

The Role of Digital Skills Gaps in Shaping AI Value Yield Among Small and Medium-Sized Enterprises

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Abstract

Artificial intelligence (AI) is diffusing quickly through the business population, yet small and medium-sized enterprises (SMEs) capture a disproportionately small share of its value. This paper examines how digital skills gaps shape what we term AI value yield: the economic value a firm realises from AI relative to the resources it commits. Using a secondary-data design, the study triangulates official enterprise statistics from Eurostat (2023–2025), two OECD evidence bases on SME AI adoption and generative AI use (2025–2026), peer-reviewed field experiments on generative AI productivity, and recent survey evidence from Nigeria. Three findings emerge. First, the size gap in AI use is wide and widening in absolute terms: in 2025, 17.0% of small EU enterprises used AI against 55.0% of large enterprises, and the large-firm share grew by roughly 14 percentage points in one year against 6 points for small firms. Second, internal digital capacity is even more unequal than AI use itself: large enterprises were about 5.6 times as likely as small ones to employ ICT specialists and about 4.2 times as likely to provide ICT training. Third, skills are the binding constraint on conversion from intent to use: among EU enterprises that considered AI but did not adopt it, 70.3% cited a lack of relevant expertise, ahead of legal and data-protection concerns, while 50% of SMEs in the OECD generative AI survey reported that employees lacked the skills to use the tools effectively. Building on absorptive capacity and complementarity theory, the paper proposes a three-stage model in which skills gaps reduce value yield at the adoption, deployment-depth and value-conversion stages. It also identifies a countervailing effect: generative AI raises the output of less-skilled workers most, so it can partly substitute for the very skills SMEs lack, provided a minimum threshold of digital literacy is in place. The paper concludes with managerial and policy implications, including skills-first adoption sequencing and threshold-oriented training for SMEs in emerging economies such as Nigeria.

Keywords: *Artificial intelligence; Digital skills gap; Small and medium-sized enterprises; AI value yield; Absorptive capacity; Generative AI; Digital divide; Nigeria*

JEL classification: *L25, M15, O33, J24*

INTRODUCTION

SMEs account for more than 99% of firms and about 60% of business-sector employment in OECD economies, yet they consistently trail larger firms in digital and advanced technologies (OECD, 2025b). Artificial intelligence is now widening that gap. Across the OECD, the share of firms using AI rose from 5.6% in 2020 to 14% in 2024, but large firms were more than three times as likely as small firms to use it (40% against 11.9%) (OECD, 2025a). In the European Union, enterprise AI use reached 20.0% in 2025, up from 8.0% in 2023, while the gap between small and large enterprises reached 38 percentage points (Eurostat, 2025a).

Adoption counts tell only part of the story. Firms differ in how deeply they use AI and in how much value they extract from each unit of investment. The OECD notes that the productivity premium of AI adopters shrinks considerably once pre-existing digital capabilities, skills and complementary investments are controlled for (OECD, 2025a). This implies that the returns to AI are not a property of the technology alone. They depend on the human capital that surrounds it.

We call this firm-level return AI value yield: the realised economic value of AI (productivity, quality, revenue or cost effects) relative to the financial, managerial and organisational resources committed to it. The concept separates three questions that adoption statistics merge: whether a firm uses AI, how deeply it embeds AI in its processes, and how efficiently it turns that use into measurable value. The term connects to recent work that frames SME AI optimisation around value yield under resource constraints (Yevsiukova, 2026).

Digital skills sit at the centre of all three questions. Yet the literature on SME AI adoption has largely treated skills as one barrier among many, measured at the adoption stage only. Little work traces how skills gaps propagate from adoption through to realised value, and evidence from emerging economies, where skills, infrastructure and finance constraints compound, remains thin (Mohammed *et al.*, 2025).

This paper addresses that gap. Its aim is to examine how digital skills gaps shape AI value yield among SMEs. It asks three research questions:

1. *RQ1*. How large is the gap between SMEs and large firms in AI use and in the internal digital capacity that supports it?
2. *RQ2*. To what extent are digital skills, rather than cost or other factors, the binding constraint on SME AI adoption and use?
3. *RQ3*. Through which mechanisms do skills gaps reduce AI value yield, and can generative AI itself offset part of the gap?

