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Effectiveness of AI-Enabled Digital Technologies on the Business Performance of Retail and E-Commerce SMEs in Lusaka, Zambia

A Convergent Mixed-Methods Case Study

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Abstract: Artificial intelligence tools have become cheap and widely available, yet there is little evidence on whether their use is associated with better performance among small and medium enterprises in Zambia. This study examined the effectiveness of AI-enabled digital technologies on the business performance of retail and e-commerce SMEs in Lusaka, using Dynamic Capabilities Theory as its main lens. A convergent mixed-methods case study combined a survey of 81 AI-adopting enterprises, selected by stratified sampling, with 25 semi-structured interviews with purposively selected managers. Generative AI was used by 82.7 percent of enterprises, while AI for inventory, accounting and payments was used by 14.8 percent or fewer, and physical-only shops were far less likely than enterprises with an online presence to use AI at all. The operational effectiveness of AI use explained 25.8 percent of the variance in dynamic capabilities, with the strongest association with seizing opportunities. Dynamic capabilities explained 11.7 percent of the variance in business performance, mainly through financial and market performance. Contextual factors did not significantly moderate the relationship between AI use and performance in the main sample, although the interaction became significant when the largest enterprises were excluded; cost, staff skills and uncertainty about data protection were the main constraints reported in both strands. The interviews showed that AI entered firms through staff experimenting with free tools for marketing and customer communication, that its output required human checking, and that only enterprises using it daily in customer engagement attributed sales growth to it. The study concludes that AI use is positively but modestly associated with the performance of Lusaka retail SMEs, and recommends moving AI from marketing into operations, role-specific training and practical data-protection guidance for small businesses.

Keywords: *Artificial Intelligence; Dynamic Capabilities; Business Performance; Small and Medium Enterprises; Zambia.*

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I. INTRODUCTION

Artificial intelligence (AI) has moved quickly from large technology firms to ordinary businesses. Cloud-based services and, since late 2022, generative AI assistants have made tools for writing, design, customer messaging and analysis available at little or no cost. Bughin et al. [1] estimated that AI could add about 13 trillion United States dollars to global output by 2030, and experimental studies show that generative AI can sharply reduce the time needed for routine writing tasks [2]. For small and medium enterprises (SMEs), which usually lack specialist staff and capital, such tools could narrow the gap with larger competitors.

Whether that promise holds in a developing economy is far less clear. Only 37 percent of Africa's population used the internet in 2023 [3], and in Zambia firm-level data on digital use are, in the words of the World Bank [4], very scarce and dated. The most recent representative figures available to that review, from the 2013 Enterprise Survey, showed that only 20 percent of firms had a website. A more recent exploratory survey found that few Zambian MSMEs used specialised software and that lack of knowledge and expertise was the main barrier to adopting AI tools [5]. The extent to which Zambian SMEs use AI, and whether it improves their performance, is therefore largely unmeasured.

Retail and e-commerce in Lusaka offer a useful setting in which to study this question. The sector combines high transaction volumes, direct customer contact and strong price competition, which are the activities in which AI is expected to make the greatest difference. Theoretically, the study draws

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on Dynamic Capabilities Theory [6], [7], which holds that technology improves performance not by being acquired but by strengthening a firm's ability to sense opportunities, seize them and reconfigure its resources.

The study pursued four objectives: (i) to establish the types of AI-enabled digital technologies adopted by retail and e-commerce SMEs in Lusaka; (ii) to examine how the operational effectiveness of AI use influences the development of dynamic capabilities; (iii) to determine the effect of AI-driven dynamic capabilities on business performance; and (iv) to analyse the contextual factors that moderate the effect of AI use on business performance. The paper contributes original mixed-methods evidence from a setting that is largely absent from the literature. Section II reviews the literature, Section III describes the method, Section IV presents the results, Section V discusses them and Section VI concludes.

II. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

➢ *Theoretical Foundations*

Three adoption theories explain why firms take up new technology. Diffusion of Innovations [8] emphasises relative advantage, compatibility, complexity, trialability and observability; the Technology-Organisation-Environment framework [9] adds the firm's internal resources and its external environment; and the Unified Theory of Acceptance and Use of Technology [10] highlights performance expectancy, effort expectancy, social influence and facilitating conditions. These theories explain uptake but say little about how use becomes performance. Dynamic Capabilities Theory fills that gap. Teece [7] describes sensing as scanning and interpreting changes in markets and technology, seizing as mobilising resources to address the opportunities identified, and transforming as reconfiguring the firm's assets and routines. These foundations remain current: TOE continues to be applied to AI adoption by SMEs [11], UTAUT has been extended into a research agenda for AI tools [12], and a recent review of three decades of dynamic capabilities research shows the theory broadening towards the orchestration of resources and ecosystems under uncertainty, including the implications of AI [13].

The conceptual framework of this study therefore links the operational effectiveness of AI use to dynamic capabilities, and dynamic capabilities to business performance, measured across the financial, operational, customer and market dimensions of the Balanced Scorecard [14]. Drawing on the socio-technical view and on Heeks's [15] design–reality gap, it treats contextual conditions, namely infrastructure, skills, finance and regulatory clarity, as moderators of the effect of AI use on performance.

➢ *AI Adoption Among SMEs*

Davenport and Ronanki [16] analysed 152 AI projects and classified business applications into process automation, cognitive insight and cognitive engagement; process automation was the most common, and modest projects succeeded more often than ambitious ones. In Africa, Mensah and Xu [17] found among 362 Ghanaian SMEs that performance expectancy and effort expectancy drove the intention to adopt e-commerce systems. Locally, Kakumbi and Phiri [18] found that Facebook and WhatsApp were the most widely used social-media platforms among clothing SMEs in Lusaka, and Mwazembe and Hapompwe [19] found that Facebook use improved marketing, customer engagement and sales among MSMEs in Lusaka's central business district. None of these studies examines AI directly.

➢ *AI Use and Dynamic Capabilities*

The information systems literature has long argued that the value of technology depends on how it is used. Brynjolfsson and Hitt [20] showed that the productivity benefits of information technology depend on complementary investments in skills, process redesign and management practices, and Bharadwaj [21] found that firms with strong IT capability outperformed comparable firms on a range of profit and cost measures. In Ghana, Gyamerah, Afshari and Asante [22] found that the IT and employee digital capabilities of 256 SMEs carried much of the effect of digital leadership on digital transformation. In South Africa, Jenkinson et al. [23] found that big data analytics capabilities improved competitive performance partly through business model innovation, and in Tanzania Rutainurwa, Mwenda and Israel [24] found that ICT capabilities affected the financial performance of manufacturing SMEs only through supply chain integration capabilities.

➢ *Dynamic Capabilities and Business Performance*

Teece [7] cautions that dynamic capabilities raise the likelihood of superior performance rather than guaranteeing it, and Eisenhardt and Martin [25] argue that in fast-moving markets they often take the form of simple, rapid routines. Empirically, Abrokwah-Larbi and Awuku-Larbi [26] found among 225 Ghanaian SMEs that AI in marketing had a positive effect on all four Balanced Scorecard dimensions, and Mushi [27] found that digital marketing strategies were positively related to SME performance in Tanzania. The effects are not always direct: Tiwasing et al. [28] found that Kenyan businesses using mobile money were more innovative than non-users but did not perform better. Experimental evidence suggests that generative AI produces some of the most immediate gains, raising the productivity of writing tasks [2] and of customer-support agents, especially less experienced ones [29]. In Zambia, mobile money use has been associated with better performance among informal businesses [30] and with greater resilience among SMEs during the COVID-19 pandemic [31], but no study has examined AI. Recent SME surveys report similar links for AI: Badghish and Soomro [11] found among 220 Saudi SMEs that AI adoption was associated with better operational and economic performance, and Al Dhaheri et al. [32] found among 487 SMEs in the United Arab Emirates that both AI applications and dynamic capabilities were linked to performance.

