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CATALYZING ENTREPRENEURSHIP AND INDUSTRIAL DEVELOPMENT THROUGH TECHNOLOGY DRIVEN SAFETY AND MAINTENANCE PRACTICES

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ABSTRACT
The mismatch between workforce competencies and the technical demands of modern industrial systems continues to limit entrepreneurship and industrial development. This study examines how technology-driven safety and maintenance practices, including predictive maintenance systems, digital monitoring tools, and automated safety protocols, can help close this skills gap and support entrepreneurial growth within industrial ecosystems. A mixed-methods design combines survey data from industrial practitioners and entrepreneurs with qualitative case studies of enterprises that have adopted such solutions. Quantitative data are analyzed with descriptive and inferential statistics, while qualitative data are examined through thematic analysis to identify recurring patterns and institutional dynamics. Survey and case-study data collection for this study is complete. The findings show that technology adoption shapes entrepreneurial capacity, workforce readiness, and industrial performance, while also revealing barriers such as limited training infrastructure, restricted access to technology, and weak institutional support. These findings inform a proposed framework linking skills development, technology integration, and safety-conscious entrepreneurship. The study contributes to discourse on sustainable industrial development and offers recommendations for policymakers, industry stakeholders, and educational institutions working to connect entrepreneurship, technology, and industrial safety for long-term economic growth.

Keywords: entrepreneurship, industrial development, maintenance practices, safety, skills gap

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1. Introduction

Industrial systems have grown more technically demanding over the past decade, and the workforce required to run them has not always kept pace. Sensors now track equipment condition in real time, software flags anomalies before they become failures, and safety protocols increasingly run through automated systems rather than manual checklists. Yet many workers, and many of the entrepreneurs who employ them, were trained under an older model of industrial work, one built around manual inspection, fixed maintenance schedules, and paper-based safety records (Adepoju & Aigbavboa, 2020). The result is a competency gap that shows up not as a single missing skill but as a pattern of hesitation around new tools, delayed adoption of digital systems, and continued reliance on reactive rather than predictive practices.

This gap matters for entrepreneurship because small and medium enterprises are usually the first to feel the cost of it. A large manufacturer can absorb the expense of retraining staff or hiring specialists; a small workshop often cannot (Oladejo et al., 2026). When maintenance failures occur without warning, or when safety incidents interrupt production, the enterprises least equipped to recover are frequently the smaller and newer ones, precisely the firms that entrepreneurship policy is meant to support. Technology-driven safety and maintenance practices, predictive maintenance systems that use sensor data to anticipate failure, digital monitoring platforms that track equipment and worker conditions continuously, and automated protocols that reduce dependence on manual compliance, offer one route through which this gap might be narrowed (Mallioris et al., 2024; Zhan et al., 2022).

The relationship is not, however, a simple matter of installing new equipment. Adoption of predictive and digital tools depends on workforce readiness, institutional support, and the cost structure facing individual enterprises. Where training infrastructure is thin or where access to reliable technology is uneven, adoption stalls even when the underlying case for it is sound (Pittri et al., 2025). Understanding how these factors interact, rather than treating technology adoption as an isolated variable, is central to explaining why some industrial ecosystems translate new safety and maintenance tools into entrepreneurial growth while others do not.

Debates over how best to close industrial skills gaps have generally moved in two directions, one favoring large-scale curriculum reform and the other favoring targeted, technology-specific short courses (Chiamogu & Chiamogu, 2025). This study leans toward evidence that can inform the latter, since broad reform is slow to implement and slower still to reach the small enterprises most affected by the gap. This study asks how technology-driven safety and maintenance practices relate to entrepreneurial capacity, workforce readiness, and industrial performance, and what barriers limit that relationship. It combines a survey of industrial practitioners and entrepreneurs with case studies of enterprises that have already adopted predictive maintenance or digital monitoring tools. The aim is not only to describe the association between technology adoption and entrepreneurial outcomes, but to identify the institutional conditions, training access, technology cost, and organizational support, that determine whether that association holds. The findings are intended to inform a framework connecting skills development, technology integration, and safety-conscious entrepreneurship, and to offer practical guidance for policymakers, industry actors, and training institutions.