The paper makes three contributions. First, it offers a three-stage model linking skills gaps to value yield at the adoption, deployment-depth, and value-conversion stages. Second, it assembles recent official and experimental evidence into a single size-class comparison of AI use and digital capacity. Third, it extends the analysis to Nigeria, an economy of roughly 39 million MSMEs, to show how the mechanisms behave under tighter constraints.

The remainder of the paper is organised as follows. It first reviews the theoretical and empirical literature, then sets out the conceptual framework and propositions before describing the method. The results are reported next, followed by a discussion of implications, and the paper closes with conclusions, limitations and directions for future research.

LITERATURE REVIEW AND THEORETICAL BACKGROUND

Skills as a Complement to Digital Technology

A long line of research shows that information technology raises productivity mainly when combined with skilled labour and reorganised work. Bresnahan *et al.* (2002) found that IT investment, decentralised workplace practices and worker skill act as complements: firms gained most when they invested in all three together. The productivity J-curve argument extends this logic to general-purpose technologies such as AI (Brynjolfsson *et al.*, 2021). Firms must first build intangible assets, including skills, data, and redesigned processes, before measured gains appear. Firms that cannot fund those intangibles stay at the bottom of the curve.

This complementarity view explains why identical AI tools yield different returns in different firms. The tool is a necessary input. The skills that surround it determine how much value it produces.

Absorptive Capacity

Cohen and Levinthal (1990) defined absorptive capacity as a firm's ability to recognise the value of external knowledge, assimilate it and apply it to commercial ends. Zahra and George (2002) separated potential capacity (acquisition and assimilation) from realised capacity (transformation and exploitation). The distinction maps closely onto AI. Recognising a promising AI use case requires potential capacity. Turning it into a redesigned, measurable process requires realised capacity. Both rest on prior related knowledge, which in SMEs is typically held by a few individuals and is rarely supported by in-house ICT specialists.

The Technology–Organisation–Environment perspective

The Technology–Organisation–Environment (TOE) framework treats adoption as the product of technological characteristics, organisational resources and environmental conditions (Tornatzky and Fleischer, 1990). Skills sit in the organisational dimension, alongside size, slack resources and managerial support. TOE-based studies of SMEs regularly identify skills as a barrier, but they usually stop at the adoption decision. They say less about what happens to the value of AI after adoption, which is the focus of this paper.

From the Access Divide to the Usage and Outcome Divides

Digital divide research has moved from a first-level divide in physical access to a second-level divide in skills and usage, and then to a third-level divide in outcomes (van Deursen and van Dijk, 2014). The same progression applies to firms. Cheap cloud and generative AI tools have narrowed the access divide for SMEs. The OECD reports that 31% of SMEs in seven countries now use generative AI, a level once confined to large firms (OECD, 2025b). The remaining divides are increasingly about skills and outcomes rather than access.

Evidence on Skills Barriers in SMEs

Official and survey data converge on skills as the leading obstacle. The OECD's G7 discussion paper identifies four structurally constrained enablers of SME AI adoption: connectivity, AI-enabling inputs (data, algorithms and compute), skills, and finance (OECD, 2025a). The OECD's 2024 survey of more than 5,000 SMEs found that half of them cited a lack of employee skills as a barrier to generative AI use (OECD, 2025b). In Nigeria, qualitative work identifies skills shortages alongside ethical concerns and regulatory gaps as socio-technical barriers that limit AI integration in SMEs (Mohammed *et al.*, 2025).

Experimental Evidence: AI as a Skill Leveller

Field and laboratory experiments add an important complication. In a study of 5,172 customer-support agents, access to a generative AI assistant raised issues resolved per hour by 14% on average and by 34% for novice and low-skilled workers, with minimal effects for the most experienced (Brynjolfsson *et al.*, 2025). In a writing experiment, ChatGPT access cut task time by about 40% and raised rated quality by about 18%, with the largest gains for weaker writers (Noy and Zhang, 2023). A field experiment with 758 consultants found strong gains on tasks inside AI's capability frontier but worse performance on a task just outside it (Dell'Acqua *et al.*, 2023).

