learning technologies	4.31	0.71
AI technologies are too complex for my business operations	4.08	0.83
I have limited access to AI-related training opportunities	4.25	0.76
My business lacks employees with AI-related skills	4.12	0.89
I lack technical support for implementing AI solutions	4.19	0.80
I am not confident in using AI-based business applications	3.97	0.92
Overall Mean	4.15	0.82

Source: Authors' survey data.

Financial constraints recorded the highest composite mean of the three barrier domains ($M = 4.27$, $SD = 0.79$; Table 2). The expense of AI software and technologies received the strongest agreement ($M = 4.42$), followed by insufficient business resources ($M = 4.36$) and limited technology financing ($M = 4.29$).

Table 2: Financial Constraints Affecting AI/ML Adoption (n = 384)

Statement	Mean	Std. Dev
AI software and technologies are expensive	4.42	0.68
My business lacks sufficient financial resources to invest in AI	4.36	0.74
Access to financing for technology investment is limited	4.29	0.81
Internet and data costs are too high	4.24	0.77
AI implementation requires resources beyond my business capacity	4.18	0.85
The cost of AI training is unaffordable	4.11	0.88
Overall Mean	4.27	0.79

Source: Authors' survey data.

The socio-cultural and institutional domain also recorded strong agreement ($M = 4.17$, $SD = 0.81$; Table 3). Inadequate government support was the highest-rated item ($M = 4.35$), followed by inadequate internet infrastructure ($M = 4.28$) and family responsibilities limiting time for learning ($M = 4.22$).

Table 3: Socio-Cultural and Institutional Barriers ($n = 384$)

Statement	Mean	Std. Dev
Women receive less technological support than men	4.11	0.82
Cultural beliefs discourage women from engaging with advanced technologies	3.89	0.95
Family responsibilities limit my time to learn AI technologies	4.22	0.77
Government support for AI adoption is inadequate	4.35	0.73
Internet infrastructure is inadequate for AI implementation	4.28	0.79
Limited awareness programmes exist for AI technologies	4.18	0.81
Overall Mean	4.17	0.81

Source: Authors' survey data.

Use was concentrated in relatively accessible applications (Table 4). AI-powered marketing tools had the highest frequent use (34.6%), whereas predictive analytics had the lowest (18.7%). Predictive analytics (56.8%) and business-intelligence tools (50.8%) were rarely used by more than half of respondents, indicating limited movement from entry-level applications to advanced, data-intensive use.

Table 4: Reported Use of AI/ML Applications ($n = 384$)

AI Application	Frequently Used (%)	Occasionally Used (%)	Rarely Used (%)
AI-powered marketing tools	34.6	39.8	25.6
Chatbots and virtual assistants	21.4	31.5	47.1
AI-based financial management tools	28.9	36.2	34.9
Predictive analytics tools	18.7	24.5	56.8
AI-driven customer relationship systems	25.8	32.3	41.9
AI-supported business intelligence tools	19.5	29.7	50.8

Source: Authors' survey data.

Hypothesis Tests and Regression Model

The regression model was statistically significant ($F = 123.684$, $p < .001$) and explained 71.8% of the variance in AI/ML adoption ($R^2 = .718$; adjusted $R^2 = .712$). All three standardised coefficients were negative and significant (Table 5). Financial constraints had the largest absolute coefficient ($\beta = -.389$, $t = -8.114$, $p < .001$), followed by technological and digital skills barriers ($\beta = -.312$, $t = -6.521$, $p < .001$) and socio-cultural and institutional barriers ($\beta = -.284$, $t = -5.978$, $p < .001$). H1, H2 and H3 were therefore supported. The source output did not provide confidence intervals, unstandardised coefficients, standard errors, degrees of freedom or diagnostic statistics, so these are not inferred in this paper.

Table 5: Multiple Regression Results

Variable	Beta	t-value	p-value
Technological and Digital Skills Barriers	-0.312	-6.521	< .001
Financial Constraints	-0.389	-8.114	< .001
Socio-Cultural and Institutional Barriers	-0.284	-5.978	< .001
R ²	0.718		
Adjusted R ²	0.712		
F-statistic	123.684		< .001

Source: Authors' survey data.