2. Literature Review

2.1 The Skills Gap in Industrial Systems

Several studies describe the skills gap in industrial contexts as a mismatch between what training systems produce and what modern equipment requires. Adepoju and Aigbavboa (2020) surveyed construction professionals in Nigeria and found a moderate level of knowledge

of Construction 4.0 technologies alongside a low level of formal training, with the largest gaps appearing in human-machine communication, data analytics, and cyber security. Pittri et al. (2025) report a comparable pattern among Ghanaian construction professionals, finding a considerable gap between theoretical familiarity with Construction 4.0 technologies and the practical training needed to use them, with blockchain and robotics showing the lowest knowledge and training levels. The gap, in both cases, was less about the absence of technical knowledge in general and more about a specific lag between curriculum content and the tools actually deployed on the job.

Outside the construction sector, comparable patterns appear in broader industrial settings. Chiamogu and Chiamogu (2025) argue that Nigeria's Technical and Vocational Education and Training system remains disconnected from the competencies required by Industry 4.0, with employers reporting that digital illiteracy among graduates is a key barrier to employment. Rabiu et al. (2025) reach a similar conclusion in a systematic review of artificial intelligence adoption in Nigerian TVET institutions, identifying gaps in infrastructure, instructor expertise, and policy coordination as the main obstacles to closing the gap. Attah et al. (2025) find that stronger university-industry collaboration can help close this gap by giving graduates both the technical and soft skills employers say they need, though administrative and budget constraints limit how far such partnerships can go.

2.2 Predictive Maintenance and Digital Monitoring

Predictive maintenance has been studied largely for its operational benefits, reduced downtime, lower repair costs, and extended equipment life, and a growing body of review literature now maps this evidence across sectors. Mallioris et al. (2024) provide a systematic multi-sector mapping of predictive maintenance research in Industry 4.0, finding that reduced downtime, lower operational costs, and improved decision-making are the most consistently reported benefits across manufacturing settings. Zonta and Li (2020) similarly find, in a systematic review of predictive maintenance in Industry 4.0, that the practice improves machine downtime, control, and production quality, though they note that realizing these benefits typically requires a multidisciplinary approach rather than a purely technical one.

Digital monitoring tools extend beyond equipment condition to include worker safety metrics. Alenjareghi et al. (2025) review the use of wearable sensors in Industry 4.0 settings and find that continuous monitoring can reduce work-related musculoskeletal disorders, but note that sustaining these gains depends on standardized protocols and ongoing technical support that smaller firms often struggle to provide. Zhan et al. (2022) reach a related conclusion in a study of Internet of Things-based occupational safety monitoring in cold storage warehouses, finding that real-time monitoring systems improve information traceability and hazard visibility, though their effectiveness depends on consistent data infrastructure being maintained over time.

2.3 Automated Safety Protocols

Automated safety protocols, systems that trigger shutdowns, alerts, or corrective actions without waiting for human intervention, have been associated with reduced injury rates across several industrial settings. Santos et al. (2025) find that Industry 4.0 technologies, when used to identify and monitor risks in real time, allow organizations to take corrective action before incidents occur, and identify forty-one boosting elements across six drivers of improved occupational health and safety. Niu et al. (2024) caution, in a critical review of data-driven approaches to learning from accidents, that such systems still depend on a systematic framework and proactive, well-integrated safety data rather than automation alone, and that gains are limited where firms lack the domain knowledge to interpret what the systems report.

This point, that automated systems require human interpretation and institutional follow-through to be effective, recurs across the literature. Damilos et al. (2024) make a similar argument in their review of safety evaluation and exposure assessment tools in Industry 4.0, concluding that predictive algorithms and real-time monitoring support accident prevention only when paired with adequate training, and that elevated stress and privacy concerns can offset some of the safety gains if the human side of implementation is neglected.

