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Assessing AI and Entrepreneurship Opportunities in a Low-Income Economy: A Case Study of Sierra Leone

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ABSTRACT

Artificial Intelligence (AI) is increasingly recognised as a driver of innovation and business development globally. However, its application within entrepreneurial activities in Sierra Leone remains limited. This study examines the opportunities for AI in entrepreneurship, focusing on awareness, application, and factors influencing adoption. The objectives include assessing the level of AI awareness, identifying areas of application, and analysing barriers to adoption among entrepreneurs. A mixed-methods approach was employed. Structured questionnaires were administered to 100 entrepreneurs across 4 major urban centres. Quantitative data were analysed using descriptive statistics, while qualitative responses were examined through thematic analysis. Findings reveal high awareness of AI but limited practical understanding and low adoption, primarily restricted to simple tools such as chatbots and basic data analysis. Key barriers include limited internet connectivity and insufficient technical skills. It is recommended that digital infrastructure be strengthened and targeted training programmes implemented to support effective AI adoption.

KEYWORDS: Artificial Intelligence (AI), Entrepreneurship, AI Adoption, Small and Medium Enterprises (SMEs), Sierra Leone, Digital Infrastructure.

1. INTRODUCTION

Rapid technological advancement has significantly reshaped global economic activities, particularly through the emergence and expansion of Artificial Intelligence (AI) (Brynjolfsson and McAfee, 2017). Across many regions of the world, AI technologies are increasingly being integrated into business operations, digital services, and decision-making systems. Through data analytics, automation, and intelligent systems, AI has enhanced efficiency, innovation, and competitiveness within modern economies. In recent years, these technological developments have also played an increasing role in shaping entrepreneurship by enabling new business models, improving productivity, and facilitating the creation of technology-driven enterprises (Obschonka and Audretsch, 2020).

Globally, entrepreneurs are increasingly leveraging AI technologies to develop innovative products and services across sectors such as finance, healthcare, agriculture, logistics, and education. Digital start-ups and technology-based enterprises have demonstrated how AI can be utilised to analyse large datasets, improve customer engagement, automate routine processes, and enhance strategic decision-making. Consequently, AI has been widely recognised as a significant driver of innovation, economic growth, and employment generation. Policymakers, international organisations, and development agencies have therefore emphasised the integration of advanced digital technologies into entrepreneurial ecosystems as a strategy for promoting sustainable economic development (UNCTAD, 2021).

Despite the growing global adoption of AI technologies, notable disparities remain between developed and developing economies in relation to technological infrastructure, digital skills, investment opportunities, and innovation support systems. In many low-income economies, the integration of AI into business activities remains limited due to structural challenges such as inadequate digital infrastructure, limited technological capacity, insufficient research and development investment, and restricted access to funding for innovation-oriented enterprises. These challenges have constrained the ability of entrepreneurs to fully utilise emerging technologies in the development and expansion of their businesses.

Nevertheless, increasing access to mobile technologies, digital platforms, and internet connectivity has begun to create new opportunities for technology-driven entrepreneurship in several developing countries. Digital transformation initiatives, combined with growing interest in technological innovation among young entrepreneurs, have contributed to the gradual emergence of start-up ecosystems in parts of Africa. Within these developments, AI possesses considerable potential to support entrepreneurial innovation through automation, data-driven insights, and intelligent service delivery.

In Sierra Leone, efforts have been undertaken in recent years to promote digital transformation, technological innovation, and entrepreneurial development. The expansion of mobile communication networks, increasing internet penetration, and the emergence of technology-oriented communities have created a foundation for digital entrepreneurship (DSTI, 2019). Furthermore, initiatives designed to encourage innovation and digital skills development have increasingly been implemented by government institutions, universities, and private organisations.

For instance, initiatives organised by the Ministry of Communication, Technology and Innovation have included innovation challenges and hackathons focusing on emerging technologies such as AI and blockchain. Universities have also contributed to entrepreneurial development through innovation competitions and entrepreneurship programmes organised by institutions such as the Institute of Public Administration and Management (IPAM), University of Sierra Leone, and Limkokwing University of Creative Technology. In addition, innovation hubs and private organisations including Freetown Innovation Lab, Bo Innovation Hub, and programmes associated with the Digital Public Goods Alliance have contributed to strengthening the entrepreneurial ecosystem. Institutional initiatives such as the Institute of Public Administration and Management (IPAM) Centre of Excellence in Entrepreneurship and Innovation have further supported entrepreneurial training, innovation development, and the nurturing of technology-based business ideas. While many of these initiatives are concentrated in urban centres such as Freetown, their influence increasingly extends to other parts of the country through digital platforms, training programmes, and expanding access to mobile technologies.