4. Discussion

The technological barrier results show that lack of knowledge, training and technical support constrains adoption even where entrepreneurs may recognise AI's benefits. This supports the TOE proposition that technological readiness is necessary for organisational adoption and the DOI proposition that perceived complexity slows diffusion. It also extends Mashapure et al.'s (2025) account of Zimbabwe's wider digital gender gap by demonstrating that capability constraints are significantly associated with the adoption of AI/ML specifically. The usage profile is consistent with this interpretation: relatively familiar marketing tools were more common than predictive analytics and business-intelligence systems, which require more specialised data and analytical capacity.

Financial constraints emerged as the strongest predictor because finance conditions several other adoption requirements at once. A business must not only acquire software or devices; it may also need reliable connectivity, data, staff training, technical support and time for experimentation. When working capital is limited, these complementary costs make even a technically suitable tool difficult to trial or sustain. This pattern is consistent with the TOE emphasis on organisational resources and with broader evidence that financing gaps and skills shortages hinder SME digitalisation (Badghish and Soomro, 2024; OECD/BCG/INSEAD, 2025). Comparable reviews emphasise that finance, knowledge and infrastructure constraints interact rather than operate independently (Oldemeyer et al., 2025; Sagala and Öri, 2024).

The Zimbabwean context intensifies this mechanism. Many women-owned enterprises are small or informal and may lack collateral, stable cash flows or access to technology-focused credit. The descriptive results show that respondents did not isolate cost to one item: they reported expensive AI technologies, insufficient internal resources, limited external finance, high internet and data costs, and unaffordable training. Finance therefore acts as a cross-cutting constraint that reduces DOI trialability and limits the organisational readiness described by TOE. Its stronger coefficient should not be read as making skills or institutions unimportant; rather, it shows that without affordable resources, entrepreneurs cannot readily act on training or policy opportunities.

Government support, internet infrastructure and family responsibilities were the leading items in the socio-cultural and institutional domain. These findings correspond with Mashapure et al. (2025), who identified structural, training and financial-inclusion constraints among women entrepreneurs in Zimbabwe, and with Malatji's (2026) account of uneven AI readiness across sub-Saharan Africa. Within the integrated framework, weak infrastructure and policy support are environmental constraints under TOE, while limited peer visibility, time and support networks can slow social learning and observability under DOI. The results therefore show that adoption cannot be explained only by the attributes of AI tools; it is embedded in a gendered entrepreneurial ecosystem.

The study's theoretical contribution is to connect TOE contexts to DOI mechanisms in a women's entrepreneurship setting. Technological barriers increase complexity; financial constraints reduce trialability and the ability to acquire compatible systems; and socio-institutional constraints weaken observability, support and diffusion through networks. The high model R^2 indicates that the three domains jointly account for a substantial share of adoption differences in this sample. At the same time, the cross-sectional design supports association rather than definitive causal claims. Recent SME evidence also supports considering organisational and environmental readiness alongside technological factors (Landini and Machado, 2026; Hamid and Artha, 2026).

5. Conclusions

AI/ML adoption among the surveyed women entrepreneurs was limited, particularly for advanced applications. All three barrier domains were negatively associated with adoption, and all three hypotheses were supported. The conclusion follows directly from the results: adoption is not constrained by a single deficit but by interacting capability, resource and ecosystem conditions. Financial constraints were the most influential barrier in the regression and had the highest composite mean, while limited AI knowledge and weak government support were prominent within the other domains.

Entrepreneurship-support organisations, universities and technology providers should offer practical, sector-specific AI training that uses low-cost tools and real business data. Programmes should progress from accessible applications such as marketing and customer communication to data preparation, forecasting and business intelligence. Mentoring, shared technical support and demonstration projects can reduce perceived complexity and make benefits more observable. Financial institutions and development partners should introduce technology-focused credit, small innovation grants, flexible repayment terms and subsidised access to connectivity, software and training. Bundling finance with vetted tools and capability support would address the cross-cutting nature of the strongest barrier and reduce the risk that credit is used for technology that firms cannot sustain.

Government should improve affordable broadband and reliable electricity, support shared digital hubs, and incorporate women-owned micro and small enterprises into national AI and digital-transformation initiatives. Gender-responsive policy should also address collateral constraints, limited awareness and the time burdens that restrict participation in training. Partnerships among public agencies, women's business associations, universities and technology firms can improve reach, trust and local relevance.