➢ *Contextual Moderators*

Contextual conditions in Zambia differ from those in the settings that produced most of this literature. The World Bank [4] reports that fibre connectivity is unreliable because of cuts and grid failures and that intermediate and advanced ICT skills are scarce. Data for Change and BongoHive [5] found that

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84.6 percent of the MSMEs they surveyed had not trained their staff in collecting and reporting data. Zambia's Data Protection Act of 2021 [33] introduced new obligations on the processing of personal data, but implementation has been slow; the Data Protection Commissioner's office was not yet operational in early 2025 [34]. Whether such conditions weaken the performance benefits of AI has not been tested in Zambia, which is the gap this study addresses.

III. METHODOLOGY

➢ *Design, Population and Sampling*

The study used a convergent parallel mixed-methods approach [35] within a case study of Lusaka's retail and e-commerce SME sector [36]. Survey and interview data were collected at the same time, analysed separately and integrated at interpretation. The target population was retail and e-commerce SMEs in Lusaka with five to 300 employees that had used at least one AI-enabled technology for at least six months. Two sampling techniques were used. The survey strand used stratified sampling, with three strata defined by business model: physical store only, online only, and omnichannel. Because no register identifies such firms, respondents within each stratum could not be drawn at random; they were recruited through visits to shops, markets and malls and through an online link, and screened for eligibility, so the survey supports analytical rather than statistical generalisation. The interview strand used purposive sampling of information-rich managers [37]. The Yamane formula applied to an estimated 102,000 active SMEs in Lusaka gave 178 respondents at a margin of error of 0.075 and 100 at 0.10. A power analysis in G*Power [38] for a three-predictor moderation model (medium effect, $f^2 = 0.15$, power 0.80, alpha 0.05) required at least 77. A target of 80 to 100 respondents was therefore set, together with 15 to 20 interviews, a range consistent with evidence that saturation in semi-structured interviews is usually reached within 12 interviews [39].

➢ *Instruments and Data Collection*

The questionnaire, built in KoboToolbox, measured operational effectiveness of AI use (six items), dynamic capabilities (six items adapted from Wang and Ahmed [40], two each for sensing, seizing and transforming), change in business performance since adoption (eight items, two per Balanced Scorecard dimension) and contextual factors (six items), all on five-point scales. It was administered online and in person at shops, markets and malls in Lusaka between 17 September and 25 October 2026. Of 157 submissions, 81 passed all the screening questions and formed the analytic sample: 43 enterprises did not use AI, 15 had used it for less than six months, and one internally contradictory response was excluded as a highly influential case (Cook's distance 2.63). Twenty-five managers were interviewed between 8 and 23 October 2026 using an eight-question guide covering adoption, use, effects and context; 16 interviews were held by telephone, seven in person and two by video call, lasting 20 to 45 minutes. Only two telephone participants agreed to be recorded, and no recording device was available, so no interview was audio-recorded; every interview was documented on a structured record sheet during the conversation, with key statements written down as close to the participant's words as possible. The ICU Research Ethics Committee granted clearance on 15 September 2026, and all participants gave informed consent.

➢ *Data Analysis*

Internal consistency was assessed with Cronbach's alpha [41]. Objective one was analysed with frequencies, multiple-response analysis and cross-tabulation by business model, using Monte Carlo exact p-values. Objectives two and three were tested with Pearson and Spearman correlations and simple linear regression with 5,000-resample bootstrap confidence intervals. Objective four was tested with moderated regression following Model 1 of Hayes [42], with mean-centred predictors [43] and simple slopes at one standard deviation below and above the mean of the moderator. The analyses were conducted in JASP [44], and the heteroscedasticity-consistent (HC3) standard errors, Monte Carlo exact tests and bootstrap confidence intervals were computed in Python using the statsmodels and SciPy libraries [45], [46]. The interview records were analysed with the six-phase thematic procedure of Braun and Clarke [47], using an Excel coding matrix, and the two strands were integrated in a joint display [48].