Despite these developments, the adoption and utilisation of AI technologies within entrepreneurial activities in Sierra Leone remain relatively underexplored, reflecting broader challenges observed across the African continent (Gwagwa et al., 2020). Limited awareness of AI capabilities, inadequate technological resources, and insufficient innovation support mechanisms may restrict the ability of entrepreneurs to fully exploit AI-driven opportunities. Furthermore, empirical research examining the relationship between AI adoption and entrepreneurial development within Sierra Leone remains limited. In the absence of sufficient evidence, the development of effective strategies aimed at supporting AI-driven entrepreneurship becomes challenging for policymakers, investors, and innovation stakeholders.

Consequently, a systematic assessment of AI-related opportunities for entrepreneurship is required in order to better understand how emerging technologies may contribute to innovation and economic development in Sierra Leone. Such an assessment may provide insights into the level of awareness of AI among entrepreneurs, the potential applications of AI in business activities, and the factors that influence the adoption of AI technologies within entrepreneurial ventures.

The aim of this study is therefore to assess the opportunities presented by AI for entrepreneurial development in Sierra Leone. In order to achieve this aim, three specific objectives are pursued: to examine the level of awareness and understanding of AI among entrepreneurs; to identify potential opportunities for the application of AI in entrepreneurial activities; and to analyse the factors influencing the adoption of AI technologies within entrepreneurial ventures. Correspondingly, the study addresses three research questions: What is the level of awareness and understanding of AI among entrepreneurs in Sierra Leone? What opportunities exist for the application of AI in entrepreneurial activities? and What factors influence the adoption of AI technologies by entrepreneurs?

The significance of this study lies in its contribution to understanding AI-driven entrepreneurship within low-income economies. Insights derived from entrepreneurs, start-up founders, and participants in innovation ecosystems provide evidence to inform policy, innovation strategies, and entrepreneurial development initiatives. However, the study is limited to entrepreneurial actors within Sierra Leone, and the findings should therefore be interpreted primarily within the national setting.

To situate the study within existing academic discourse, the following section reviews relevant literature on Artificial Intelligence and entrepreneurship, with particular attention to its applications, opportunities, and adoption challenges in both developed and low-income economies.

2. MATERIALS AND METHODS

2.1 Materials

The integration of Artificial Intelligence (AI) into business activities has been widely recognised as a significant development in modern economies. Within the literature, AI is conceptualised not only as a tool for improving efficiency, but also as a mechanism for generating new forms of business value. It has been established that AI reduces the cost of prediction, thereby enabling entrepreneurs to make more informed decisions under conditions of uncertainty (Agrawal et al., 2018). Through the use of machine learning and natural language processing, patterns within large datasets are identified and applied to guide business operations. Furthermore, the strategic use of AI reshapes how firms create value, with data increasingly treated as a critical business asset. While these perspectives emphasise efficiency and optimisation, they collectively indicate a deeper structural transformation in entrepreneurial decision-making processes within digitally advanced environments.

The use of intelligent systems has contributed to the emergence of new business models and a shift towards data-driven entrepreneurship. Predictive analytics has been applied to improve supply chain processes, while language-based systems have supported customer management without a corresponding increase in labour. As a result, a new phase of entrepreneurship has been recognised, in which data and algorithms play a central role in decision-making (Obschonka and Audretsch, 2020). In addition, the automation of routine tasks reduces the time and effort required for operational activities, thereby enabling greater focus on innovation and strategic development (Davenport and Ronanki, 2018). When considered alongside earlier arguments on prediction and efficiency, these developments demonstrate that AI is not merely enhancing existing processes, but is fundamentally redefining the nature and logic of entrepreneurial activity.