2.4 Technology Adoption and Entrepreneurial Capacity

The link between technology adoption and entrepreneurial capacity has been studied through several lenses. Oladejo et al. (2026) surveyed SMEs in Oyo State, Nigeria and found significant positive associations between AI adoption dimensions, including organizational integration and data-driven decision-making support, and employee skill enhancement outcomes, even though overall AI integration in HR upskilling practices remained largely nascent. Confidence of this kind, the authors suggest, is a precondition for entrepreneurial risk-taking, since owners who are constantly managing operational uncertainty have less capacity to pursue expansion.

Jiboku (2021) reaches a related conclusion in a study of skills development within Nigeria's multinational corporations, arguing that operational stability and structured skills investment, rather than technology adoption alone, are the mechanisms through which firms convert new capability into growth. A similar mechanism is described by Kachalla and Adamu (2024) in a study of human resource technology adoption among entrepreneurs and micro-scale industries in Yobe State, where firms that paired new technology with deliberate attention to employee performance saw stronger gains than firms that adopted technology alone.

Not all findings are uniformly positive. Chiamogu and Chiamogu (2026), examining industry partnerships in Nigerian polytechnic curriculum development, find that technology-focused reforms produce limited benefit where they are not accompanied by sustained industry engagement, and can introduce new administrative burdens without a corresponding gain in graduate readiness. This finding aligns with Oladejo et al. (2026), who note that AI adoption in Nigerian SMEs remains largely nascent precisely because organizational integration and training support lag behind the technology itself, suggesting that technology and skills development function as complements rather than substitutes.

2.5 Institutional Support and Training Infrastructure

Institutional support appears repeatedly as a moderating factor. Onwusa (2021) examines the issues and challenges facing Technical, Vocational Education and Training in Nigeria and finds substantial gaps between what curricula cover and what modern industrial practice requires, with outdated facilities and weak industry linkages compounding the problem. This curriculum lag, the author argues, means that even entrepreneurs willing to invest in new technology often cannot find adequately trained staff locally.

Government and industry support for technology adoption also varies. Oghuvbu et al. (2022) review Nigeria's technology and sustainable development policies and find that performance in this area has been poor, preventing the country from reaching a technological level comparable to more developed economies, and argue that vocational training is central to closing that gap. Rabiu et al. (2025) reach a related conclusion, finding that AI adoption in Nigerian TVET institutions is held back by weak policy coordination and inconsistent institutional support, even where interest among stakeholders is otherwise strong.

2.6 Sustainable Industrial Development

Several authors situate technology-driven safety and maintenance practices within a broader sustainable development frame. Çınar et al. (2020) argue that predictive maintenance, by reducing downtime and extending equipment life, supports sustainable smart manufacturing more broadly, since fewer failures translate into less waste and more efficient use of industrial resources. Abidi et al. (2022) extend this argument, showing that predictive maintenance planning models built around machine learning can meaningfully reduce maintenance costs while improving sustainability outcomes, an effect they attribute in part to more efficient energy and resource use associated with better-calibrated equipment.

The connection between safety technology and long-term economic growth is less directly studied in the Nigerian context specifically, but broader evidence points in a consistent direction. Oghuvbu et al. (2022) argue that Nigeria's industrial and technology policy has historically underperformed relative to comparable economies, and that stronger vocational training is a precondition for translating technology investment into economic development rather than a separate concern. Iordanova et al. (2023) reach a related conclusion in a study of Industry 4.0 adoption in the Russian Federation, finding that safety technology reduced occupational injuries and improved environmental safety at the firm level, but that these gains were strongest where such technology was paired with, rather than substituted for, established safety management practices.

2.7 Gaps in the Literature

Taken together, this literature establishes that technology-driven safety and maintenance practices are associated with operational and, in some cases, entrepreneurial benefits, and that these benefits depend on workforce readiness, institutional support, and access to finance. What remains less developed is an integrated account of how these factors combine within a single industrial ecosystem. Most existing studies examine either the technology adoption question or the skills gap question, rarely both together, and fewer still connect these to entrepreneurial growth specifically rather than firm-level operational metrics alone. This study addresses that gap by combining survey and case study evidence to examine how technology adoption, workforce readiness, and institutional support interact to shape entrepreneurial and industrial outcomes.