IV. RESULTS

➢ *Sample and Measurement*

Omnichannel enterprises made up 66.7 percent of the 81 respondents, physical-only enterprises 18.5 percent and online-only enterprises 14.8 percent. Most enterprises (61.7 percent) employed five to 19 people, and 71.6 percent of respondents held a bachelor's degree or higher. Table 1 shows that all four composite scales exceeded the 0.70 reliability threshold. Item 30 (cost management) was removed from the performance scale because its corrected item-total correlation was 0.168 and its wording was ambiguous; among the 71 respondents who answered all eight items, its removal raised alpha from 0.761 to 0.836 (0.835 for the 72 who answered the seven retained items, as in Table 1). With 81 respondents, the moderation model had a post-hoc power of 0.80, against 0.93 for the simple regressions. Younger and smaller enterprises rated their AI use as more effective (Kruskal-Wallis $p = 0.005$ for age and $p = 0.031$ for size), whereas business model, size and age were not significantly related to the other variables.

Table 1 Reliability and Descriptive Statistics of the Composite Scales

Scale	Items	Alpha	Mean	SD
Operational effectiveness of AI use	6	0.765	3.79	0.53
Dynamic capabilities	6	0.828	3.85	0.57
Business performance (item 30 removed)	7	0.835	4.01	0.41
Contextual factors	6	0.728	3.25	0.58

Note. n = 81, Except Business Performance (n = 77 for the Composite; n = 72 for Alpha). Scales Range from 1 to 5.

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➢ *Types of AI-Enabled Technologies Adopted*

Fig. 1 shows that generative AI was by far the most widely used technology (82.7 percent), followed by AI marketing and content tools (51.9 percent), image and video tools (51.9 percent) and customer-service chatbots (38.3 percent). AI for inventory, accounting, e-commerce personalisation and payments was each used by 17.3 percent of enterprises or fewer. Adoption was recent but intensive: 60.5 percent had used AI for six months to a year, and 69.1 percent used it daily or several times a day. Among adopters, no technology differed significantly by business model. Whether firms adopted AI at all, however, differed sharply: among all 140 profiled enterprises, only 46.3 percent of physical-only shops used AI, against 70.8 percent of online-only and 81.3 percent of omnichannel enterprises ($\chi^2 = 15.28$, $p < 0.001$, $V = 0.330$). Of the 81 adopters, 81.5 percent sold online, mostly through social media and WhatsApp rather than dedicated online stores, so online selling was the main route through which AI reached these firms.