In advanced economies, AI is increasingly utilised by start-ups to transform industries such as finance, healthcare, and logistics (Chalmers et al., 2021). However, this body of literature remains disproportionately focused on high-technology firms operating in developed environments, with low-income economies receiving limited scholarly attention despite possessing fundamentally different structural and resource conditions (Khan et al., 2024). This imbalance suggests that dominant conclusions within the literature may lack external validity when applied to such settings. For countries such as Sierra Leone, where access to advanced technologies remains constrained, the applicability of AI-driven business models is therefore uncertain and insufficiently theorised.

In developing economies, the adoption of advanced digital systems is shaped by structural constraints. Essential requirements such as reliable electricity supply, digital infrastructure, and technical skills are frequently inadequate (Kshetri, 2020). While studies in advanced economies primarily emphasise efficiency gains and innovation potential, research in African economies highlights infrastructural limitations, systemic barriers, and issues of data exclusion, indicating that barriers to AI adoption are multidimensional rather than purely infrastructural (Gwagwa et al., 2020). Furthermore, Kshetri (2020) specifically emphasises infrastructural readiness as a foundational precondition for technology adoption. Taken together, these perspectives underscore that the barriers to AI adoption vary significantly across economic environments and cannot be reduced to a single factor. Consequently, the digital divide must be understood not only in terms of access, but also in terms of the capacity to develop and apply advanced technologies.

In addition to infrastructural constraints, the requirement for large and digitised datasets presents a critical limitation. The phenomenon of data poverty has been documented, indicating that marginalised populations and informal economies are often excluded from global data ecosystems (Abebe et al., 2021). AI systems depend on continuous access to high-quality and relevant data. However, business records and consumer data remain largely undigitised in low-income economies. Furthermore, regulatory frameworks often lag behind technological developments, raising concerns regarding data governance and privacy (Jobin et al., 2019). Taken together, these factors demonstrate that both technical and institutional deficiencies jointly constrain the effective deployment of AI.

Despite these constraints, opportunities for AI-driven entrepreneurship are increasingly recognised in low-income settings. The expansion of mobile technologies and digital payment platforms has created alternative pathways for innovation. Evidence indicates that digital solutions are adopted rapidly when aligned with local needs and constraints (Friederici et al., 2020). In contrast to the resource-intensive models observed in advanced economies, AI applications in low-income environments tend to be more adaptive, incremental, and locally adapted (Khan et al., 2024). This suggests that innovation is not necessarily limited by resource scarcity, but is instead reconfigured by it.

The structure of low-income economies further shapes the adoption of AI, particularly due to the dominance of the informal sector. Informal enterprises often operate outside formal regulatory systems and lack structured financial records (Nguimkeu and Okou, 2021). Consequently, conventional enterprise technologies are frequently unsuitable. However, mobile-based digital platforms provide alternative pathways for technological integration, including simplified AI tools such as conversational systems and automated record-keeping applications (Kshetri, 2021). This contrast highlights a transition from formal, data-intensive systems towards more accessible, flexible, and decentralised technological solutions.

These dynamics are particularly evident in Sierra Leone, where agriculture, informal trade, and mobile money constitute central components of economic activity. However, limited attention has been given to how entrepreneurs engage with and apply AI in practice. In addition, demographic factors such as gender significantly influence access to digital technologies. Female entrepreneurs face persistent barriers related to infrastructure, finance, and technical skills (Mariscal et al., 2019). This indicates that unequal access to AI technologies is likely to reinforce existing socio-economic inequalities, thereby limiting inclusive innovation.

The role of entrepreneurial ecosystems in supporting technological innovation has been widely acknowledged. These ecosystems consist of networks of institutions, organisations, and individuals that facilitate business development. Across Africa, the growth of innovation hubs, incubators, and university-led programmes has contributed to the expansion of digital entrepreneurship (Friederici et al., 2020). However, while these platforms provide access to mentorship, funding, and technical support, their effectiveness remains uneven across regions. This suggests that the presence of such ecosystems is insufficient in isolation, and that their impact depends on the degree of coordination and resource alignment within the broader system.

The importance of institutional collaboration has been emphasised through the Triple Helix model, which highlights interactions between universities, industry, and government (Etzkowitz and Leydesdorff, 2000). However, in many African economies, these relationships remain weak and fragmented (Kruss et al., 2015). While knowledge is often generated within academic institutions, its translation into scalable business solutions is limited. This indicates that the primary constraint lies not in knowledge production, but in the mechanisms required for effective knowledge transfer and application.

