Machine Learning Adoption Among Technopreneurs in Gweru, Zimbabwe

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***Abstract* - This paper explored the present condition, operating challenges and facilitators of Artificial Intelligence (AI) and Machine Learning (ML) among Technopreneurs at Gweru, a secondary city in Zimbabwe. The research incorporated the use of qualitative exploratory design and Technology-Organization-Environment (TOE) framework in which semi-structured interviews were held with 23, purposely sampled, Technopreneurs in different fields. The results showed that there is a young-adoption environment, with merely 26 percent of Technopreneurs already taking action with AI/ML, and 35 percent are still in the investigative stages. The sectoral analysis showed that there was more implementation in fintech (37.5) and strong exploration in agritech (30%). The greatest impediments identified were infrastructural constraints which were common and presented as an untrustworthy power, an expensive and slow internet, and expensive cloud service. The other impediments were critical knowledge gaps that require informal learning and lack of familiarity with AI/ML ventures by investors. On the other hand, collaborative peer learning networks, resource sharing and incremental adoption models became some of the important enablers. Specifically, the paper has emphasized the exponential nature of an "AI divide" necessitated by computational needs and suggested locally based suggestions, such as the creation of AI hubs, the development of local cloud infrastructure, formalizing training and mentorship, and training investors on how to faster accelerate AI-based Technopreneurship. This study bridged a significant gap in the knowledge on AI/ML adoption outside of main sources of innovation in emerging economies.**

***Keywords:* AI adoption, Technopreneurship, Developing Countries, Gweru, TOE Framework**

I. Introduction

The accelerated development of artificial intelligence (AI) and machine learning (ML) have provided the businesspersons with the world with unprecedented chances to innovate, streamline activities, develop new products and services, and scale their operations [1]. These state-of-the-art technologies in developing nations can allow a leapfrog or bypass conventional developmental limitations and factor in unique socio-economic issues in the field of healthcare, agriculture, financial inclusion, and resource management [2], but there are difficult barriers to adoption and effective application of AI/ML among Technopreneurs. [3] The state of Zimbabwe offers an interesting example to the study of the dynamics of AI/ML adoption among Technopreneurs. Although the country has faced serious problems such as hyperinflationary times, shortages of foreign currencies, Zimbabwe has shown greater strength and traces of innovations in the technological sector. This potential can be tested by the success of the EcoCash that has reached an over 90 percent mobile penetration and revolutionized the financial inclusion via mobile money [4]. Moreover, the nation has a young, more technologically inclined population, as well as an entrepreneurial ecosystem that has potential, and is growing, but has more systematic challenges, including infrastructural inadequacy, skill shortage, lack of risk capital and regulatory vagueness that could choke the overall adoption of these new technologies outside the early adopters. Linked searches in Africa, meaning an increasing awakening and discovery [2]. Nonetheless, substantive adoption, meaningful innovation, committed output of research and substantial investment are concentrated. Egypt, South Africa, Nigeria, and Kenya are calculated as the major contributors to AI research, development, and venture financing, which qualifies as a devastating urban innovation divide on the continent [6]. It is in this gap that this paper has highlighted the urgent need to conduct specific, localized research on countries outside the established centers, specifically in countries such as Zimbabwe where the national AI governance is still emerging [7]. It is in this local context that Gweru, the third largest city in Zimbabwe and the capital of the Midlands Province, becomes a very relevant and instructive location of this study. Gweru, being a major second urban centre, reflects the nature and the predicament of most non-capital cities in the developing world that are struggling to join the digital economy. The city has a rich economic foundation, which covers manufacturing, higher education, and service industries, and the increasing number of aspiring and established Technopreneurs. Although Gweru may not be a densely ecosystem as that in Harare, it provides a valuable opportunity to explore the process of AI/ML adoption in non-Primary innovation hubs. Its Technopreneurs work within the context of a larger economic and policy environment in Zimbabwe but with more locally unique problems that may include less dependable high-speed internet connectivity than that in the capital, lower access to technical professional talent and venture capital, and physical distance to largest governmental and institutional support institutions [8]. On the other hand, Gweru can also introduce their own enablers, including good local business networks, university connections that provide potential talents and research partnership, reduced costs of operation, and the ability to create AI solutions to meet regional requirements in agriculture, mining, or logistics. The knowledge of the present condition, obstacles, and opportunities and possible routes of AI/ML adoption within the Technopreneurial community of Gweru in particular with the issue of resource scarcity and policy voids is consequently not only crucial to developing local economic opportunities and innovation but will also prove useful in the context of similar secondary cities in Zimbabwe and the Sub-Saharan continent as a whole struggling to locate an appropriate place where AI technologies can be implemented in their entrepreneurial businesses. This paper aims to fill this very important gap by exploring the actualities of AI/ML application among Technopreneurs in Gweru. In this research, three research questions have been discussed:

