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REIMAGINING ENTREPRENEURSHIP EDUCATION IN THE AI ERA WITHIN RESOURCE-CONSTRAINED SETTINGS: A PEDAGOGICAL RENAISSANCE**Fidel Isheanesu Mugunzva^{1*}, Germinah Evelyn Chiloane-Tsoka², Ntise Hendrick Manchidi³**^{1*,2,3} *Department of Applied Management, College of Economic and Management Sciences, University of South Africa, Preller Street, Muckleneuk Pretoria, 0002, South Africa**E-mails: ^{1*}fmugunzva@gmail.com (Corresponding author); ²chiloge@unisa.ac.za; ³manchnh@unisa.ac.za**Received 18 May 2026; accepted 10 August 2026; published 30 September 2026*

Abstract. How can artificial intelligence (AI) technologies transform entrepreneurship education (EE) in resource-constrained settings? This study explores this question through an investigation of technology adoption at a South African university. Our findings reveal three key phenomena that challenge conventional views on digital transformation in higher education. First, students often lead technological innovation informing faculty in using AI agents and platforms. Second, resource limitations drive what we term “adaptive digital bricolage,” where basic AI technologies are combined in creative ways to achieve advanced EE outcomes. Third, rather than eroding traditional practices, AI platforms can preserve and enhance indigenous entrepreneurial knowledge. Using an integrated theoretical framework by drawing from the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT) and Technological Pedagogical Content Knowledge (TPACK), we show that successful digital transformation depends more on leveraging local innovation than on significant resource investment. These findings offer new insights for institutions operating in resource-constrained environments, suggesting pathways to achieve technological advancement while preserving local knowledge systems.

Keywords: entrepreneurship pedagogy; Artificial Intelligence technologies; entrepreneurship education; indigenous knowledge integration; adaptive digital bricolage

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JEL Classifications: L26, I20, I25

1. Introduction

The integration of artificial intelligence (AI) into entrepreneurship education (EE) heralds a transformative shift in pedagogical practices, offering unprecedented opportunities to democratise access, personalise learning and bridge skill gaps in rapidly evolving economies (Chen et al., 2024). While the potential of AI to reshape higher education is widely acknowledged, its application in resource-constrained environments where technological infrastructure limitations, cultural contexts and institutional capacities differ markedly from well-resourced settings remains underexplored. Moreover, while existing scholarship predominantly examines digital transformation through a Western-centric lens, emphasising technological infrastructure and financial investment as prerequisites for success (Berglund et al., 2020). We find this narrative overlooking the unique dynamics of institutions in the Global South, where constraints may catalyse unconventional innovation and where cultural preservation intersects with technological adoption in ways that challenge dominant patterns.

Three critical gaps persist in current literature. First, studies on AI in EE disproportionately focus on technologically advanced environments, neglecting how resource limitations in developing economies shape adaptive strategies. Second, while innovation under constraints is recognised in entrepreneurship theory, its pedagogical implications particularly how students and faculty collaboratively navigate technological adoption are rarely examined. Third, the interplay between AI agents and indigenous knowledge systems remains poorly understood with discussions often framing technology as a threat to cultural preservation rather than a potential enabler. These gaps limit our understanding of how resource-constrained institutions can leverage local strengths to achieve sustainable digital transformation.

This study addresses these gaps by investigating AI integration in EE at a South African university where resource scarcity and cultural diversity create fertile ground for reimagining entrepreneurial pedagogy. We query: *How do resource constraints and cultural contexts shape AI adoption in EE and what innovative practices emerge from these dynamics?* Through this lens, we uncover three findings that redefine conventional narratives of technological change: (1) reverse technology adoption, where students inform faculty in AI tool usage (2) adaptive digital bricolage, the creative recombination of basic technologies to achieve advanced outcomes and (3) the role of AI in preserving and enhancing indigenous entrepreneurial knowledge. By synthesising the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT) and Technological Pedagogical Content Knowledge (TPACK) framework, we propose a context-sensitive model of digital transformation that prioritises local innovation over resource abundance.

2. Literature Review

The integration of AI into EE has sparked significant scholarly debate (Chen et al., 2024), yet critical gaps persist in understanding how resource constraints and cultural contexts shape this transformation. This review synthesises four interrelated themes, that is, AI's role in EE pedagogy, digital transformation tensions, innovation under constraints and cultural preservation to expose limitations in current frameworks and justify the necessity of this study.