Government strategies and educational initiatives have contributed to the development of digital and entrepreneurial skills (Banga and te Velde, 2018). In Sierra Leone, similar efforts are observed through innovation hubs and university programmes, although their capacity to support advanced AI technologies remains constrained. When compared with more developed innovation systems, these initiatives operate at an early stage of institutional maturity. This suggests that while foundational progress has been achieved, significant limitations remain in enabling advanced technological adoption.

To explain technology adoption, several theoretical frameworks have been applied. The Technology, Organisation, and Environment framework identifies technological characteristics, organisational readiness, and external environmental conditions as key determinants (Tornatzky et al., 1990). However, evidence indicates that small businesses in developing economies face disproportionately severe constraints, including high costs and limited technical expertise (Díaz-Arancibia et al., 2024). This suggests that the framework does not fully capture the intensity and interaction of barriers present in low-income environments.

Similarly, the Unified Theory of Acceptance and Use of Technology explain how user expectations and facilitating conditions influence adoption (Venkatesh et al., 2003). However, its applicability to AI remains limited due to the complexity, opacity, and data-dependence of such systems. In addition, concerns regarding trust in automated systems significantly influence adoption behaviour (Dietvorst et al., 2015). When considered collectively, these limitations indicate that existing models are insufficient for explaining AI adoption, particularly within resource-constrained and institutionally fragmented settings. This reinforces the need for environment-sensitive analytical approaches.

The case of Sierra Leone remains significantly underrepresented within the literature on digital entrepreneurship. Although national strategies have recognised the importance of digital transformation for economic growth (DSTI, 2019), empirical research on AI and entrepreneurship remains extremely limited. Given the country's distinct economic structure, findings derived from other regions cannot be assumed to apply directly. This highlights a critical gap in both empirical evidence and theoretical application.

There is limited empirical evidence regarding the awareness and application of AI among entrepreneurs in Sierra Leone, which constrains the development of effective policies and support mechanisms. While existing literature highlights the transformative potential of AI, it also demonstrates that its adoption in low-income economies is shaped by a complex interplay of infrastructural, institutional, and data-related constraints. This gap underscores the need for locally grounded research examining awareness, opportunities, and factors influencing AI adoption.

To address this gap, the following section outlines the research methodology adopted to investigate AI awareness, application, and adoption among entrepreneurs.

2.2 Research Methodology

A mixed-methods research design was adopted to assess Artificial Intelligence (AI) awareness, opportunities, and factors influencing its adoption among entrepreneurs in Sierra Leone. In line with the study objectives, attention was focused on entrepreneurs' awareness of AI, perceived and actual applications of AI in business activities, and the determinants shaping its adoption in a low-income economic setting. A convergent mixed-methods approach was employed; whereby quantitative and qualitative data were collected concurrently, analysed separately, and integrated during interpretation (Creswell and Plano Clark, 2018). This design enabled the study to capture measurable patterns of AI awareness and adoption while also providing empirical insights into entrepreneurial experiences. In addition, the convergent design facilitated the systematic comparison and integration of quantitative results with qualitative findings, thereby strengthening the overall interpretation of the data. The integration of findings enhanced analytical depth through triangulation and improved the credibility of the results (Tashakkori and Teddlie, 2010).

The target population consisted of entrepreneurs, start-up founders, small and medium enterprise (SME) owners, and participants within innovation hubs and entrepreneurship development programmes across Sierra Leone. These groups were selected because they represent key actors involved in business creation, innovation, and technological decision-making. Both formal and informal enterprise owners were included to reflect the structure of the national economy, where informal entrepreneurship plays a dominant role. Individuals without direct involvement in business decision-making were excluded to ensure that the study captured informed entrepreneurial perspectives relating to AI awareness and adoption behaviour.