Taken together, these studies suggest that generative AI can compress skill differences in well-defined tasks. They also show that users need enough judgement to recognise where the tool fails. That combination, substitution within a frontier and a minimum skill threshold to use it safely, is central to the framework developed next.

Research Gap

The literature establishes that skills matter for adoption and that AI's effects vary with worker skill. What is missing is an account that links firm-level skills gaps to the full chain from adoption to realised value, tested against current size-class data and extended to an emerging economy. This paper provides that account.

CONCEPTUAL FRAMEWORK AND PROPOSITIONS

We model AI value yield as the product of three sequential conversion stages. A firm's digital skills endowment, both specialist (ICT professionals) and general (staff and managerial digital literacy), conditions how efficiently it passes through each stage. Losses compound: a firm that converts at 50% at each of three stages retains only 12.5% of the potential value.

Fig. 1 presents this three-stage model schematically. It shows the digital skills endowment conditioning each stage, the three conversion stages (Adoption, Depth and Value) through which potential value passes, and the resulting AI value yield, together with the dashed feedback path through which generative AI can partially substitute for missing skills at the value-conversion stage.

Stage 1: Adoption (The Extensive Margin)

The firm recognises a use case and decides to deploy AI. Skills gaps act here through potential absorptive capacity: firms without specialist or informed managerial knowledge struggle to identify relevant applications or to judge vendor claims.

Stage 2: Deployment Depth (The Intensive Margin)

The firm moves from a single tool or pilot to AI embedded in core processes, with data pipelines, integration, and governance. Skills gaps act through realised absorptive capacity: integration, data preparation and process redesign require technical and organisational skills that many SMEs do not hold in-house.

Stage 3: Value Conversion

The firm turns deployed AI into measured gains. Skills act through user competence and complementary organisational change: staff must use the tools well, judge outputs and redesign workflows around them.

Generative AI enters the model as a partial substitute for skills. Within a task frontier, it raises the output of less-skilled workers most, which lifts conversion at Stage 3. However, it requires a minimum literacy threshold: users must be able to