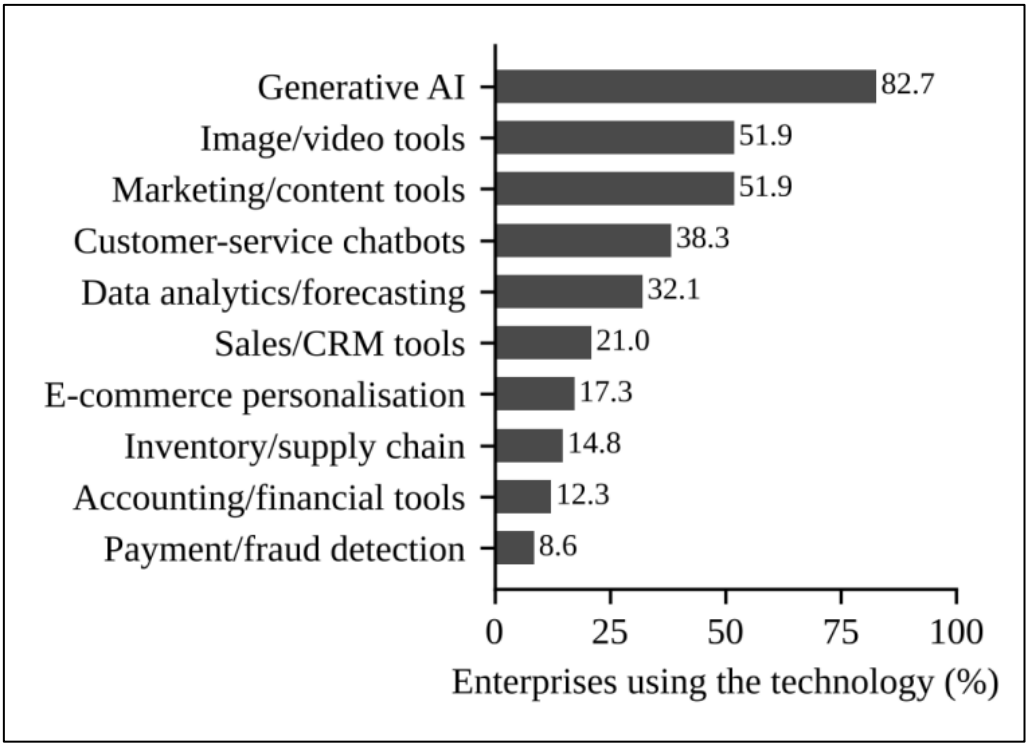

Fig 1 Percentage of Enterprises Using Each AI-Enabled Technology (Multiple Response, n = 81).

All 25 interviewees used a generative AI assistant, most often ChatGPT, and most also used WhatsApp Business automation (20) and Canva's AI features (19). In 18 enterprises AI had been introduced by an employee, usually in marketing or sales, who had first used it personally, while four adoptions were led by the owner or manager. Only one participant described using AI with sales and stock records:

"We use ChatGPT for promotional messages, campaign ideas, customer communication and sometimes menu or product ideas. The marketing team also uses Canva AI for posters. Our sales and operations records are still mainly managed through Excel and our existing systems." (P04)

➢ *Operational Effectiveness and Dynamic Capabilities*

Operational effectiveness of AI use was moderately correlated with dynamic capabilities ($r = 0.508$, $p < 0.001$; Spearman $\rho = 0.571$). In regression (Table II) it explained 25.8 percent of the variance in dynamic capabilities ($\beta = 0.508$, $p < 0.001$; HC3 $p < 0.001$), and the bootstrap confidence interval excluded zero. The association was strongest for seizing ($\beta = 0.513$) and weakest for transforming ($\beta = 0.358$). Interviews explained this pattern. Fourteen participants said AI made market and product research faster, and ten described acting on opportunities more quickly, but only seven had used AI to redesign processes. Sixteen insisted that AI output had to be checked before use:

"The biggest concern is accuracy. Staff can become overconfident because an AI answer sounds professional. We require them to verify specifications before giving technical advice to a customer." (P09)

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Table 2 Regression Results for Objectives Two and Three

Dependent variable (predictor)	n	R^2	β	p
Dynamic capabilities (OE)	81	0.258	0.508	< 0.001
Sensing (OE)	81	0.170	0.412	< 0.001
Seizing (OE)	81	0.263	0.513	< 0.001
Transforming (OE)	81	0.128	0.358	0.001
Business performance (DC)	77	0.117	0.342	0.002
Financial (DC)	78	0.133	0.365	0.001
Process efficiency (DC)	80	0.019	0.138	0.224
Customer (DC)	80	0.030	0.175	0.121
Market (DC)	77	0.096	0.311	0.006

Note. OE = Operational Effectiveness of AI Use; DC = Dynamic Capabilities; β = Standardised Coefficient.

➢ *Dynamic Capabilities and Business Performance*

Respondents reported improvement in almost every area of performance since adopting AI; process efficiency improved for 95.0 percent and revenue for 91.0 percent. Dynamic capabilities explained 11.7 percent of the variance in business performance (β = 0.342, p = 0.002; HC3 p = 0.024), a relationship carried by financial (β = 0.365) and market (β = 0.311) performance. The result held when 16 respondents outside the retail scope and six in non-senior roles were excluded (n = 60, β = 0.355, p = 0.005), and when the 14 enterprises with 100 or more employees were excluded (β = 0.492, p < 0.001). A supplementary test of the indirect effect through dynamic capabilities was not significant (95% CI −0.044 to 0.227), so the study does not claim formal mediation. In the interviews, every participant described efficiency gains, but only seven attributed higher sales to AI, all of them firms using AI daily with customers, and 13 had not measured its effect on sales:

"The clearest benefit has been efficiency. Marketing content that used to take several hours can now be prepared much faster. We have not been able to say that AI alone increased sales." (P03)