A combination of purposive, convenience, and snowball sampling techniques was employed to recruit participants (Saunders et al., 2019). Purposive sampling was initially used to identify respondents within innovation hubs, incubators, and university-led entrepreneurship programmes, ensuring the inclusion of participants with exposure to digital innovation environments. This was followed by convenience and snowball sampling to reach independent and informal entrepreneurs through professional and peer networks. A total of 100 respondents was obtained for the study, which is considered appropriate for an exploratory investigation of this nature. While the use of non-probability sampling may limit statistical generalisability, it is considered suitable for exploratory research in settings where a comprehensive sampling frame is unavailable and informal entrepreneurial activity is dominant. These conditions make probability-based sampling difficult to implement. Therefore, the selected approach enabled access to otherwise hard-to-reach participants while ensuring the inclusion of diverse entrepreneurial experiences across sectors such as trade, services, and agriculture. Data were collected from respondents located in major urban centres across Sierra Leone, including Freetown, Bo, Kenema, and Makeni. The inclusion of participants from these geographically diverse locations enhanced the representativeness of the sample and provided broader insights into entrepreneurial experiences across different regions of the country.

Data were collected using a structured questionnaire administered electronically via Google Forms. This method was selected due to its efficiency, standardisation, and suitability for reaching geographically dispersed respondents (Bryman, 2016). The questionnaire was designed in alignment with the study objectives and included both closed-ended and open-ended questions. Closed-ended items were used to measure levels of AI awareness, access to digital infrastructure, perceived opportunities for AI application in business activities, and barriers to adoption. Open-ended questions allowed respondents to provide deeper insights into entrepreneurial experiences, practical challenges, and perceived opportunities associated with AI use. The questionnaire also incorporated conditional branching (skip logic) to ensure that respondents were only presented with relevant questions based on their responses.

Prior to the main data collection, a pilot test of the questionnaire was conducted with three respondents who possessed characteristics similar to the target population. The purpose of the pilot test was to assess the clarity, relevance, and structure of the questionnaire items. Feedback obtained from the pilot test was used to refine the wording of questions and improve the overall design of the instrument, thereby enhancing its validity and reliability. In addition, the instrument was developed based on existing literature and aligned with established constructs to further ensure its validity.

Quantitative data were analysed using descriptive statistical techniques, including frequencies and percentages, to identify patterns in AI awareness, access, perceived opportunities, and adoption levels. Microsoft Excel was utilised for data organisation, descriptive analysis, and graphical presentation to support interpretation. Qualitative data obtained from open-ended responses were analysed using thematic analysis, following the approach outlined by Braun and Clarke (2006). This involved systematic coding, identification of recurring themes, and interpretation of patterns related to opportunities for AI in entrepreneurship, structural constraints, and adoption behaviour. The integration of quantitative and qualitative findings enabled triangulation and strengthened the overall validity and interpretive depth of the study.

Ethical considerations were strictly observed throughout the research process. Participation was voluntary, and informed consent was obtained prior to data collection. Participants were provided with clear information regarding the purpose of the study and the intended use of their responses. No personally identifiable information was collected, and confidentiality was maintained at all stages of the research process (Bell et al., 2022). Participants were also informed of their right to withdraw from the study at any point without any adverse consequences.

Despite these measures, certain limitations are acknowledged. The use of non-probability sampling may introduce bias and limit the generalisability of findings. In addition, reliance on electronic questionnaires may exclude individuals with limited digital access or low levels of digital literacy. However, these limitations are acceptable given the exploratory nature of the study and the structural constraints of the research environment. The findings should therefore be interpreted as indicative rather than statistically generalisable.

The following section presents and analyses the study's findings in relation to the research objectives and relevant literature.

3. FINDINGS AND DISCUSSIONS

3.1 Demographic Characteristics

A total of 100 respondents participated in the study, comprising entrepreneurs, start-up founders, and small business owners operating across major urban centres in Sierra Leone. The demographic profile provides critical insights into the structure of the entrepreneurial population and establishes a foundation for interpreting subsequent patterns of AI awareness, application, and adoption.

In terms of gender distribution, respondents were predominantly female (64%), while males accounted for 36%. This reflects a strong presence of women within entrepreneurial activities, particularly in small-scale and informal enterprises. This finding aligns with existing evidence highlighting the significant contribution of female entrepreneurs to informal sector productivity in Sub-Saharan Africa (Nguimkeu and Okou, 2021). However, prior studies indicate that female entrepreneurs often face structural constraints in accessing digital technologies, finance, and technical skills (Mariscal et al., 2019). Therefore, despite high participation, disparities in access to technological resources may shape patterns of AI awareness and adoption.