The Evolving Role of AI in EE Pedagogy: Overlooking Contextual Realities

Existing scholarship highlights AI's potential to personalise learning and enhance experiential training through virtual simulations. Although these contributions offer valuable insights, a notable gap emerges in their predominant focus on technologically privileged institutions such as in the global North. Such studies often assume universal availability of high-speed connectivity, advanced digital infrastructure and pre-existing technological competencies. These are conditions that remain aspirational rather than operational in many under-resourced Global South educational contexts. For instance, AI-powered adaptive learning platforms applauded in Global North contexts for personalising instruction may struggle to function in regions such as Zimbabwe where mobile data costs consume a significant portion of household incomes and where devices frequently malfunction due to dust, heat or inadequate maintenance. This disparity invites critical reflection on how assumptions about technological parity may inadvertently marginalise institutions and students navigating infrastructural or socio-economic constraints. Hence, addressing this oversight is vital to fostering inclusive, equitable applications of AI in EE that transcend resource disparities.

By foregrounding this limitation, we aim to broaden the dialogue around AI-driven pedagogical innovation urging scholars to consider contextual realities that shape educational access (Chari, 2024). Doing so not only strengthens academic rigour but also advances the pursuit of pedagogical equity in an increasingly digitised learning landscape.

Digital Transformation in Higher Education: A False Binary

In our examination of digital transformation discussions, we find ourselves grappling with a persistent dialectic, that is, techno-optimists champion digital tools as emancipatory instruments capable of democratising opportunity, while techno-skeptics foreground their role in entrenching systemic inequities (Martinez-Rodriguez et al., 2023). Though this binary is widely acknowledged, our research reveals a troubling gap in scholarly dialogue specifically in how institutions operating within resource-scarce environments reconcile these competing visions. We argue that dominant analytical models such as the TAM fall short in explaining the adaptive strategies institutions employ to mediate between aspirational technological ideals and the material realities of infrastructural precarity. This gap not only obscures the lived complexities of technological adoption but risks perpetuating theoretical frameworks detached from the improvisational pragmatism we observe in under-resourced contexts. For example, Ifraheem et al., (2024) demonstrate AI's efficacy in boosting student engagement but their model presupposes institutional support for training and infrastructure which is a luxury unavailable to educators relying on "bricolaged" tools. Conversely, Heeks, (2007) analysis of failed digital initiatives highlights the dangers of what we may deem as "transplanting" Western models without contextual adaptation, yet their work falls short of identifying strategies for leveraging constraints as catalysts for innovation. This gap reveals a critical need for frameworks that recognise resource limitations not as deficits but as drivers of context-specific solutions.

Resource Constraints and Innovation: Beyond Deficit Narratives

Emerging scholarship from the Global South challenges the assumption that technological advancement requires substantial investment. This has led to scholars such as Ng'ambi et al., (2016) to document how South African educators repurpose basic mobile technologies for collaborative learning while Vishwanath et al., (2017) illustrate how Indian institutions use low-cost virtual reality (VR) tools to simulate business environments. These studies seem to align with Winter, (2013) concept of "constraint-driven innovation," which posits that scarcity fosters creativity. This has recently been exemplified by DeepSeek AI, a start-up firm from China which outperformed most well-resourced US-based AI firms, including OpenAI, Gemini and Llama in benchmark evaluations despite operating on a fraction of their budgets/resources proving that innovation and global competitiveness need not correlate with financial scale (Gao, et al., 2025; Normile, 2025). Back to our study's context, from our observation, we have come to note that existing literature largely examines technological adaptation in isolation neglecting its pedagogical implications. For instance, how do student-faculty dynamics shift when students become technology mentors? How might improvised tools reshape curricular design? By focusing on technical outcomes rather than pedagogical processes, current literature fails to capture the transformative potential of constraints in EE, a gap this study addresses through its exploration of reverse adoption and adaptive bricolage.