➢ *Contextual Factors as Moderators*

Contextual conditions were rated close to neutral (mean 3.25). Among adopters, the main challenges were the cost of AI (71.6 percent), limited staff skills (58.0 percent) and data security and privacy (54.3 percent), whereas the 43 non-adopters cited limited awareness of suitable tools most often (62.8 percent). Table III shows that the interaction between operational effectiveness and contextual factors was not significant (B = −0.361, p = 0.085, ΔR^2 = 0.037). Simple slopes ran in a negative direction, with the effect of AI use larger where conditions were weaker (B = 0.451, p = 0.008) than where they were stronger (B = 0.054, p = 0.654). The interaction reached significance only among enterprises with fewer than 100 employees (p = 0.035), so the pattern is treated as a possibility for future research rather than a finding.

Table 3 Moderated Regression of Business Performance

Predictor	B	SE	p
Constant	4.026	0.045	< 0.001
Operational effectiveness (centred)	0.253	0.089	0.006
Contextual factors (centred)	0.073	0.086	0.399
Interaction	−0.361	0.207	0.085

Note. n = 77; R^2 = 0.116; Bootstrap 95% CI for the Interaction −0.802 to 0.068; Maximum VIF = 1.23.

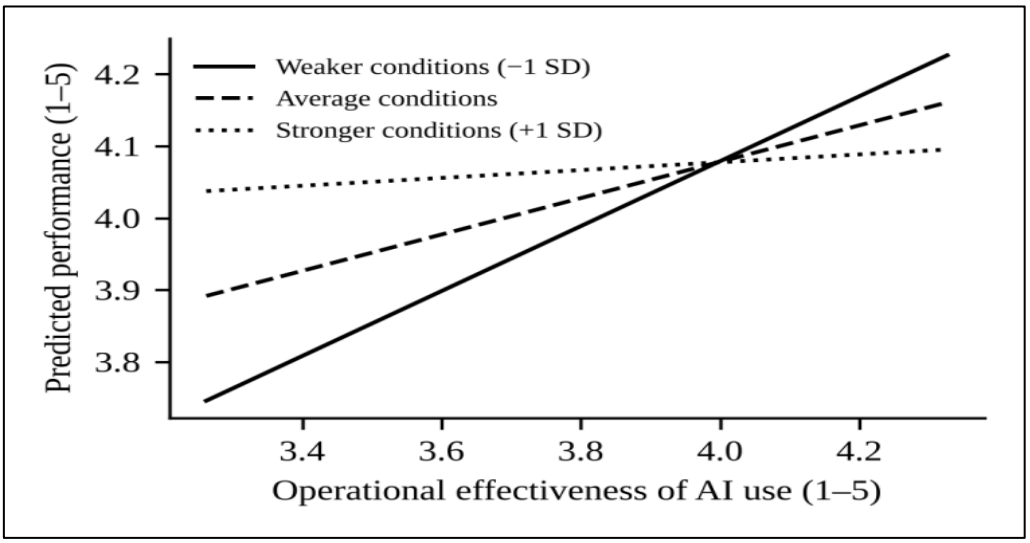

Fig 2 Predicted Business Performance by Operational Effectiveness at Three Levels of Contextual Factors.

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The interviews, by contrast, showed contextual factors to be constantly present. Internet reliability or cost was raised by 24 participants and staff skills and subscription costs by 14 each. Sixteen avoided entering customer data into public AI tools, and several were unsure what the data-protection law required:

"When it comes to Data Protection, we know there is an ACT in Zambia, but sensitization and enforcement have been scanty hence fear of breaking the law is inevitable." (P02)

Table 4 Joint Display of Integrated Findings

Objective	Survey	Interviews	Integration
1. Types adopted	Generative AI 82.7%; operational AI 14.8% or less; adoption far lower among physical-only shops	All 25 use generative AI; adoption mostly staff-led; AI rarely linked to stock systems	Convergent; interviews explain why free general-purpose tools dominate
2. AI use and capabilities	$\beta = 0.508$, $R^2 = 0.258$; strongest for seizing	Faster research and campaigns; little process redesign; output must be checked	Convergent; interviews explain the weak transforming effect
3. Capabilities and performance	$\beta = 0.342$, $R^2 = 0.117$; financial and market	Efficiency universal; 7 of 25 attribute sales growth to AI	Convergent on efficiency; divergent on revenue
4. Contextual moderators	Interaction not significant ($p = 0.085$; significant without the largest firms, $p = 0.035$); cost, skills, privacy main challenges	Internet, cost, skills and data protection limit benefits	Convergent on factors; divergent on moderation