The age distribution reveals a predominantly young entrepreneurial population, with 74% aged between 20 and 29 years and 20% between 30 and 39 years. Only 2% were above 40 years, while 4% were under 20, with no respondents aged 50 and above. This concentration within younger cohorts suggests a digitally exposed and potentially innovation-oriented population. Younger entrepreneurs are generally more open to emerging technologies, which may facilitate AI adoption (Obschonka and Audretsch, 2020). However, their relatively early career stage may simultaneously constrain access to financial resources and managerial experience required for implementing more advanced technological solutions.

Geographically, respondents were concentrated in Freetown (42%), followed by Bo (26%), Makeni (18%), and Kenema (14%). This spatial concentration reflects the role of Freetown as the primary economic and technological hub. It further indicates that access to business opportunities, customer markets, and internet connectivity is unevenly distributed. Urban environments typically provide stronger digital infrastructure and innovation ecosystems (Kshetri, 2020; Friederici et al., 2020), suggesting that AI adoption is likely to be spatially uneven, favouring entrepreneurs in urban centres.

Educational attainment among respondents was notably high, with 74% holding a bachelor's degree, 10% postgraduate qualifications, and 12% diplomas, while only 4% reported secondary education. Although this indicates a relatively skilled sample, the persistence of adoption barriers observed in subsequent sections suggests that education alone does not guarantee technological adoption. This reinforces the argument that enabling infrastructure, practical exposure, and institutional support are equally critical (Díaz-Arancibia et al., 2024).

In terms of business structure, sole proprietorships dominated (56%), followed by informal businesses (25%), partnerships (11%), and limited companies (8%). This confirms the prevalence of small-scale and informally structured enterprises, which are typically characterised by limited capital and reduced capacity for technological investment (Nguimkeu and Okou, 2021). Consequently, AI adoption is more likely to occur through low-cost and accessible tools rather than complex enterprise-level systems.

Sectoral distribution shows that trade or commerce (51%) and services (28%) dominate, with smaller shares in technology (9%), manufacturing (5%), agriculture (1%), beauty (3%), and fashion (3%). This reflects the structure of the Sierra Leonean economy, which is largely service- and trade-oriented. These sectors are generally less data-intensive and less digitally integrated, implying that AI adoption is likely to be incremental and concentrated in functional areas such as marketing and customer engagement (Khan et al., 2024).

The business lifecycle further indicates a relatively young ecosystem. The vast majority are in their early stages, with 47% operating for 1–3 years and 29% for less than one year. The remaining businesses are older, with 11% operating for 4–6 years and only 13% operating for more than six years. While early-stage firms are often flexible and innovation-oriented, they are also constrained by limited resources, which may restrict investment in advanced technologies (Davenport and Ronanki, 2018).

Firm size reinforces this pattern, with 70% employing between 1 and 5 individuals, confirming the dominance of micro-enterprises. Another 19% employed between 6 and 20 individuals, while only 11% employed more than 20. Such firms typically lack the financial and technical capacity required for large-scale technological adoption.

Access to internet connectivity varied significantly, with 39% reporting limited access, 24% moderate access, 18% reliable access, and 19% no access. This uneven distribution represents a fundamental structural constraint, as most AI applications rely on stable internet connectivity (Gwagwa et al., 2020).

Overall, the demographic profile reveals a young, relatively educated, and predominantly female entrepreneurial population operating within small-scale and trade-oriented businesses. While these characteristics suggest potential for digital engagement, they are simultaneously constrained by infrastructural limitations and resource constraints. This duality provides a critical framework for understanding the awareness–adoption gap identified in subsequent sections.

RQ1. What is the level of awareness and understanding of AI among entrepreneurs in Sierra Leone?

The findings indicate that awareness of Artificial Intelligence among respondents is high, with 93% reporting awareness. However, this widespread awareness does not translate into equivalent levels of understanding.

A majority of respondents (55%) reported only a basic understanding, while 25% indicated moderate understanding, 13% advanced understanding and the remaining 7% no understanding. This demonstrates a clear awareness–understanding gap, suggesting that exposure to AI does not necessarily translate into practical or technical competence. This finding aligns with existing literature, which emphasises that digital exposure alone is insufficient for technological capability development (Agrawal et al., 2018).