- How well are Technopreneurs in Gweru city adopting AI/ML?
- Which are the main obstacles and opportunities of AI/ML use in Technopreneurs in Gweru?
- How can Technopreneurship powered by AI be expedited in Gweru?

II. Literature Review

Technopreneurship can be defined as entrepreneurship with technology as the central facilitator of the business model, value proposition and disruption of the market [2][9]. It is a very important engine of diversification, employment and innovation-based growth of the developing economies. It applies digital technologies to develop scalable solutions, and is often taking local problems and making them applicable to a wider audience [5]. In Sub-Saharan Africa (SSA), there is a visible Technopreneurship revolution, which was driven by the growth of mobile penetration, the development of a large youth base, and a new understanding of how innovation is central to development [10]. The trend of this increase is not, however, even. Relatively developed ecosystems of active venture capital, specialized incubators and accelerators, strong research connections, and critical mass of technical talent are actively supporting AI development in major hubs like Lagos (Nigeria), Cape Town, Johannesburg, (South Africa), Nairobi (Kenya), and Cairo (Egypt) but are not present in secondary cities and other countries not included in these hubs [11], [12].There are high structural constraints in secondary cities and other countries that are not members of these hubs. There are chronic capital gaps that are severely restricting the growth of Technopreneurs , risk-taking capital, like angel or venture funding, beyond the major centers. This puts Technopreneurs into high dependence on bootstrapping, grants, or inadequate micro-finance, which in turn limits scalability and investments in complicated technologies like AI/ML [8], [13]. The other limitations like ineffective power sources, lack of affordable high-speed fiber broadband and logistic difficulties have a severe impact on the progress and implementation of the data-intensive applications required in AI/ML [14]. In addition to this, the number of STEM graduates is increasing, but there is also a consistent issue with skill mismatch, as the educational programs of universities tend to prioritize the intellectual knowledge of the future employees instead of practical and innovative skills such as advanced data science, ML engineering, and AI ethics. This scarcity is often exacerbated in the non-capital cities [15]. These challenges are further exacerbated by regulatory uncertainty in digital business models, data privacy and new technologies, making the regulation unpredictable and risking more compliance issues [5] due to new technologies. However, new ecosystems in nations like Tanzania, Uganda, Ghana and Rwanda show progress through niche orientation, building local talent pipeline, and through more enabling policies [16]. This trend is encouraging and, therefore, requires a context-based study, especially with regard to the implementation of technologies, such as AI/ML, in secondary cities, like Gweru, Zimbabwe.