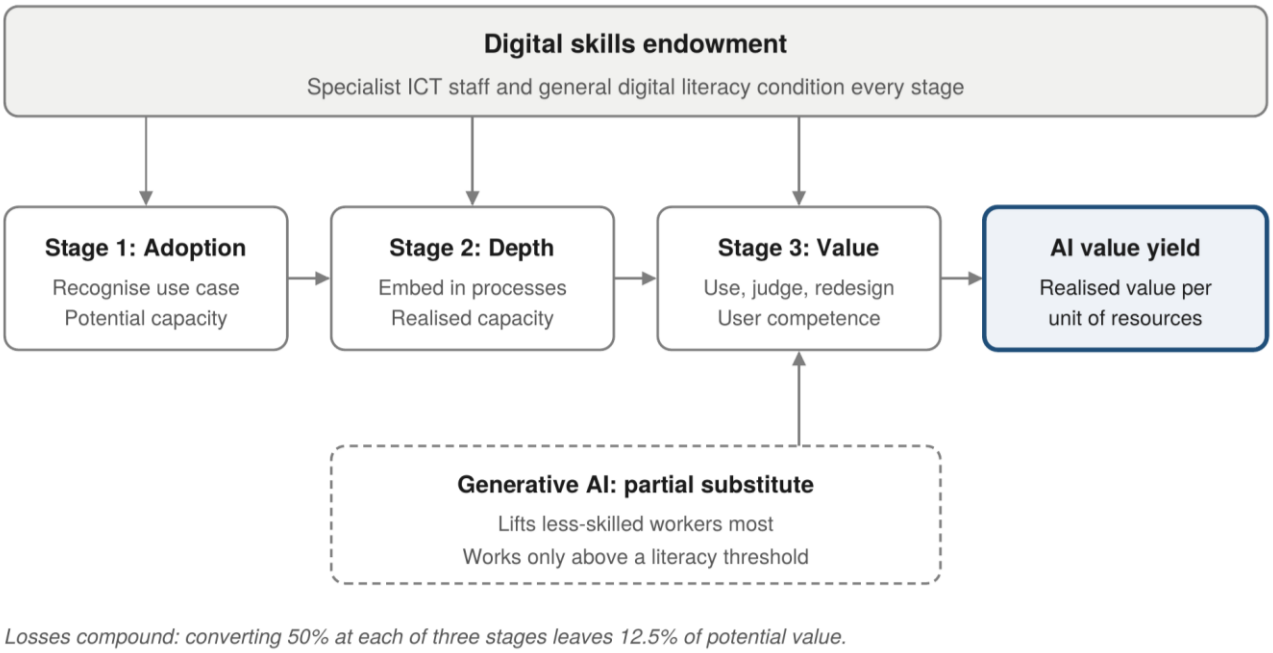


Fig. 1: The Skills Gap–AI Value Yield model. Digital skills condition each conversion stage; generative AI can offset part of the Stage 3 loss once workers clear a minimum literacy threshold. *Source*: author.

prompt, verify, and recognise failure. Below that threshold, generative AI can lower quality.

From this model we derive five propositions:

1. *P1*. The SME–large firm gap in internal digital capacity is wider than the gap in AI use, because AI use can be bought in while capacity must be built.
2. *P2*. Among firms that consider AI, lack of expertise is a more frequent reason for non-adoption than cost.
3. *P3*. Skills gaps reduce value yield at every stage, so the gap in realised value between SMEs and large firms exceeds the gap in adoption rates.
4. *P4*. Generative AI narrows within-firm skill differences on well-defined tasks, partly offsetting the Stage 3 penalty for SMEs.
5. *P5*. The offset in P4 holds only above a minimum digital literacy threshold. Where that threshold is not met, as is more common in emerging economies, the skills penalty dominates.

METHODOLOGY

Research Design

The study uses a secondary-data, evidence-triangulation design. It combines official statistics, multi-country survey evidence, peer-reviewed experiments and national survey reports to assess the propositions. This design suits the research questions because harmonised, size-disaggregated enterprise data already exist at scale, and because the mechanisms in the model operate at different levels (firm, task and economy) that no single dataset captures.

Data Sources

Table 1 lists the evidence streams used in the study, their sources, coverage, and the research questions and propositions each stream is used to assess.

Indicators and Analysis

Size classes follow the Eurostat convention: small enterprises employ 10–49 persons, medium 50–249, and large 250 or more. Micro-enterprises with fewer than 10 persons are outside the scope of Eurostat and most OECD enterprise data.

The analysis proceeds in four steps. First, we compute the large-to-small ratio for each indicator (the large-firm share divided by the small-firm share) to compare the size gap in AI use with the size gap in digital capacity (*P1*). Second, we compare the frequency of skills-related and cost-related reasons for non-adoption (*P2*). Third, we combine the stage-specific evidence to assess compounding losses (*P3*). Fourth, we read the experimental and Nigerian evidence against *P4* and *P5*.

Data Limitations

Three limitations should be noted. Indicators come from different survey years (2023–2025), so ratios compare structural gaps rather than a single cross-section. Barrier percentages refer to enterprises that ever considered AI, which was only 11.1% of EU enterprises in 2025, not to all enterprises. Finally, the study does not observe value yield directly at the firm level; it infers stage losses from adoption, capacity, and productivity evidence. These limits are revisited in the concluding discussion of limitations.

RESULTS

The Size Gap in AI Use and Digital Capacity (*RQ1*, *P1*)

The gap between small and large enterprises is wider for digital capacity than for AI use itself. Table 2 sets the indicators side by side, reporting the small- and large-firm shares, the percentage-point gap, and the large-to-small ratio for each.

Three patterns stand out. First, every capacity indicator shows a larger ratio (4.2 to 8.3) than AI use (3.0 to 3.4). Large enterprises are about 5.6 times as likely to employ ICT specialists and 8.3 times as likely to recruit them, while they are about 3.2 times as likely to use AI. This supports *P1*: SMEs can buy access to AI tools more easily than they can build the people who make those tools productive.