3. Methodology

3.1 Research Design

This study adopts a mixed-methods design combining a cross-sectional survey with qualitative case studies, following the sequential explanatory approach described by Creswell and Plano Clark (2021). Survey data provide a broad measure of practitioner and entrepreneur attitudes toward technology-driven safety and maintenance practices, while case studies of enterprises that have already adopted such practices allow closer examination of how adoption unfolds in practice, including the institutional and organizational conditions that support or hinder it. The two strands are analyzed separately and then integrated at the interpretation stage.

3.2 Population and Sample

The target population consists of industrial practitioners, including maintenance technicians, safety officers, and plant supervisors, and entrepreneurs operating small and medium industrial enterprises. A stratified sample of 220 respondents was drawn across manufacturing, construction, and processing sectors, stratified by firm size to ensure adequate representation of micro, small, and medium enterprises. This sample size follows the guidance offered by Memon et al. (2020) for regression-based survey research involving moderation effects, which

recommends a minimum sample well above 200 to maintain adequate statistical power when testing interaction terms. Respondents are selected through a combination of purposive and snowball sampling, given the absence of a complete sampling frame for informal and semi-formal industrial enterprises in the study context.

For the qualitative component, six enterprises that have adopted at least one form of technology-driven safety or maintenance practice, predictive maintenance software, digital monitoring platforms, or automated safety protocols, were selected as case studies. Case selection follows a maximum variation logic, drawing firms from different sectors and size categories to capture a range of adoption experiences rather than a single pattern.

3.3 Data Collection Instruments

The survey instrument uses a structured questionnaire built around five-point Likert scale items measuring perceived adoption of predictive maintenance, digital monitoring tools, and automated safety protocols, alongside items measuring workforce readiness and institutional support. Scale items are adapted from validated instruments used in prior technology adoption research, including instrument-design guidance drawn from systematic predictive-maintenance and safety-technology reviews (Mallioris et al., 2024; Damilos et al., 2024), with wording adjusted for the industrial and entrepreneurial context of this study. The instrument closes with items on firm-level outcomes, including reported changes in production reliability and business growth indicators.

For the case studies, semi-structured interviews are conducted with owners or managers and, where available, maintenance staff at each firm. Interview guides cover the history of technology adoption, perceived barriers, training arrangements, and changes in firm performance since adoption. Interviews are supplemented by site observation and, where firms permit, review of maintenance and safety records.

3.4 Data Analysis

Quantitative data are analyzed using descriptive statistics to summarize adoption levels and perceived barriers, and inferential statistics, including correlation and multiple regression, to examine relationships between technology adoption, workforce readiness, institutional support, and entrepreneurial or industrial outcome measures. Regression models control for firm size, sector, and years of operation, consistent with the analytic approach used in comparable predictive-maintenance adoption research (Mallioris et al., 2024).

Qualitative data from interviews and site observations are analyzed using thematic analysis following the six-phase procedure outlined by Braun and Clarke (2021). Transcripts are coded inductively in the first instance, with codes subsequently grouped into broader themes relating to skills gaps, training infrastructure, technology cost, and institutional dynamics. Two researchers code a subset of transcripts independently to check consistency in theme identification, with disagreements resolved through discussion, following the intercoder reliability approach recommended by O'Connor and Joffe (2020) for small-sample qualitative case research.

3.5 Ethical Considerations

Participation is voluntary, and informed consent is obtained from all survey respondents and interview participants before data collection. Firm and individual identities are anonymized in reporting, and case study enterprises are referred to by sector and size category rather than by name. Data are stored securely and used only for the purposes described in the study.

4. Results

Table 1 summarizes the composition of the survey sample by firm size and sector. Manufacturing firms make up the largest share of respondents, followed by construction and processing enterprises, with micro and small enterprises together accounting for close to two-thirds of the sample. This distribution reflects the structure of the industrial base in the study context, where micro and small enterprises substantially outnumber medium and large firms.