A. The use of AI/ML in Emerging Markets.

It is becoming widely appreciated that Artificial Intelligence (AI) and Machine Learning (ML) has the potential to enable major productivity gains, innovation, and solving urgency developmental issues in the emerging economies [17]). The possible uses cut across industries that are vital to these economies such as precision agriculture, fintech to further financial inclusion, predictive healthcare diagnostics, supply chain optimization and personalized education [18]. Some of these advocates have even discussed on how AI would allow leapfrogging or skipping the usual process of development [19]. Nevertheless, the empirical fact of AI/ML adoption in SSA shows a lot of disparities and enormous obstacles, and it is not about the narrative of leapfrogging anymore. The underlying digital divide is a significant barrier; restricted and expensive high-bandwidth internet, unstable power, and poor access to cloud computing services create severe limitations to the practicability of data-intensive AI applications, especially when it comes to resource-limited small businesses, and these shortcomings are usually more acute beyond large metropolitan regions [2]. Another significant obstacle is data scarcity and quality since the AI models can only process high-quality and large amounts of data that are relevant. Numerous SSA nations have disjointed, siloed, or non-digitized information, with poorly developed data-governance systems, which are grossly restrictive of the availability of the fuel needed to drive AI [20] Moreover, there is an acute skills shortage. Inadequate supply of AI/ML expertise like data scientists, ML engineers and AI ethicists and overall AI illiteracy among entrepreneurs and managers, is a barrier to strategic cognition and AI application in the business [11]. Financial limitations also come into play as the expenses of procuring AI tools in the form of licenses and APIs, recruiting limited talent, computing power, and data collection are usually expensive to start-ups and SMEs with limited financial capabilities [6]. Compounding these issues are regulatory uncertainty and ethical risks; the lack of explicit national AI policies, enforceable data protection legislation and ethical principles, and perceived risk, creates ambiguity, and raises justified concerns of bias, fairness and accountability in AI uses in an environment commonly beset by poor institutional regulation [21]. Although the literature often dwells upon adoption drivers in large companies or major technological centers [12], little work has been conducted to investigate the issue of AI/ML adoption among Technopreneurs living in secondary cities in the countries that are lagging in digital policy development. Such a gap requires a localized study that would comprehend how these issues appear and are negotiated on the micro-level in a small city like Gweru.

B. Intelligence Governance and Policy frameworks in Africa.

Formulation of AI strategies and governance models on a national level is now more considered important to ensure that the benefits of AI are maximized, the risks also are limited, and that AI innovation is responsible [22]. On the African continent, there is a wide variation in the AI governance realization. Countries like Rwanda, Benin, Egypt, Morocco, Mauritius, Tunisia, Sierra Leone, and Senegal, are already developing or already implemented specific AI policies and data governance[1] ,[2]. These models are oriented to national capacity building, research and development, the required infrastructure, developing ethical principles, and priority sectors to use AI, and Rwanda is often mentioned as an example of countries with plans to implement AI as part of a larger agenda of digital economy or ICT policy. This is the latter category of policy lag into which Zimbabwe has been dragged. The country has a National ICT Policy and has already come up with a Data Protection Act [23] and an overall national AI strategy or governance that remains infantile [24]. Nonetheless, the regulation is uncertain because there are no guidelines on such vital aspects as the use of data to train AI, accountability of algorithms, and liability frameworks in the decisions made by AI, as well as AI-specific intellectual property, which introduces perceived risk and makes compliance more challenging [21], [24]. This gap is also associated with the lack of coordinated government support infrastructure, i.e., specific funding, infrastructure, or skills programs aimed directly to promote AI innovation among start-ups and SMEs.

C. Theoretical Framework

It was the Technology-Organization-Environment (TOE) framework [26] that was used to understand technology adoption with regard to the study. The TOE framework assumes that there are three contexts, namely, technological, organizational, and environmental, in which the probability and the success of technological innovation adoption are held. It offers an effective prism to examine the adoption of technology in organizations in terms of higher-level qualities and not the individual behavior [27]. The technology context is the internal as well as external technologies of a company. This includes the available technological infrastructure, availability of emerging technologies as well as perceived advantages and compatibility of the innovation with the existing systems and processes [26]. To adopt AI in the context, it would incorporate maturity, access, and complexity of AI/ML tools, platforms, and algorithms, and the data infrastructure needed to support the technologies. Some factors that are important in the context of adoption are the degree to which AI/ML is perceived to be better than the existing methods, provides benefits such as greater efficiency, new products/services, enhanced decision making, and lower cost [3] how AI/ML fits with the existing values of the Technopreneurial venture, past experiences, and the current technological infrastructure [26], [28] and the initial investment, the recurrent cost of operation and the hidden cost of AI/ML adoption, implementation, These are size of organization, organization structure, management support, human resources, organizations culture, and availability of slack resources [26]. In the case of Technopreneurs, with their typical lean start-up, the organizational setting features firm size and scope [29], managerial structure and human [28], [30] and innovative capacity. The environmental context covers the outside environment where the organization is located. This involves the industry structure, competition, government policies and regulations, customer and partner preparedness [26]. To Technopreneurs, this is the rate of change and predictability in the Technopreneurs target markets[4], government regulation and support [24], the availability and accessibility of critical needs enabling infrastructure, such as access to the broadband internet, reliable power availability, and effective financial systems [24].