Second, the absolute gap in AI use is widening even as the ratio falls slightly. Between 2024 and 2025, the share of large

Table 1: Evidence streams, sources, and coverage.

Evidence stream	Source	Coverage	Used for
Enterprise AI use	Eurostat ICT usage in enterprises survey, dataset isoc_eb_ai (Eurostat, 2025a)	About 157,000 EU enterprises with 10+ persons employed, 2023–2025	*RQ1*, *P1*, *P3*
Barriers to AI use	Eurostat isoc_eb_ai, reasons for non-use among enterprises that considered AI	EU-27, 2024–2025	*RQ2*, *P2*
Internal digital capacity	Eurostat ICT specialists and ICT training indicators (Eurostat, 2025b)	EU-27, 2023–2024	*RQ1*, *P1*
Population digital skills and SME digital intensity	Eurostat Digitalisation in Europe, 2026 edition (Eurostat, 2026)	EU-27, 2023 and 2025	Context, *P5*
SME AI adoption across G7	OECD (2025a) discussion paper for the G7	G7 and OECD economies, 2020–2024	*RQ1*, *P3*
Generative AI in SMEs	OECD (2025b) survey	5,000+ SMEs in seven countries, late 2024	*RQ2*, *P4*
Task-level productivity	Brynjolfsson *et al.* (2025); Noy and Zhang (2023); Dell'Acqua *et al.* (2023)	Field and controlled experiments	*RQ3*, *P4*, *P5*
Emerging-economy context	EDC and eTranzact (2025); GIZ DTC Nigeria; NCC; Oxford Insights via Dataphyte (2026)	Nigeria, 2024–2026	*P5*

Table 2: AI use and internal digital capacity by enterprise size, EU and OECD.

Indicator	Year	Small firms (%)	Large firms (%)	Gap (pp)	Large-to-small ratio
Enterprises recruiting or trying to recruit ICT specialists (EU)	2023	6.23	51.87	45.6	8.3
Enterprises employing ICT specialists (EU)	2024	14.04	78.44	64.4	5.6
Enterprises providing ICT-related training to staff (EU)	2023	17.21	72.62	55.4	4.2
Firms using AI (OECD)	2024	11.9	40.0	28.1	3.4
Enterprises using AI (EU)	2025	17.00	55.03	38.0	3.2
Firms using AI (OECD)	2025	17.4	52.0	34.6	3.0

Sources: Eurostat (2025a, 2025b); OECD (2025a, 2026).

EU enterprises using AI rose by about 13.9 percentage points, against about 5.8 points for small enterprises (Eurostat, 2025a). Small firms are catching up in relative terms but falling further behind in absolute terms.

Third, the general digital baseline differs as well. In 2025, 71% of EU SMEs reached a basic level of digital intensity, against 96% of large businesses (Eurostat, 2026). The general workforce is also short of skills: about 40% of EU residents lacked at least basic digital skills in 2025, far from the Digital Decade target of 80% coverage by 2030 (Eurostat, 2026).

Skills as the Binding Constraint (*RQ2*, *P2*)

Skills, not cost, are the leading reason that interested firms do not adopt AI. In 2025, only 11.1% of EU enterprises had ever considered using AI without adopting it. Among those, 70.3% cited a lack of relevant expertise, 53.6% cited unclear legal consequences, 52.7% cited data-protection concerns, and only 17.8% said AI was not useful (Eurostat, 2025a). The expertise barrier barely moved from 2024, when it stood at 70.9%, while the share saying AI was not useful fell from 20.7% (Eurostat, 2025a). Firms increasingly believe AI is useful but still lack the people to use it.

The expertise barrier is reported by small firms slightly more often than by large ones (70.9% against 65.1% among firms that considered AI), so the barrier is nearly universal rather than an SME peculiarity (Eurostat data as reported by AI World, 2026). Cost does not appear among the leading reasons. These figures support *P2*.

The OECD's generative AI survey points the same way. Half of SMEs reported that employees lacked the skills to use generative AI effectively (OECD, 2025b). Twice as many SMEs said generative AI raised their need for highly skilled workers (20%) as said it lowered it (9%), with data analysis and creativity named as the skills that had gained most in importance (OECD, 2025b).