Cultural Preservation and Digital Integration: Reconciling Competing Narratives

The interplay between technological advancement and cultural preservation continues to provoke scholarly debate (Siliutina et al., 2024) leading to some scholars examining asymmetrical power dynamics in technological diffusion. Scholars such as Roturier & Beau, (2022) contend that insufficiently examined adoption of Western digital infrastructures risks destabilising indigenous epistemologies through imperceptible epistemological displacement. Conversely, emerging research guided by African relational philosophies offers counter-narratives as Abubakre's et al., (2023) posit compelling evidence in what they term "Digital Ubuntu" which puts an emphasis on communal reciprocity and context-aware innovation. Hence, the concept of digital ubuntu can transform technology integration into an act of cultural reaffirmation rather than erosion. In so doing, this dialectic underscores the necessity of examining not merely AI technological tools but the philosophical frameworks through which societies negotiate their adoption. Be that as it may, what unsettles us, is that emerging scholarship critique both positions for neglecting a critical third axis: the pedagogical agency of digital tools in actively preserving cultural knowledge through participatory archiving, intergenerational storytelling platforms and decolonial AI-driven language revitalisation (George et al., 2024). This tripartite tension between epistemic erosion, relational reclamation and agentic cultural transmission demands rigorous interrogation. For this reason,

the urgent question, then is not whether technology preserves culture, but may be how we ethically amplify the marginalised voices redefining preservation itself.

3. Theoretical Framework

3.1 The Inadequacy of Existing Theoretical Models in Resource-Constrained Contexts

The integration of AI into EE within resource-constrained environments presents unique challenges that existing theoretical frameworks inadequately address. While established models such as the TAM, UTAUT and TPACK have proven valuable in explaining technology adoption in well-resourced contexts, they exhibit critical limitations when applied to the complex realities of developing economies.

TAM as a foundational model in understanding individual technology adoption conceptualises acceptance through perceived usefulness and perceived ease of use (Davis, 1989). However, we concur with Abubakre et al., (2021) arguments that TAM's individual-centric perspective fails to account for the collective, community-oriented decision-making processes prevalent in African educational contexts. Moreover, TAM's assumption of voluntary adoption becomes problematic in resource-constrained settings where technology choices are often dictated by availability rather than preference and where users must creatively repurpose available tools regardless of their intended design (Rattanasampan & Kim, 2002).

Similarly, while UTAUT (Venkatesh et al., 2003) extends TAM by incorporating social influence and facilitating conditions, we argue that it maintains a top-down perspective that assumes institutional or peer-driven adoption. Hence, this model inadequately explains scenarios where students, as digital natives, become primary change agents who mentor faculty in technology use, a phenomenon increasingly observed in developing world contexts (Ng'ambi et al., 2016). Furthermore, UTAUT's "facilitating conditions" construct assumes the presence of adequate infrastructure and support systems, conditions often absent in resource-constrained environments where users must create their own facilitating conditions through improvisation and creativity.

Lastly, the TPACK framework (Mishra & Koehler, 2006), while valuable for understanding the intersection of technology, pedagogy and content knowledge, presupposes access to formal educational technologies and structured institutional support. We must acknowledge that TPACK's conceptualisation of technological knowledge assumes familiarity with purpose-built educational technologies rather than the creative repurposing of consumer applications for educational purposes, a common practice in resource-limited settings.

3.2 Theoretical Gaps in Understanding Digital Transformation in the Global South

Three critical gaps emerge from the existing theoretical landscape that necessitate a more nuanced framework for understanding AI adoption in resource-constrained EE contexts.

Gap 1: Unidirectional Technology Transfer Assumptions

Our discussion so far highlights that existing models assume hierarchical technology diffusion patterns where adoption flows from institutional authorities to end-users. This assumption becomes problematic in contexts where students possess superior digital literacy compared to faculty, creating reverse knowledge flows that challenge traditional power dynamics in educational settings (Prensky, 2001). Given this, current theories lack constructs to explain how digital natives can serve as change agents who drive institutional transformation from the bottom up.

Gap 2: Resource Abundance Bias

We should stress that traditional TAMs implicitly assume access to appropriate technologies and supporting infrastructure (Venkatesh et al., 2012). This "resource abundance bias" renders these models inadequate for explaining how educational institutions creatively combine available tools to achieve desired outcomes despite

limitations. The concept of “making do” with available resources, what Lévi-Strauss (1966) termed bricolage, requires theoretical frameworks that can account for constraint-driven innovation rather than treating resource limitations as mere barriers to adoption.