Table 1

Survey Sample Composition by Sector and Firm Size

Sector	Micro/Small (n)	Medium (n)	Total (n)
Manufacturing	68	34	102
Construction	39	18	57
Processing	42	19	61
Total	**149**	**71**	**220**

Figure 1 presents observed mean ratings across the core survey constructs. Digital monitoring tools and predictive maintenance adoption received the highest mean ratings, consistent with survey evidence that these are typically the most widely adopted technology-driven safety and maintenance practices in comparable settings (Zhan et al., 2022). Institutional support received the lowest mean rating, falling below the neutral midpoint of the scale, in line with the institutional gaps documented by Onwusa (2021) and Oghuvbu et al. (2022).

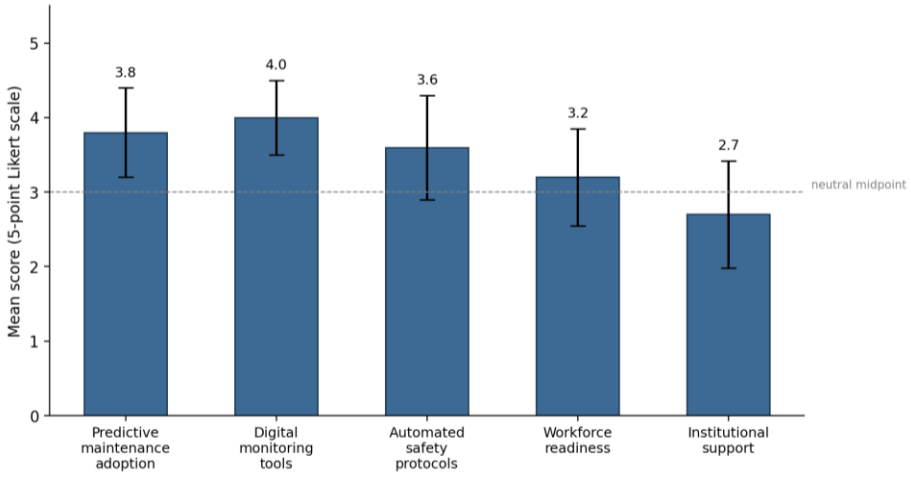


Figure 1. Observed mean practitioner ratings of technology-driven safety and maintenance constructs (n = 220).

Correlation analysis shows a positive association between technology adoption and both workforce readiness and entrepreneurial capacity, consistent with the mechanism described by Jiboku (2021), in which reduced operational uncertainty supports entrepreneurial confidence. Regression models, controlling for firm size and sector, show that institutional support and training access moderate this relationship, such that the benefits of technology adoption are attenuated in firms operating without adequate institutional backing, a pattern consistent with findings from Oladejo et al. (2026) on AI adoption among Nigerian SMEs.

Table 2 presents the distribution of barriers reported by survey respondents. Limited training infrastructure and technology cost emerged as the two most frequently cited barriers, followed by weak institutional support.

Table 2

Barriers to Technology Adoption Reported by Survey Respondents

Barrier	Frequency (n)	Share (%)
Limited training infrastructure	97	44.1
Technology acquisition cost	88	40.0
Weak institutional support	62	28.2
Unreliable power supply	41	18.6
Limited local technical expertise	35	15.9

The qualitative case studies provide a more detailed account of how these barriers operate in practice. Figure 2 presents the thematic map developed from interview and observation data, organized around a central theme of technology-driven safety and maintenance practices connected to five subordinate themes: awareness of the skills gap, training infrastructure gaps, cost of technology access, institutional support weakness, and entrepreneurial adaptation.