The cross-sectional, self-report design limits causal interpretation and may be affected by common-method and social-desirability bias. The sampling frame and random-selection procedure were not documented; therefore, probability sampling and population representativeness cannot be verified. Construct-specific reliability coefficients, questionnaire distribution and response counts, sectoral and regional sample profiles, regression confidence intervals, and diagnostic statistics were also unavailable. These omissions limit the assessment of measurement quality and robustness. The findings should not be generalised automatically beyond the surveyed women entrepreneurs.

Future research should use longitudinal or mixed-method designs to examine how adoption changes after financing or skills interventions. Sector-specific studies could distinguish the needs of agriculture, retail, tourism, manufacturing and professional services. Properly specified interviews or focus groups could explain how household responsibilities, collateral conditions, infrastructure reliability and perceptions of risk shape actual decisions. Further studies should also test whether business size, formality, location and prior digital maturity moderate the relationships identified here.

CRediT Authorship Contribution Statement

Moyo, T.: Conceptualisation, methodology, investigation, data curation, formal analysis and writing—original draft. Zvitambo, K.: Supervision, validation and writing—review and editing.

Acknowledgments/Funding

The authors thank the women entrepreneurs who participated in the study and the academic reviewers who provided comments on the manuscript.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

The data supporting the findings are available from the corresponding author upon reasonable request, subject to participant confidentiality and applicable ethical restrictions.

Ethical Approval Statement

The study involved human participants who voluntarily completed a questionnaire. Informed consent was obtained from all participants, and confidentiality and anonymity were maintained throughout the research process. Formal ethics committee approval was not required for this type of non-interventional, questionnaire-based research.

Use of AI Statement

During preparation of this manuscript, the author used OpenAI ChatGPT to support drafting, language structuring and editorial formatting. The author reviewed and edited the content, verified the cited literature, and takes full responsibility for the final manuscript.

References

- Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of technology–organization–environment framework. *Sustainability*, 16(5), 1864. <https://doi.org/10.3390/su16051864>
- Cochran, W. G. (1977). *Sampling Techniques* (3rd ed.). John Wiley & Sons.
- Creswell, J. W., & Creswell, J. D. (2023). *Research Design: Qualitative, Quantitative, and Mixed Methods Approach* (6th ed.). SAGE Publications.
- 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., Al-Busaidi, K. A., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Wright, R. (2023). “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, 102642. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2022). *Multivariate Data Analysis* (9th ed.). Cengage Learning.
- Hamid, E. S., & Artha, B. (2026). Artificial intelligence adoption, implementation barriers, and business impact in small and medium-sized enterprises: A systematic literature review. *Archives of Business Research*, 14(7), 86–110. <https://doi.org/10.14738/abr.1407.12031>
- Landini, C., & Machado, M. C. (2026). A systematic review on organizational adoption and performance constructs related to artificial intelligence in SMEs. *Discover Artificial Intelligence*, 6, Article 721. <https://doi.org/10.1007/s44163-026-01460-4>
- Malatji, M. (2026). Bridging the AI divide in sub-Saharan Africa: Challenges and opportunities for inclusivity. *arXiv*. <https://doi.org/10.48550/arXiv.2601.06145>

- Mashapure, R., Nyagadza, B., Muzondo, P., Mutanda, B., Mthombeni, A., Tapera, J., & Hamunakwadi, P. (2025). Bridging the digital technology gender gap: Challenges faced by women entrepreneurs in Mashonaland West Zimbabwe. *Journal of Asian and African Studies*. <https://doi.org/10.1177/00219096251369519>
- OECD/BCG/INSEAD. (2025). *The Adoption of Artificial Intelligence in Firms: New Evidence for Policymaking*. OECD Publishing. <https://doi.org/10.1787/f9ef33c3-en>
- Oldemeyer, L., Jede, A., & Teuteberg, F. (2025). Investigation of artificial intelligence in SMEs: A systematic review of the state of the art and the main implementation challenges. *Management Review Quarterly*, 75, 1185–1227. <https://doi.org/10.1007/s11301-024-00405-4>
- Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). Free Press.
- Sagala, G. H., & Őri, D. (2024). Toward SMEs digital transformation success: A systematic literature review. *Information Systems and e-Business Management*, 22, 667–719. <https://doi.org/10.1007/s10257-024-00682-2>
- Saunders, M., Lewis, P., & Thornhill, A. (2023). *Research Methods for Business Students* (9th ed.). Pearson.
- Tornatzky, L. G., & Fleischer, M. (1990). *The Processes of Technological Innovation*. Lexington Books.