The dominance of informal information sources further reinforces this pattern. Social media was the primary source (66%), followed by formal education (32%), internet articles (20%), training programmes (19%), and peers (16%). This indicates that awareness is largely shaped by accessible but unstructured channels, which may contribute to fragmented or superficial understanding.

Perceptions of AI were generally positive but characterised by uncertainty. A majority agreed that AI improves efficiency (69%) and supports decision-making (54%). However, perceptions of relevance to small businesses were more divided, with 52% agreeing and 31% disagreeing. This suggests that a notable proportion of respondents still perceive AI as more applicable to larger or technologically advanced firms.

Interestingly, cost was not widely perceived as a primary barrier, with 61% disagreeing that AI is too expensive. Instead, uncertainty was more evident in relation to trust (35% neutral) and technical complexity (29% neutral), indicating that ambiguity and limited understanding, rather than resistance, shape attitudes towards AI.

Overall, these findings demonstrate that awareness is widespread but largely superficial. The key challenge, therefore, lies not in increasing exposure, but in transforming awareness into practical and applicable knowledge.

RQ2. What opportunities exist for the application of AI in entrepreneurial activities?
AI adoption was reported by 42% of respondents, which is substantially lower than the awareness level (93%) identified earlier. This confirms the existence of a significant awareness–adoption gap, suggesting that structural and capability constraints limit implementation.

Among AI users, adoption was concentrated in accessible tools. Chatbots (57.1%) were most common, followed by data analysis tools (33.3%), financial automation (23.8%), and operational tools (21.4%). This demonstrates that entrepreneurs prioritise low-cost and user-friendly solutions that deliver immediate and observable benefits.

AI applications were most prominent in marketing (61.9%), customer service (45.2%), and operations (42.9%). These areas typically involve lower implementation complexity and provide direct benefits. In contrast, more complex applications such as supply chain management (16.7%) were less common, reflecting limitations in data availability and infrastructure.

Despite moderate adoption, perceived impact was highly positive, with 78.6% reporting high or very high impact. This indicates that even basic AI applications can generate substantial value, particularly in improving efficiency and supporting decision-making.

Perceptions of opportunities were also strongly positive. Majorities agreed that AI enhances productivity (66%), supports growth (75%), improves competitiveness (68%), and creates new opportunities (68%). Additionally, 78% considered AI beneficial within their sector.

Thematic analysis further revealed that opportunities are primarily concentrated in marketing (32%), efficiency and automation (19%), and data-driven decision-making (15%). These areas align closely with actual usage patterns, suggesting that adoption is driven by immediate practicality rather than technological sophistication.

Overall, while AI adoption remains limited, its perceived value is high. This indicates that the primary constraint is not perceived usefulness, but the ability to operationalise AI within existing resource limitations.

RQ3. What factors influence the adoption of AI technologies by entrepreneurs?
The findings indicate that AI adoption is shaped by a combination of infrastructural, technical, and organisational factors.

Access to internet services emerged as a key determinant, with 50% indicating great or very great influence. Similarly, technical skills were identified as critical, with 46% indicating strong influence. These findings highlight the importance of both infrastructure and human capital.

In contrast, cost and access to finance showed more varied influence, suggesting that financial constraints, while relevant, are not the primary barrier. This challenges conventional assumptions and indicates that infrastructural and capability-related constraints are more significant in this setting.

Barrier analysis supports this conclusion, with poor internet connectivity (69%), lack of awareness (52%), and lack of skills (42%) identified as the most significant challenges. These findings demonstrate that structural and knowledge-based barriers outweigh purely financial considerations.

Despite these constraints, readiness for adoption was high, with 83% indicating moderate to very high readiness, and 85% expressing likelihood of future use. This suggests that willingness to adopt AI is not the primary limitation.

Support needs were dominated by training and education (77%), followed by access to technology (51%) and partnerships (40%). This highlights the importance of ecosystem-level support.