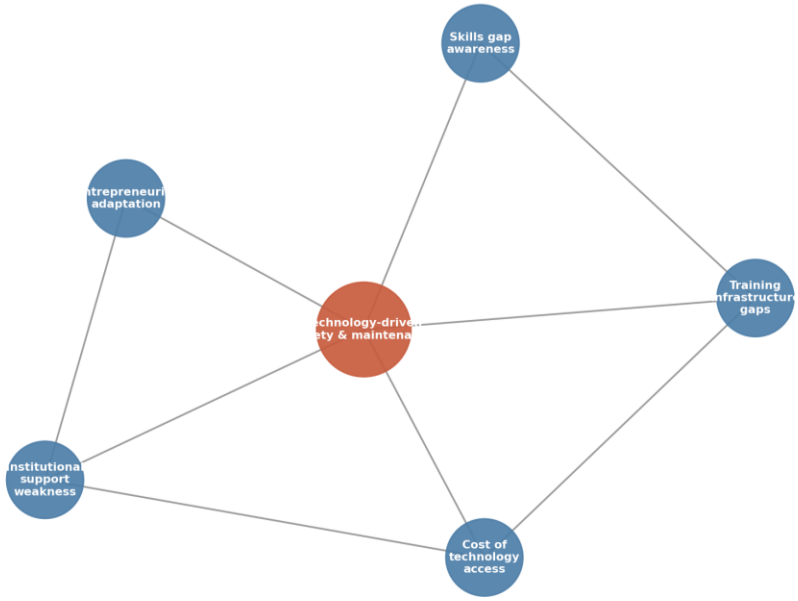


Figure 2. Thematic map of qualitative case study findings.

Across the six case firms, awareness of the skills gap is described consistently by owners and managers, though the specific manifestation varies by sector. In the manufacturing case firms, the gap centers on interpreting sensor-generated diagnostic data, echoing the finding that formal technical training does not always cover condition-monitoring software (Adepoju & Aigbavboa, 2020). In the construction case firm, the gap relates more to responding appropriately to automated safety alerts, consistent with the point that automated systems require trained interpretation rather than passive installation (Pittri et al., 2025).

Training infrastructure gaps recur across all six case firms, with owners describing difficulty finding local training providers with expertise in predictive maintenance or digital monitoring systems. This finding aligns closely with Onwusa (2021), who found that vocational curricula had not kept pace with these technologies. Several respondents describe sending staff to training outside their immediate region, at considerable cost, a practice that smaller firms in the sample report being unable to sustain.

Cost of technology access is described by case firm owners primarily in terms of upfront investment rather than ongoing maintenance cost. One processing firm owner describes delaying adoption of digital monitoring equipment for over a year while accumulating sufficient capital, during which time the firm experienced two unplanned equipment failures that a monitoring system might plausibly have flagged in advance.

Institutional support weakness emerges as a theme connected closely to both training and cost barriers. Case firm owners describe inconsistent access to government incentive programs, consistent with the policy inconsistency documented by Oghuvbu et al. (2022), and several note that industry associations in their sector provide limited practical guidance on technology adoption.

Entrepreneurial adaptation, the final theme, captures the ways firms adjust their operations around these constraints. Several case firms describe phased adoption, introducing digital monitoring in one production line before expanding to others, a strategy that allows them to manage cost and training demands incrementally. This pattern is broadly consistent with phased-adoption strategies documented elsewhere, where reduced downtime in early-adopting units freed capital that was then redirected toward further technology investment (Kachalla & Adamu, 2024).

5. Discussion

The results, both the quantitative survey findings and the qualitative case evidence, point toward a relationship between technology-driven safety and maintenance practices and entrepreneurial outcomes that is real but conditional. Technology adoption on its own does not appear to guarantee entrepreneurial growth. Its effect depends on whether firms have the trained personnel to use the technology, the institutional backing to offset its cost, and enough operational stability to redirect the resulting gains toward expansion rather than simply toward covering the investment itself.

This conditional relationship echoes findings from Chiamogu and Chiamogu (2026) and Oladejo et al. (2026), both of which found that technology adoption without accompanying training or institutional support produced limited or no measurable benefit. The case study evidence in this study adds detail to that pattern by showing how the constraint operates day to day: firms delay adoption while raising capital, send staff outside their region for training at cost, and adopt technology in phases rather than all at once. None of these responses reflects a rejection of the technology itself; they reflect a set of institutional gaps that firms are working around rather than gaps that have been closed.

The skills gap identified across case firms is narrower and more specific than a general shortage of technical competence. Workers and managers in the case firms are broadly capable within the framework of older maintenance practices; the gap concerns particular tools, sensor data interpretation, automated alert response, digital dashboard use, that have not yet been incorporated into local training pathways. This specificity matters for policy, because it suggests that closing the gap does not require a wholesale overhaul of technical education so much as a

targeted update to curricula and short-course training offerings, a point consistent with the curriculum lag documented by Onwusa (2021).