Gap 3: Cultural Homogenisation Assumptions

Western-developed theoretical models often assume cultural contexts where individual autonomy, technological determinism and linear progress are valued (Hofstede, 2001). These assumptions fail to capture how collectivist cultures, indigenous knowledge systems and non-linear approaches to problem-solving influence technology integration patterns in African educational contexts (Seleke et al., 2025). Therefore, the absence of cultural sensitivity in existing models limits their explanatory power in contexts where technology adoption must align with local values and knowledge systems.

3.3 An Integrated Resource-Constrained Technology Adoption (RCTA) Framework

To address these theoretical gaps, we propose an integrated Resource-Constrained Technology Adoption (RCTA) framework that synthesises insights from TAM, UTAUT and TPACK while incorporating three novel theoretical constructs that emerge from resource-constrained contexts: reverse adoption dynamics, adaptive digital bricolage and indigenous knowledge integration. An Integrated Resource-Constrained Technology Adoption (RCTA) Framework is presented below in Figure 1.

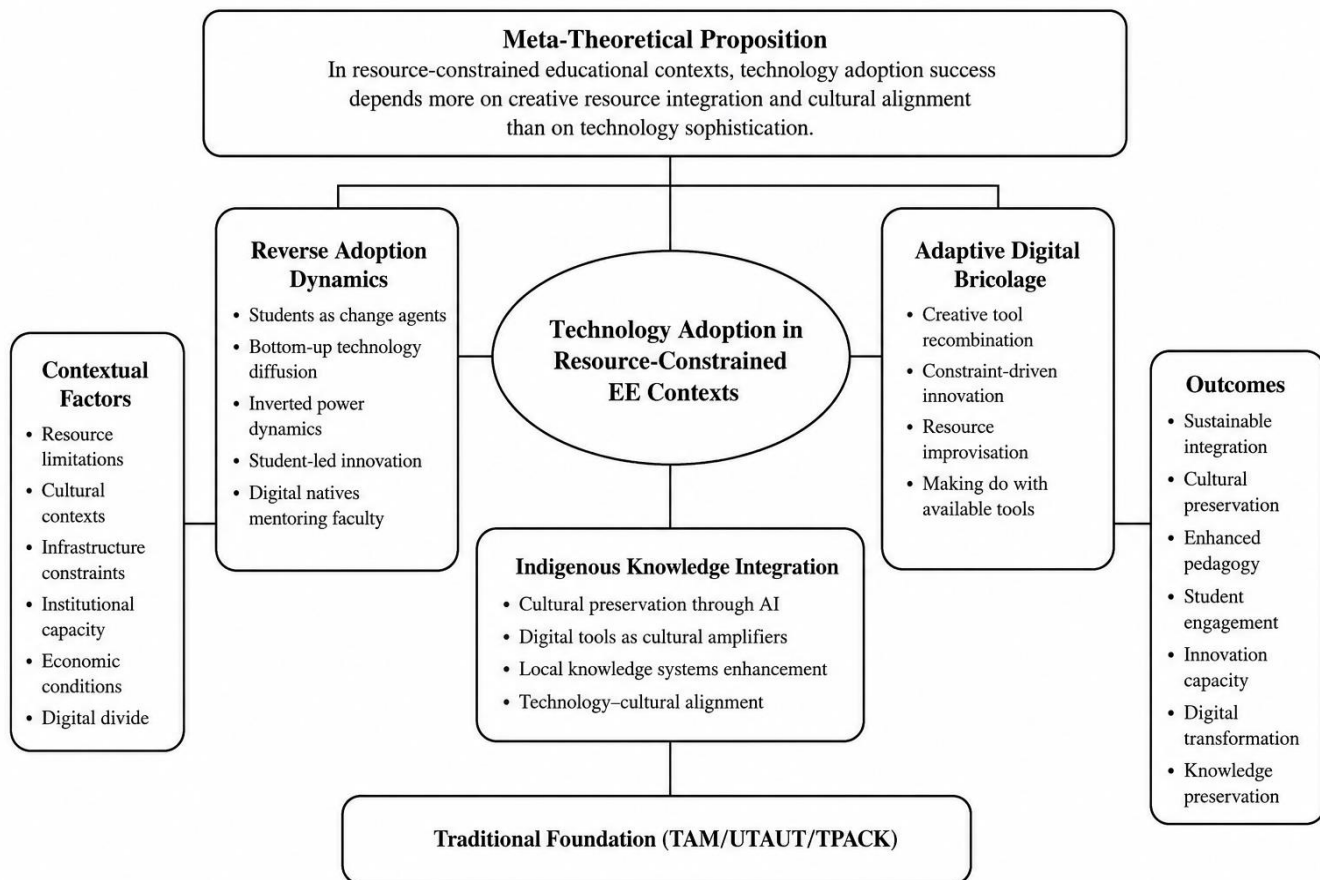


Figure 1. An Integrated Resource-Constrained Technology Adoption (RCTA) Framework

Traditional foundation (bottom layer) - shows the established TAM, UTAUT and TPACK elements that form the base of the framework.