These findings align with the Technology–Organisation–Environment (TOE) framework (Tornatzky et al., 1990). However, they extend this framework by demonstrating that, in low-income environments, infrastructural limitations function as primary constraints rather than secondary environmental factors. Similarly, while broadly consistent with Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), the findings suggest that facilitating conditions are more critical than behavioural intention.
Overall, the findings highlight a consistent gap between awareness and adoption, shaped primarily by infrastructural and capability-related constraints. These insights provide the basis for the conclusions and recommendations presented in the following section.

4. CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

This study examined the opportunities presented by Artificial Intelligence (AI) for entrepreneurial development in Sierra Leone, with a focus on awareness, application, and factors influencing adoption. The findings reveal a clear gap between high levels of awareness and relatively low levels of practical understanding and adoption. While most entrepreneurs are familiar with AI, this awareness remains largely superficial and does not translate into effective utilisation within business activities, indicating that exposure alone is insufficient for capability development.

Where adoption occurs, it is primarily limited to simple, accessible, and low-cost applications such as chatbots and basic data analysis tools. This reflects a preference for solutions that deliver immediate and observable benefits within resource-constrained environments, while more advanced and data-intensive applications remain uncommon.

Despite limited adoption, perceptions of AI are strongly positive. Entrepreneurs widely recognise its potential to enhance efficiency, support decision-making, and promote business growth, indicating that resistance is not a major barrier. Instead, adoption is primarily constrained by infrastructural and capability-related factors, particularly limited access to reliable internet connectivity and insufficient technical skills. These constraints significantly restrict the effective use of AI.

The structure of the entrepreneurial ecosystem, dominated by micro and informal enterprises, further shapes adoption patterns by favouring accessible and user-friendly tools over complex systems. Financial constraints, while relevant, are secondary to infrastructural and skills-related limitations.

Overall, the study demonstrates that the central challenge is not a lack of awareness or willingness to adopt AI, but the limited capacity to translate awareness into practical application. By highlighting the dominant role of infrastructural and capability-related constraints, this study shows that in low-income economies, these factors are more decisive than attitudinal barriers in shaping AI adoption. This provides important insights for both policy and practice in advancing AI-driven entrepreneurship.

4.2 Recommendations

Based on the findings, several practical and policy-oriented recommendations are proposed to support the effective adoption and utilisation of AI in entrepreneurial activities in Sierra Leone.

First, strengthening digital infrastructure should be prioritised, particularly in improving the reliability and affordability of internet connectivity. Given the dependence of AI applications on stable digital access, expanding broadband coverage and reducing geographical disparities, especially beyond major urban centres, are essential for enabling adoption.

Second, targeted capacity-building initiatives are needed to enhance practical AI skills among entrepreneurs. Training programmes should emphasise applied and business-oriented use of AI tools rather than theoretical knowledge, demonstrating how such technologies can be integrated into everyday operations. Universities, innovation hubs, and entrepreneurship programmes should play a central role in delivering accessible and relevant training.

Third, efforts should be made to promote the development and dissemination of low-cost and user-friendly AI solutions tailored to small and informal enterprises. Given the structure of the entrepreneurial ecosystem, scalable and simplified tools are more likely to achieve widespread adoption. Collaboration between technology providers, local developers, and entrepreneurs is critical to ensure alignment with local business needs.

In addition, strengthening the broader entrepreneurial ecosystem is essential. Innovation hubs, incubators, and support programmes should be expanded to provide mentorship, technical assistance, and access to digital resources. Greater collaboration between universities, industry, and government institutions should be encouraged to facilitate knowledge transfer and innovation development, consistent with the Triple Helix model.

Promoting inclusive AI adoption is also important. Given the strong participation of female entrepreneurs, targeted interventions should address disparities in access to digital tools, skills, and resources to ensure equitable participation in AI-driven opportunities.

Finally, government agencies should strengthen and expand existing policy frameworks and strategic initiatives to more effectively support AI adoption among small businesses. This includes enhancing incentives for digital innovation, increasing support for start-ups, and further integrating AI into national development strategies to create a more enabling environment for sustainable technological advancement.

Further research is recommended to extend this study by incorporating larger and more diverse samples, including rural entrepreneurs. Longitudinal studies could provide insights into how AI adoption evolves over time, while comparative research across African countries may deepen understanding of AI-driven entrepreneurship in low-income economies.

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