Compounding Losses Across Stages (*RQ3*, *P3*)

The evidence points to losses at each of the three stages, consistent with *P3*.

- *Adoption.* The 70.3% expertise barrier shows skills gaps blocking firms that have already recognised AI's relevance. The much larger group that neither used nor ever considered AI, roughly 69% of EU enterprises in 2025 (100% minus 20.0% users and 11.1% non-adopting considerers), suggests that potential absorptive capacity is also missing.
- *Deployment depth.* The OECD describes SME AI use as largely peripheral and classifies adopters into four maturity types (Novices, Optimisers, Explorers and Champions) based on digital maturity, complexity of use and scope of application (OECD, 2025a). With only 14.04% of small EU enterprises employing ICT specialists, few SMEs hold the in-house capacity to move beyond off-the-shelf tools.
- *Value conversion.* The OECD finds that the productivity premium of AI adopters shrinks considerably once firms' prior digital capabilities, skills and complementary investments are controlled for (OECD, 2025a). Part of what appears to be an "*AI effect*" is a skills effect.

Generative AI as a Partial Substitute for Skills (*RQ3*, *P4*)

The experimental literature supports P4. Generative AI raised productivity by 34% among novice and low-skilled support agents, compared with 14% on average (Brynjolfsson *et al.*, 2025). In professional writing, it cut task time by about 40% and raised quality by about 18%, with the weakest writers gaining the most (Noy and Zhang, 2023).

SME survey data are consistent with this. Among SMEs that used generative AI and had experienced a skills gap, 39% said the technology helped compensate for it (OECD, 2025b). A third of SMEs said generative AI reduced staff workload, and 14% said it reduced their reliance on external contractors (OECD, 2025b). The great majority, 83%, reported no effect on overall staff needs (OECD, 2025b).

The offset has limits. Consultants using GPT-4 performed worse on a task just outside the tool's capability frontier than those working without it (Dell'Acqua *et al.*, 2023). The substitution effect therefore requires users who can tell when the tool is wrong.

The Emerging-Economy Case: Nigeria (*P5*)

Nigeria illustrates how the mechanisms behave under tighter constraints. The country has more than 39 million MSMEs (EDC and eTranzact, 2025). National AI adoption rose from 8.7% in the first quarter of 2025 to 10.1% in the first quarter of 2026, still low by international standards (Dataphyte, 2026).

The skills picture is mixed. Nigeria's human capital score in the Government AI Readiness Index rose from 31 to 49 between 2024 and 2025 (Dataphyte, 2026). A GIZ digital maturity study classified 61% of MSMEs as "*Reinventors*" actively using digital tools, 27% as "*Adaptors*" open to

digitalisation but needing support, and 12% as "*Sceptics*" (GIZ Digital Transformation Center Nigeria, 2024). Connectivity has improved, with 140.6 million active internet subscriptions and 48.7% broadband penetration reported for June 2025 (Shehu, 2025).

However, studies of Nigerian SMEs consistently name inadequate digital skills together with unreliable electricity, poor connectivity and cost misconceptions as barriers (Mohammed *et al.*, 2025). These constraints interact. A firm that loses power or connectivity loses the ability to practise with AI tools, which slows the skills formation needed to clear the literacy threshold in *P5*. The Nigerian evidence is therefore consistent with P5: where general digital skills and infrastructure are uneven, the skills penalty is more likely to outweigh the substitution benefit of generative AI.

DISCUSSION

Interpreting the findings

The central finding is that the SME disadvantage in AI is primarily a capacity disadvantage rather than an access disadvantage. Generative AI and cloud services have lowered the price of entry, which is why the ratio of large-firm to small-firm AI use has eased slightly. The capacity indicators, however, show ratios of 4 to 8. Because value yield depends on capacity at every stage, the gap in realised value is likely to exceed the gap in adoption rates, as *P3* predicts.

The widening absolute gap reinforces this reading. Large firms entered 2025 with more specialists, more training and more digital intensity, so each additional year of AI diffusion adds more to their stock of applications than to that of small firms. This matches the complementarity and J-curve arguments: firms that already hold the intangible complements move up the curve faster (Bresnahan *et al.*, 2002; Brynjolfsson *et al.*, 2021).