Three Novel Constructs (main focus areas)

- Reverse adoption dynamics (top left) - Students as change agents leading technology adoption.
- Adaptive digital bricolage (top right) - Creative use of basic tools to achieve advanced outcomes.
- Indigenous knowledge integration (bottom centre) - Using AI to preserve and enhance cultural knowledge.
- Central processing core - Where technology adoption occurs in resource-constrained EE contexts.
- Context factors (left) - Environmental influences like resource limitations, cultural contexts and infrastructure constraints.
- Outcomes (right) - Results including sustainable integration, cultural preservation and enhanced pedagogy.

Design Features

- Color-coded sections for easy identification.
- Directional arrows showing relationships and flow.
- The meta-theoretical proposition highlighted at the top.
- Interactive elements showing how all components work together.

Novel Theoretical Constructs

Construct 1: Reverse Adoption Dynamics

We introduce “reverse adoption dynamics” as a theoretical construct that explains how digital natives (typically students) can serve as primary change agents who drive technology adoption among digital immigrants (typically faculty) within educational institutions. This construct extends traditional diffusion theory by recognising that expertise and influence can flow upward through organisational hierarchies, particularly in rapidly evolving technological contexts (Attewell, 1992).

Construct 2: Adaptive Digital Bricolage

Building on Lévi-Strauss's (1966) concept of bricolage and its application to organisational contexts (Baker & Nelson, 2005), we propose “adaptive digital bricolage” as the creative recombination of available digital tools and platforms to achieve educational objectives that would typically require more sophisticated or expensive technologies. This construct explains how resource constraints can catalyse innovation rather than merely inhibit technological progress.

Construct 3: Indigenous Knowledge Integration

We conceptualise “indigenous knowledge integration” as the process by which digital technologies are leveraged to preserve, enhance and transmit local cultural knowledge and practices within formal educational settings. This construct challenges the false dichotomy between technological advancement and cultural preservation, proposing instead that digital tools can serve as vehicles for cultural continuity (Oladokun et al, 2024).

Framework Dynamics and Interactions

Our RCTA framework posits that technology adoption in resource-constrained educational contexts results from the dynamic interaction between traditional adoption factors (usefulness, ease of use, social influence) and context-specific factors (reverse adoption dynamics, adaptive bricolage capabilities and indigenous knowledge integration needs).

The framework suggests that successful technology integration depends on achieving congruence between available resources, cultural values, pedagogical objectives and community needs. Unlike traditional models that treat resource constraints as barriers, our framework positions them as potential catalysts for innovative practices that may offer advantages over resource-abundant approaches.

Meta-Theoretical Proposition - In resource-constrained educational contexts, technology adoption success will be determined more by the creative integration of available resources and cultural alignment than by the sophistication or expense of the technologies employed.

3.4 Theoretical Contributions and Implications

This integrated framework makes several key theoretical contributions to the technology adoption literature:

- 1) extends technology acceptance theory - by incorporating cultural relevance and resource accessibility as additional determinants of perceived usefulness, we expand TAM's applicability to non-Western contexts;
- 2) reconceptualises social influence - our framework challenges UTAUT's assumption of top-down social influence by demonstrating how reverse mentoring can drive institutional change;
- 3) introduces constraint-based innovation theory - our concept of adaptive digital bricolage contributes to understanding how limitations can foster creativity and innovation in educational technology use;
- 4) bridges technology and culture - the indigenous knowledge integration construct offers a theoretical foundation for understanding how technologies can support rather than threaten cultural preservation efforts.

These theoretical contributions provide a foundation for understanding technology adoption patterns in resource-constrained contexts while offering insights that may be applicable to well-resourced environments seeking to foster innovation and cultural sensitivity in their technology integration efforts. The RCTA framework thus serves not merely as a descriptive tool but as a prescriptive guide for educational institutions operating in resource-constrained environments, suggesting pathways for leveraging local strengths and constraints to achieve meaningful technological transformation while preserving cultural values and knowledge systems.