III. Methodology

The paper had a qualitative exploratory design to explore the complex, context-specific notions of AI/ML adoption amongst Technopreneurs in Gweru, Zimbabwe. Qualitative approaches were chosen so as to obtain a more profound, deep knowledge of the lived experiences, perceptions, and contextual barriers/enablers of the participants [31]. The study was carried out in the time period of March to May 2025, which is in accordance with research methodological consistency in which design options directly answer research questions [32]. It used purposive sampling with maximum variation [26] to sample 23 Technopreneurs who are based in Gweru. The participants were picked in various sectors like fintech, agritech, and healthtech and AI/ML Exposure where the criteria involved sampling among non-adopters and those actively implementing it. The on-line interviews (n=5) and face-to-face interviews (n=18) were semi-structured, and an interview guide was in accordance with the TOE framework [26]. The mean duration of every interview was 35 minutes.

A. Data Analysis

It proceeded through six steps of analysis [33], which used reflexive thematic analysis of 23 transcripts of interviews with an average length of 35 minutes on each interview and one mix of an online (n=5) and face-to-face (n=18) interview. Qualitative analysis software was done using NVivo software. Verbatim familiarization in 48 hours; analytic memo immersive reading, deductive + inductive approach coding through TOE framework, 47 codes were generated (15 Technological, 18 Organizational, 14 Environmental) and Inter-coder reliability. Theme Development The candidate themes (n=12) narrowed to 8 final themes divided by dimensions of TOE validated the theme review, theme saturation and negative case analysis followed by reporting of 2-4 representative quotes per theme; structured to respond to 3 research questions.

Qualitative richness was placed more than statistical extrapolation; interpretive decisions in cross-sectional design on theme building. The analysis of data conducted showed that there were 8 themes that disclosed patterns of adoption, barriers/enablers that can be grouped into the TOE framework to answer all research questions.

B. Ethical Considerations

Participants gave informed consent, which was in writing and pseudonyms were used in place of identities. The data was saved on the safe storage devices that could only be accessed by the authors.

IV. Findings

A. Present AI/ML Adoption Condition among Technopreneurs in Gweru City.

The study indicates a promising and an emergent AI/ML adoption environment among Gweru Technopreneurs with increasing experimentation and selective application to important areas.

B. Levels of Adoption and Distribution.

Out of the 23 participants, 39% (n=9) were non-adopters who had not used AI/ML technologies, 35% (n=8) were explorers, who had tried simple AI/ML tools and 26% (n=6) were active implementers who had used working AI/ML solutions (Figure 1). Through this distribution, the environment of early-stage adoption is mostly seen by a large margin with a lot of opportunity to grow.

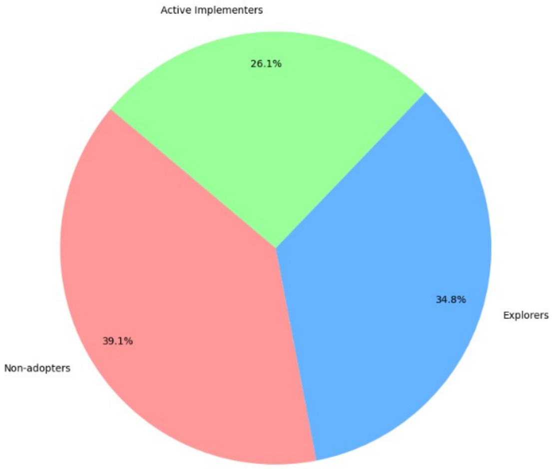

Fig. 1. Overall AI/ML adoption status among Technopreneurs in Gweru (n=23)

Sectoral analysis revealed differential adoption patterns as shown in Figure 2. Fintech demonstrated the highest implementation rate (34.7%) achieving active implementation. Agritech showed strong exploration activity (30%) in the explorer category. Healthtech exhibited cautious adoption, with only 1 of 4 participants achieving implementation. E-commerce and edtech sectors showed minimal engagement, primarily remaining in non-adopter categories.