Theoretical Implications

The study makes three theoretical contributions. First, it extends absorptive capacity theory to AI by mapping potential capacity onto the adoption stage and realised capacity onto deployment depth and value conversion. Second, it adds a substitution mechanism to the complementarity view. Generative AI is not only complemented by skills; within a task frontier it can stand in for them, which complementarity models alone do not predict. Third, it introduces a threshold condition. Substitution operates only above a minimum level of digital literacy, which explains why the same tools may narrow skill gaps in high-literacy economies while leaving them intact in lower-literacy settings.

Managerial Implications

For SME owners and managers, the findings suggest four practical steps:

1. *Build skills before buying tools.* Given that expertise, not cost, blocks most interested firms, a small training budget is likely to raise value yield more than an equivalent spend on software licences.
2. *Train to the threshold first.* Basic prompting, output verification and data hygiene for all staff should come before advanced or specialist training, because they unlock the substitution effect.
3. *Target well-defined, high-volume tasks.* Customer support, drafting and routine analysis sit inside the capability frontier, where the gains for less-experienced staff are largest.
4. *Borrow capacity where it cannot be built.* Shared ICT specialists, sector associations, university partnerships and managed service providers can supply the realised absorptive capacity that few SMEs can hire.

Policy Implications

Policy should shift emphasis from adoption subsidies to skills formation. SMEs in the OECD survey said they most welcomed training, financial assistance, information campaigns and business mentoring (OECD, 2025b). Training programmes should be pitched at the literacy threshold rather than at advanced AI engineering, since most SME jobs need practical AI use rather than model development.

For Nigeria and similar economies, skills policy cannot be separated from infrastructure. Reliable power and affordable connectivity are preconditions for the repeated practice through which workers build AI skills. Programmes that pair subsidised connectivity or shared work hubs with hands-on training are more likely to raise value yield than either measure alone. Support should also be segmented: the large "Adaptor" group of Nigerian MSMEs identified by GIZ is the natural first target, since these firms are willing to digitalise but need help.

CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

Conclusion

Digital skills gaps are the main reason SMEs extract less value from AI than large firms. The size gap in internal digital capacity, with large-to-small ratios of 4.2 to 8.3, is wider than the gap in AI use itself, with ratios of 3.0 to 3.4. Among EU firms that considered AI but did not adopt it, 70.3% cited a lack of expertise. Skills gaps act at the adoption, deployment-depth, and value-conversion stages, so their effects compound. Generative AI offers a partial remedy because it lifts the output of less-skilled workers most, but only once a minimum level of digital literacy is in place. For SMEs, the most effective route to higher AI value yield is therefore skills-first: build threshold literacy across the workforce, then scale AI use on well-defined tasks.

Limitations

This study has four main limitations. First, it relies on secondary data drawn from different survey years, so the comparisons describe structural gaps rather than a single synchronised cross-section. Second, the Eurostat and OECD enterprise data exclude micro-enterprises with fewer than 10 persons employed, which make up most firms in Nigeria and many other economies. Third, value yield is inferred from adoption, capacity and task-level productivity evidence rather

than measured directly at the firm level. Fourth, the Nigerian evidence draws on industry and survey reports with differing methods, so it supports the propositions qualitatively rather than as a formal test.

Future Research

Future work should measure AI value yield directly, for example through firm-level panel data linking skills inventories, AI deployment depth and productivity outcomes. Researchers could test the literacy-threshold proposition (P5) through randomised training interventions in SMEs, comparing basic AI literacy training with advanced technical training. Studies covering micro-enterprises and informal firms in Sub-Saharan Africa are particularly needed, as is research on how intermediaries such as shared service centres and digital hubs supply absorptive capacity to small firms.

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Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy, have been completely observed by the author.

Life Science Reporting

The study uses only published aggregate data and did not involve human participants.

Data Availability

All data analysed are publicly available from the sources listed in the references. Eurostat indicators can be retrieved from the datasets isoc_eb_ai, isoc_ske_itspen2, isoc_ske_itrcrs and isoc_ske_itts.

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