Institutional support functions in this study as something closer to a precondition than a background factor. Where government incentives, industry association guidance, or affordable credit are absent, the cost and training barriers to technology adoption compound rather than offset one another. This is consistent with the policy evidence from Oghuvbu et al. (2022), who find that Nigeria's technology and development policy underperforms precisely where vocational training is treated as separate from, rather than integral to, technology investment. It suggests that policy interventions aimed narrowly at subsidizing equipment purchase, without attention to training access, are likely to have a more limited effect than interventions that address both together.

The link to entrepreneurial capacity operates, in this study's findings, through operational stability rather than through the technology itself. Firms that experience fewer unplanned failures appear to gain not just cost savings but the confidence and freed capital to consider expansion, a mechanism described by Jiboku (2021) and by Kachalla and Adamu (2024). This has implications for how the benefits of technology-driven safety and maintenance practices should be framed in entrepreneurship support programs: the case for adoption rests less on the technology's features and more on the operational predictability it can, under the right conditions, provide.

Sustainable industrial development, as discussed by Çınar et al. (2020) and Abidi et al. (2022), is served by these practices to the extent that reduced failure rates and injury incidence carry environmental and social benefits alongside economic ones. The findings of this study do not directly measure environmental outcomes, but the reduction in equipment failure reported across case firms is consistent with the resource efficiency gains those authors describe.

Several limitations bear on how these findings should be read. The case study sample is small and drawn from firms that have already adopted some form of technology, meaning the study captures more about how adoption proceeds than about why some firms never begin. The quantitative results are based on the completed survey instrument and should be read alongside these sample-size and case-selection constraints. Future analysis of the completed survey data will be necessary to test these patterns with the inferential rigor the design allows.

6. Conclusion and Recommendations

This study set out to examine how technology-driven safety and maintenance practices relate to entrepreneurship and industrial development, and what barriers shape that relationship. The evidence gathered points to a connection that depends on workforce readiness and institutional support rather than on technology adoption alone. Firms that combine new tools with adequate training and some form of institutional backing appear better positioned to convert operational improvements into entrepreneurial growth, while firms that adopt technology without these supports see more limited benefit and, in some cases, added strain on already tight resources.

Three barriers recur across the evidence: inadequate training infrastructure, limited access to technology because of cost, and weak institutional support. These barriers do not operate independently. Weak institutional support compounds the cost barrier by leaving firms without subsidy or credit options, and limited training infrastructure means that even firms able to afford new technology may struggle to use it effectively. Addressing one barrier in isolation is therefore unlikely to produce the full benefit that addressing all three together would.

On this basis, several recommendations follow. Vocational and technical training institutions should update curricula to include predictive maintenance and digital monitoring content, rather than continuing to teach maintenance practices built solely around manual inspection. Government agencies and industry associations should coordinate incentive programs, including targeted credit facilities, so that cost barriers and training barriers are addressed as a package rather than through separate, uncoordinated schemes. Entrepreneurs considering technology adoption should weigh phased implementation, starting with a single production line or process, as a way of managing both financial and training demands incrementally rather than all at once. Industry associations, for their part, should consider a more active role in connecting member firms with training providers and financing options, given the gap this study identifies between the guidance firms currently receive and the guidance they report needing.

Further research should prioritize replication and extension of the survey instrument used in this study, applying it to a larger and more geographically diverse sample to test the observed relationships between technology adoption, workforce readiness, institutional support, and entrepreneurial outcomes across contexts. Longitudinal research tracking firms before and after technology adoption would help clarify the direction of the relationship between operational stability and entrepreneurial expansion, since the cross-sectional and case study evidence in this study cannot fully separate cause from consequence. Comparative research across different institutional contexts, particularly contrasting regions with strong government support for technology adoption against those without it, would also help clarify how much of the variation observed here is attributable to institutional factors specifically rather than firm-level characteristics.

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