4. Research Methodology

Research Design and Philosophical Underpinnings

To produce valuable insights and make a relevant input to the debate surrounding technology integration in EE, we employed a qualitative exploratory design grounded in the interpretive paradigm. By so doing, we acknowledged the socially constructed nature of technology adoption in educational settings. Therefore, the choice of interpretivism aligned with our research objectives to understand how primary stakeholders navigate technology integration within resource-constrained environments while preserving indigenous knowledge systems in EE. Our epistemological stance recognises knowledge as co-constructed through interaction between researchers and participants (Guba & Lincoln, 1994). This approach was particularly relevant given the emergence of unexpected patterns such as reverse technology adoption and adaptive digital bricolage which required deep engagement with participants' lived experiences.

Sampling

The study was conducted at the University of South Africa (UNISA), focusing on the Department of Applied Management (Entrepreneurship). UNISA's position as a major African university operating in a resource-constrained environment while pursuing digital transformation made it an ideal setting for examining our research questions. Data collection was conducted in two distinct phases as part of an iterative qualitative research approach. The first phase, conducted from October 2022 to January 2023, involved 17 participants and formed the foundation of the doctoral research. Following initial analysis and the emergence of key theoretical constructs, a second phase was conducted from May to August 2024, adding 8 additional participants to deepen our

understanding of the phenomena and achieve comprehensive theoretical saturation. This two-phase approach reflects the iterative nature of qualitative inquiry where initial findings inform subsequent data collection to ensure robust theoretical development (Charmaz, 2014). Purposive sampling was employed to recruit 25 participants: 14 final-year entrepreneurship students and 11 faculty members. This sample size aligns with Saunders and Townsend's (2016) recommendations for qualitative research involving semi-structured interviews (5-25 participants) and proved sufficient to reach theoretical saturation. Saturation was achieved by the 22nd interview, with three additional interviews conducted to ensure completeness.

Ethical Considerations and Informed Consent

Ethical approval for this study was obtained from the University of South Africa's College of Economic and Management Sciences Research Ethics Review Committee (Ref # 2022_CRERC_007 (FA) and permission from the Research Permission Subcommittee of the UNISA Senate, Research, Innovation, Postgraduate Degrees and Commercialisation Committee (Ref # 2022_RPC_023). Hence, written informed consent was obtained from all participants prior to their involvement in the study. The informed consent process included providing participants with a detailed information sheet outlining the study's purpose, procedures, potential risks and benefits, confidentiality measures and their rights as participants. All participants signed consent forms, indicating their voluntary participation and understanding that they could withdraw from the study at any time without penalty. All data collection procedures adhered to the principles outlined in the UNISA Policy on Research Ethics and particular attention was given to ensuring participant privacy and confidentiality. Therefore, to protect participant identities, pseudonyms were assigned during data analysis and reporting as reflected in the participant demographics table 2. All interview recordings and transcripts were securely stored with password protection and only the research team had access to the raw data.

Sample Size

This sample size of 25 participants aligns with established qualitative research principles, which prioritise depth over breadth to achieve theoretical saturation. Data saturation is the point at which new data ceases to yield novel insights (Guest et al., 2006; Hennink et al., 2019). The heterogeneous nature of the participant pool encompassing diverse academic roles (students, lecturers, professors) and experience levels necessitated a moderately larger sample than typical homogeneous qualitative studies. While Guest et al. (2006) suggests 12 interviews often suffice for saturation in homogeneous groups, Hennink et al. (2019) recommend 16–24 participants for heterogeneous contexts to ensure both code saturation (exhaustion of thematic categories) and meaning saturation (depth of understanding). Hence, our final sample of 25 participants balanced these guidelines while remaining manageable for in-depth analysis. Theoretical saturation was systematically assessed using an iterative approach. Preliminary coding of the first 18 interviews established core themes, with subsequent interviews analysed for emergent patterns. By the 22nd interview, code frequency stabilised and no significant new themes emerged in the four interviews, confirming saturation. This process ensured robustness without unnecessary expansion of the sample. The participant demographics (Table 1) reflect deliberate diversity in age, educational attainment and geographic distribution, capturing a range of perspectives on technology adoption in EE. This strategic composition, rather than sheer quantity, underpins the study's analytical rigour and contextual relevance.