C. Types of AI/ML Applications in Use

Active implementers and explorers utilized various AI/ML applications, reflecting both opportunity recognition and resource constraints. Chatbots were the most common application, with fintech and healthtech entrepreneurs deploying customer service chatbots. Participant 21, a healthtech implementer, described: *"Our WhatsApp chatbot handles most of the patient inquiries, freeing up our nurses for critical cases."*

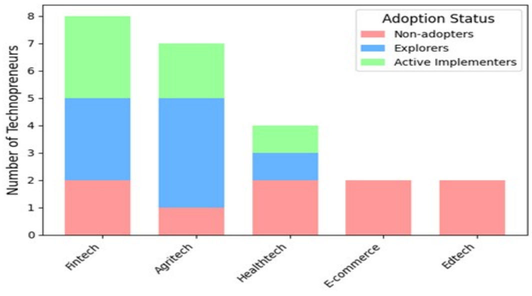

Fig. 2. Adoption status

D. AI/ML adoption status by sector among Technopreneurs in Gweru

Predictive analytics were mostly applied in agritech in the prediction of crop yield and weather forecasting. Agrotech explorer participant 12 said: "We predict rainfall patterns with machine learning, which are not particularly sophisticated at the moment.

Computer Vision was confined to agritech to detect crop disease and quality. Participant 4 observed: "Identifying crop diseases is one of the tasks that the AI can identify more effectively than the majority of the farmers, yet another issue is to make them believe it. The use of Recommendation systems was also low and mainly applied in e-commerce as product recommendations.

E. Key Obstacles and facilitators to AI/ML adoption.

The thematic analysis showed that there were interrelated barriers and enablers arranged into the Technology-Organization-Environment framework, where infrastructure limitations, knowledge gap, and financial constraints were identified as the main barriers and collaborative networks and incremental approaches were identified as the main enablers.

1) Barriers

a) Technological Barriers

The infrastructure constraints were identified as the most common obstacle and all 23 respondents cited power and connectivity issues as the major challenges. Load-shedding was universally explained as the biggest enemy by the participants (Participant 7, Fintech). Participant 1, elaborated: You can never run machine learning models when the power goes off after every four hours. The unreliability of the power supply system led to the business people investing in costly backup systems with prices that fluctuated between USD2,000 to USD5,000 to have sufficient solar systems.

Other than electricity, internet reliability and prices were also a great challenge. Participant 7 observed: The internet is very costly and slow. It will require 12 hours to train an AI model that would have required 2 hours in South Africa and this is assuming that the connection does not become unstable. Cost-related considerations were also highlighted especially by non-adopters as the factor that influenced non-adoption of AI/ML. The active implementers stressed the prohibitive price of cloud services. Participant 6 noted: "AWS and Google Cloud are developed market priced. We require local solutions or subsidized access to enable AI to work on small businesses such as ours.

b) Organizational Barriers

The process of knowledge acquisition turned out to be an important organizational obstacle, and the participants referred to the adoption of AI/ML as the process of ongoing self-education without any formal training infrastructure. There were also technical knowledge gaps even among the active implementers. Participant 22 confessed, "*I learned Python and TensorFlow by the YouTube videos*". Participant 13 is a non-adopter of e-commerce, and she described it as follows, "*I am aware of the fact that AI may assist with the customer recommendations, but I have no idea where to learn it. The closest suitable option would be in Harare, and I cannot spend weeks away without my business*". Cases of knowledge transfer were also witnessed. Participant 5 explained, "*I am aware of the technology, and it is challenging to train my team. We do not have organized resources that are in our local language*."

c) Environmental Barriers

The market environment barriers had a huge influence on the adoption decisions. Participant 6 described: When I was explaining to potential investors how we were planning to build chatbots, they questioned why patients cannot call someone directly. They are not aware of the efficiency or the scalability.

2) Key Enablers

In spite of the competition, the participants noted that collaborative approaches were essential enablers. According to participant 2, "*we have a WhatsApp group where we share resources, discuss issues and celebrate wins. Our casual university of learning AI*". Participant 17 described it as follows: "*Three of us have a high-performance laptop that is custom designed to train models. It is cheaper and we will support one another when there are technical issues*."

F. Suggestions on Accelerating AI-Driven Technopreneurship

The experiences and opinions of the participants identified numerous methods of expediting sustainable and inclusive AI-based Technopreneurship in Gweru.