V. DISCUSSION

The dominance of generative AI departs from the pattern reported by Davenport and Ronanki [16], in which back-office process automation was most common. In Lusaka, AI arrived not as an investment project but through free, general-purpose tools that individual employees could try on their own phones. This is what Diffusion of Innovations predicts for tools with clear relative advantage and high trialability [8], and the bottom-up route mirrors the social influence and facilitating conditions of UTAUT [10]. It also extends the established use of Facebook and WhatsApp by Lusaka SMEs [18], [19]: AI reached these firms through the platforms they already used for marketing.

The association between operational effectiveness and dynamic capabilities supports the argument that technology creates value through how it is used rather than through its possession [20], [21]. The stronger association with seizing than with transforming suggests that AI has so far made Lusaka retailers faster rather than different, consistent with the view that dynamic capabilities in fast-moving markets often take the form of simple, rapid routines [25]. The need to verify AI output, raised by most interviewees, echoes the design–reality gap [15]: AI produced value where staff adapted generic output to local conditions.

The modest association between dynamic capabilities and performance is consistent with Teece's [7] caution that capabilities raise the likelihood of better performance without guaranteeing it, and with African evidence that digital technologies do not always improve performance directly [24], [28]. Near-universal efficiency gains match experimental evidence on generative AI [2], [29], but gains in revenue were attributed to AI only by enterprises using it daily in customer engagement. Survey respondents reported higher revenue far more often than interviewees attributed sales growth to AI, probably because the survey asked about change since adoption from any cause; positive self-reporting may also have contributed [49]. Unlike the data-driven decision-making studied by Brynjolfsson and McElheran [50], the AI used in Lusaka produced content rather than informing stock or pricing decisions, which is a plausible reason the association with performance is modest.

The absence of significant moderation is consistent with Mushi [27], who found that the external environment did not moderate the effect of digital marketing on SME performance in Tanzania. The interviews suggest why. The constraints were shared by almost every firm, which leaves little variation for a moderation test, and they appear to act earlier in the process, confining AI to low-cost marketing uses rather than changing the payoff from a given level of use. Uncertainty about data protection stands out: it was the most divisive contextual item, the only one to reach the .05 level as a moderator when tested on its own, and a reason many interviewees gave for keeping customer data out of AI tools, which is understandable given the slow implementation of the Data Protection Act [34].

VI. CONCLUSION AND RECOMMENDATIONS

The use of AI-enabled digital technologies is positively but modestly associated with the performance of retail and e-commerce SMEs in Lusaka. Effective AI use is associated with stronger dynamic capabilities, especially the ability to seize opportunities, and those capabilities are in turn associated with better financial and market performance. The narrow, marketing-focused way in which AI is currently used limits these benefits. Theoretically, the findings support the application of Dynamic Capabilities Theory to resource-constrained SMEs while showing that, in this setting, AI use is associated with seizing and sensing well before transformation.

Three recommendations follow. Owner-managers should extend AI from marketing into operations, for example by using AI assistants with the sales and stock records they

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already keep, formalise the verification of AI output, and begin measuring AI's contribution to sales. Government digital agencies should support practical, role-specific AI training and awareness campaigns for non-adopters, especially physical-only shops. The Office of the Data Protection Commissioner should issue simple guidance for small businesses on the use of customer data with AI tools.

The study has limitations. The sample of 81 only just reached the planned 80 to 100; the data are cross-sectional and self-reported, so the relationships are associations rather than proof of cause; the moderation result was not stable across samples; all but two interviewees came from omnichannel enterprises, and non-adopters were not interviewed; and the interviews were analysed from record sheets rather than verbatim transcripts. Future research should use larger probability samples, longitudinal designs with objective sales data, and comparisons between adopters and non-adopters.

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