Distribution of Participants

We interviewed 25 participants across both phases, comprising fourteen final-year entrepreneurship students and eleven faculty members. As shown in Figure 2, the faculty members constituted 44%, while the student sample constituted 56% of the total participants. Participants worked within the Entrepreneurship department, specifically. Pseudonyms were given to each participant at sample selection. The participant number was attached to the department, such as ES1 denoting Entrepreneurship Student Participant 1, FM1 denoting Faculty Member Participant 1 and so on.

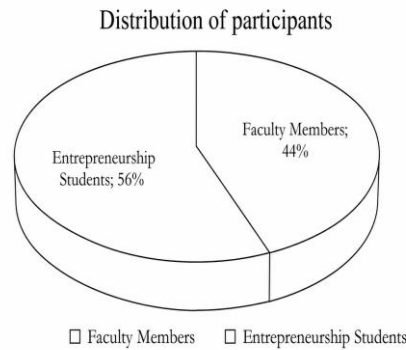
**Figure 2.** Distribution of participants*Source:* Illustrated by the authors

Table 1 below provides a summarised description of the participants in the study. The participants are divided into two groups: faculty members identified as FM1- FM11 and entrepreneurship student participants identified as ES1-ES14. Regarding educational level, the study includes undergraduate, honours, masters and doctorate level participants with most participants being at the undergraduate level. The faculty members encompass professionals at various levels, including lecturers, senior lecturers, associate professors and full professors.

Table 1. Participant Demographics

Participant	Location	Education Level	Age Bracket	Department	Experience/Level
FM1	Pretoria	Masters	35-45	Entrepreneurship	5 Years
FM2	Pretoria	Doctorate	45-55	Entrepreneurship	7 Years
FM3	Pretoria	Honours	25-35	Entrepreneurship	3 Years
FM4	Pretoria	Doctorate	35-45	Entrepreneurship	5 Years
FM5	Pretoria	Masters	35-45	Entrepreneurship	4 Years
FM6	Pretoria	Masters	25-35	Entrepreneurship	3 Years
FM7	Pretoria	Doctorate	45-55	Entrepreneurship	5 Years
FM8	Pretoria	Masters	25-35	Entrepreneurship	4 Years
FM9	Pretoria	Doctorate	35-45	Entrepreneurship	7 Years
FM10	Pretoria	Masters	35-45	Entrepreneurship	6 Years
FM11	Pretoria	Doctorate	55-65	Entrepreneurship	10+ years
ES1	Johannesburg	Undergraduate	25-35	Entrepreneurship	Year 3
ES2	Midrand	Undergraduate	21-25	Entrepreneurship	Year 3
ES3	Polokwane	Undergraduate	25-35	Entrepreneurship	Year 3
ES4	Durban	Undergraduate	21-25	Entrepreneurship	Year 3
ES5	Pretoria	Undergraduate	25-35	Entrepreneurship	Year 3
ES6	Pretoria	Undergraduate	21-25	Entrepreneurship	Year 3
ES7	Nelspruit	Undergraduate	25-35	Entrepreneurship	Year 3
ES8	Johannesburg	Undergraduate	21-25	Entrepreneurship	Year 3
ES9	Johannesburg	Undergraduate	35-45	Entrepreneurship	Year 3
ES10	Cape Town	Undergraduate	21-25	Entrepreneurship	Year 3
ES11	Johannesburg	Undergraduate	25-35	Entrepreneurship	Year 3
ES12	Kimberly	Undergraduate	45-55	Entrepreneurship	Year 3
ES13	Bloemfontein	Undergraduate	25-35	Entrepreneurship	Year 3
ES14	East London	Undergraduate	25-35	Entrepreneurship	Year 3

Source: Illustrated by the authors

Data Collection

Semi-structured interviews were conducted using video conferencing platforms (MS Teams and Zoom) across both data collection phases. Phase one interviews were conducted from October 2022 to January 2023, while phase two interviews took place from May to August 2024. The interview protocol was refined between phases based on initial findings, allowing for deeper exploration of emergent themes while maintaining consistency in core research questions.