1) Power and Connections Solutions

Respondents always stressed on having reliable infrastructure. Participant 6 proposed: "We should have a local AI hub - a place with good power, high data speed, and technical advice. Individual actions are not sufficient. "Local Cloud computing facilities are crucial . Several respondents suggested that they should come up with local or regional cloud computing solutions to overcome cost and accessibility obstacles.

2) Local Training Programs

The participants supported practice based, locally delivered AI/ML training programs. One of the recommendations of participants 14 was, we need practical classes that provide practical application rather than theory. Demonstrate on how the local issues that can be resolved with AI.

3) Mentorship Networks

The effectiveness of informal peer learning networks implied the possibility of formal mentorship programs between the experienced implementers and novice implementers.

4) Investor Education

Interviewees noted that investor education concerning AI/ML possibilities and local implementation is required.

5) Demonstration Projects

Some of the participants proposed pilot projects to show AI/ML worth to the doubtful customers and investors.

6) Development of Regulatory Framework

Although it was not extensively covered, a few respondents also said that there were no definitive frameworks of AI governance to offer any certainty in business planning.

V. DISCUSSION

The section draws conclusions about the findings and takes into account the contributions of the study to the knowledge on the topic of AI/ML adoption among Technopreneurs in developing economies.

A. Current State of ML Adoption

The discovery that 26% of Gweru Technopreneurs have already attained active implementation of AI/ML, and 35% are still in the exploration stages is consistent with some macro trends in the developing economies [34], [35]. The adoption distribution here represents the early majority stage of technology diffusion that [36] described and adoption is increasing but is also limited by systemic barriers. The difference in adoption patterns with fintech and agritech as the most active of implementation (37.5) and exploration (57) respectively supports past studies indicating that the adoption of technology across industries is vastly different depending on the technological preparedness and market pressures [28]. The increased rate of fintech adoption is reflective of other low-income/middle-income countries in Sub-Saharan Africa, where mobile financial services have traditionally been the basis of technological innovation [37] .The high rates of chatbots and natural language processing apps adoption (50% of adopters) reflect the tendencies of Technopreneurs to promote AI/ML solutions that have immediate and clearly noticeable advantages and is aligned with the diffusion properties of relative advantage and observability [37] attributes. Complexity also appears to be a major barrier; average adoption of more advanced applications like computer vision (25%), and recommendation systems (17%) are an indication in support of the fact that technological complexity is indeed an adoption constraint [26]. The incremental adoption pattern among all active implementers would indicate that AI/ML integration would need to be built up in capabilities rather than transformative in technology. This observation challenges the premises of swift digital change and justifies [22] argument in favor of evolutionary and not revolutionary means of technology adoption in third world countries.

B. ML Implementation Barriers and Enablers.

1) Barriers

The discovery of infrastructure bottlenecks as the major impediment is an expansion of past literature on the adoption of technology in developing nations [38]. Nonetheless, the given study also sheds some light on the particular impact of the infrastructure barriers on AI/ML adoption, and the compounding impact of electricity instability, internet limitations, and cloud computing costs were revealed.The observation that the cost of power instability is forcing entrepreneurs to spend between USD$2,000 and USD$5,000 on backup systems shows that the lack of infrastructure poses prohibitive entry barriers to the adoption of AI/ML. This goes beyond the usual debates of digital divides to point to what could be referred to as an AI divide, where the computer patterns of AI/ML add more points of technological exclusion. This is informed by the way the participants describe infrastructure challenges which show that the lack of basic infrastructure complicates higher-order technological capabilities. This result confirms the demand to use infrastructure-first strategies to develop digitally [39] and outlines the needs of AI/ML implementation. The learning as we go theme is a paradox of having to build AI/ML skills without formal educational facilities, which Technopreneurs have to create themselves. This observation is consistent with [40] notion of absorptive capacity by pointing at how entrepreneurs in resource poor nations acquire technological capabilities by necessity-driven innovation. The overuse of informal learning networks and YouTube tutorials, although showing exceptional resilience, also shows the weakness of the ad hoc capacity building. The challenges experienced by the participants in transferring knowledge to their organizations imply that the process of self-directed learning can be effective in helping individuals adopt AI/ML but not in helping organizations scaled. The observation that investors demonstrate a weak level of awareness of AI/ML ventures demonstrates how the barriers of financial ecosystems are not only capital supply but also technological knowledge among financial sources. This serves as an echo to the past findings on limit of venture capital in developing economies [41]. The difficulties of the participants in gauging the benefits of AI/ML to stakeholders are mirrors of the difficulty in assessing intangible technological value especially where there is a possible lack of formal performance measurement systems [42].

2) Enablers

The process of the development of peer learning networks and resource-sharing initiatives proves that entrepreneurs can create common solutions to personal limitations. The discovery that there are others that have a high-performance laptop is one of the examples of innovative means to overcome the lack of resources by implementing collaborative methods of consumption. These partnership models are not merely cost sharing models but also knowledge transfer models and support systems. This observation aids in the realization of the development of an innovation ecosystem idea in developing economies as it happens naturally, hence the need to argue in favor of community-based technological development [5]. The suggestions to make AI-powered Technopreneurship go fast. The recommendations by the participants indicate interventions that are necessitated to enhance the speed of AI-induced Technopreneurship, and at the same time, remain sustainable and inclusive. The interest of the participants in building local AI centers with sufficient power and internet access is consistent with effective patterns in other African settings, including the Rwanda innovation hubs and the technology corridors within Kenya [5]. The proposal of local cloud computing infrastructures will support the arguments in favor of the development of technological infrastructure regionally, as it concerns the costs and the data sovereignty. The fact that the participants made the appeal of courses that should be hands-on and should teach the real application rather than theory only shows that practical and contextual education programs are needed. This observation confirms the idea that industry-academia collaboration is useful in the creation of AI/ML capabilities [42] and that local relevance matters in curriculum development. According to the success of informal peer learning networks, there is a possibility of scaling the methods by using formalized mentorship programs. This discovery helps in the realization of how tacit knowledge transfer is exhibited in technological innovation and how it can be formalized to have more extensive effects. The focus on educating investors by the participants shows that development of financial ecosystems needs more than capital presence, they need technological literacy amongst people providing funding.

Union efforts in AI regulation and advocates in the argument of active policy-making. The focus on the public-private collaboration is based on the recognition that the adoption of AI/ML will need to involve the activities of multiple stakeholders coordinated to facilitate the ecosystem strategy to the technological evolution [24].

C. Theoretical Implications

The paper contributes to the knowledge on technology adoption among developing economies in several theoretical ways. The results show the combined effects of infrastructure limitations, lack of knowledge, and market preparedness factors to form compounding obstacles to AI/ML adoption. It is in line with the TOE framework that emphasizes the interdependence of technological, organizational, and environmental forces. The research highlights the adoption behaviors unique to AI/ML technologies, i.e. the significance of incremental adoption, external alliances, and social learning networks. The findings can be added to the literature of the spread of emerging technologies in developing economies. The rise of informal collaborative network and resource-sharing programs offers the understanding of the occurrence of innovation ecosystems to self-organize in reaction to systemic constraints.

1) Implications in Practice and Policy

The implications of the findings on the practitioners, policymakers, and development partners are great. The effectiveness of gradual adoption strategies and peer learning networks indicates that entrepreneurs need to concentrate on incremental development of capabilities and learning networks, instead of trying to bring about wholesome transformation in technology. The identified infrastructure limitations indicate that the implementation of AI/ML needs the initial investments in power and connectivity infrastructure. Investor education is necessary, which emphasizes the role of financial ecosystem development and technological infrastructure.

2) Universities

The practical, context-specific training focus of the participants implies that the capacity-building training programs must focus on practical learning and local application building as opposed to the theoretical knowledge transfer.

VI. Conclusion

The paper gives detailed empirical data on the use of AI/ML among the Technopreneurs in Zimbabwe and shows not only considerable opportunities but also serious obstacles. Although the adoption rates are comparatively low because of the lack of infrastructure, skills, and funding, the early adopters show significant improvements in their performance, which may mean that AI-based entrepreneurship can be highly promising.

The results indicate the necessity of concerted actions of the government, the business community, and global developmental partners to overcome systematic obstacles and establish facilitating conditions under which AI can be applied. The international competition has found a new platform in AI, and countries have realized that it can contribute to economic success and national interests. To compete successfully in this race, Zimbabwe has to invest strategically in infrastructure, human capital and regulatory environment. The research has a contribution to both the scholarly and the policy formulation as it has evidence-based information on the trend of technology adoption in developing nations.

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