Initial Interview Guide Construction

The development of our interview guide followed a systematic three-stage process informed by our integrated theoretical framework and preliminary literature review. Drawing from established protocols in technology acceptance research (Venkatesh et al., 2003) and EE studies (Chen et al., 2024), we constructed an initial semi-structured interview guide containing 24 open-ended questions organised around four thematic areas (see Appendix):

1. **Technology Integration Experiences** (6 questions)
 - Current use of digital tools in EE
 - Challenges and facilitators in technology adoption
 - Perceptions of technology's role in learning/teaching
2. **Resource Context and Adaptation** (7 questions)
 - Institutional resources and constraints
 - Creative responses to resource limitations
 - Collaborative practices in technology use
3. **Cultural and Knowledge Dynamics** (6 questions)
 - Integration of local entrepreneurial knowledge
 - Cultural considerations in technology adoption
 - Preservation and transmission of indigenous practices
4. **Learning and Teaching Relationships** (5 questions)
 - Faculty-student interactions around technology
 - Knowledge sharing patterns
 - Changes in traditional educational hierarchies

Pilot Testing and Refinement

Prior to data collection, we conducted pilot interviews with three participants (two students & one faculty member) not included in the main study. These pilot sessions revealed several critical issues:

Language and Cultural Sensitivity Concerns:

- Initial questions contained Western-centric assumptions about individual technology ownership.
- Technical terminology required clarification in multilingual contexts.
- Questions about “innovation” needed reframing to include indigenous knowledge systems.

Question Refinement Examples:

- Original: “How do you personally use AI tools in your studies?”
- Revised: “Can you describe any AI tools or technologies you’ve used or seen used in entrepreneurship learning, whether individually or in groups?”
- Original: “What barriers prevent AI technology adoption?”
- Revised: “What challenges have you or your colleagues faced when trying to use AI tools and how have you worked around these challenges?”

Following pilot testing, the interview guide was reduced to 18 questions with enhanced probes and culturally appropriate language. A multilingual glossary of technical terms was developed to ensure consistent understanding across participants.

Data Analysis Framework

Data analysis followed a rigorous three-phase process using ATLAS.ti software. The final phase as shown in table 3 below involved integrating categories into overarching themes that aligned with our theoretical framework while remaining grounded in the data. This process revealed how reverse adoption patterns, adaptive bricolage and indigenous knowledge integration interact within resource-constrained educational environments.

Emergent Concept Development: From Data to Theory

A critical methodological transparency issue involves clarifying how our key theoretical concepts emerged from data versus being imposed through our theoretical framework. We employed a systematic inductive process that we document below.

Initial Open Coding (Grounded Approach): In the first phase of analysis, we deliberately bracketed our theoretical assumptions and engaged in open coding using participants' own language and concepts. This revealed several unexpected patterns:

- Students frequently described “teaching” or “showing” faculty members how to use technologies.
- Participants used terms like “making a plan” to describe creative technology use.
- Cultural preservation emerged as a spontaneous theme when participants discussed technology benefits.

Pattern Recognition and Concept Formation: Three patterns emerged consistently across interviews that had not been anticipated in our initial theoretical framework:

1. Bottom-up Technology Leadership:
 - 12 of 14 students described instances of informing faculty about digital tools.
 - 8 of 11 faculty acknowledged learning from students.
 - This pattern emerged independently of our questions about hierarchies or power dynamics.
2. Creative Resource Recombination:
 - Participants consistently described combining multiple basic tools to achieve complex objectives.
 - This pattern appeared in 23 of 25 interviews without direct prompting about constraints or innovation.
 - The concept of “making a plan” appeared 27 times across transcripts.
3. Technology as Cultural Bridge:
 - 18 participants spontaneously discussed using AI digital tools to preserve or share cultural knowledge.
 - This emerged from questions about learning benefits, not from questions about culture.
 - Participants framed technology as helping rather than threatening cultural continuity.

Concept Naming and Theoretical Integration: Only after identifying these empirical patterns, we began connecting them to existing theory and developing our conceptual labels:

- Reverse adoption emerged from the bottom-up technology leadership pattern, informed by but extending diffusion of innovations theory.
- Adaptive digital bricolage was derived from the creative recombination pattern, drawing on Lévi-Strauss’s bricolage concept.
- Indigenous knowledge integration reflected participants’ own framing of technology as culturally supportive.

Theoretical Validation Process

To ensure our theoretical concepts remained grounded in data rather than imposed, we employed several validation strategies:

Participant Verification:

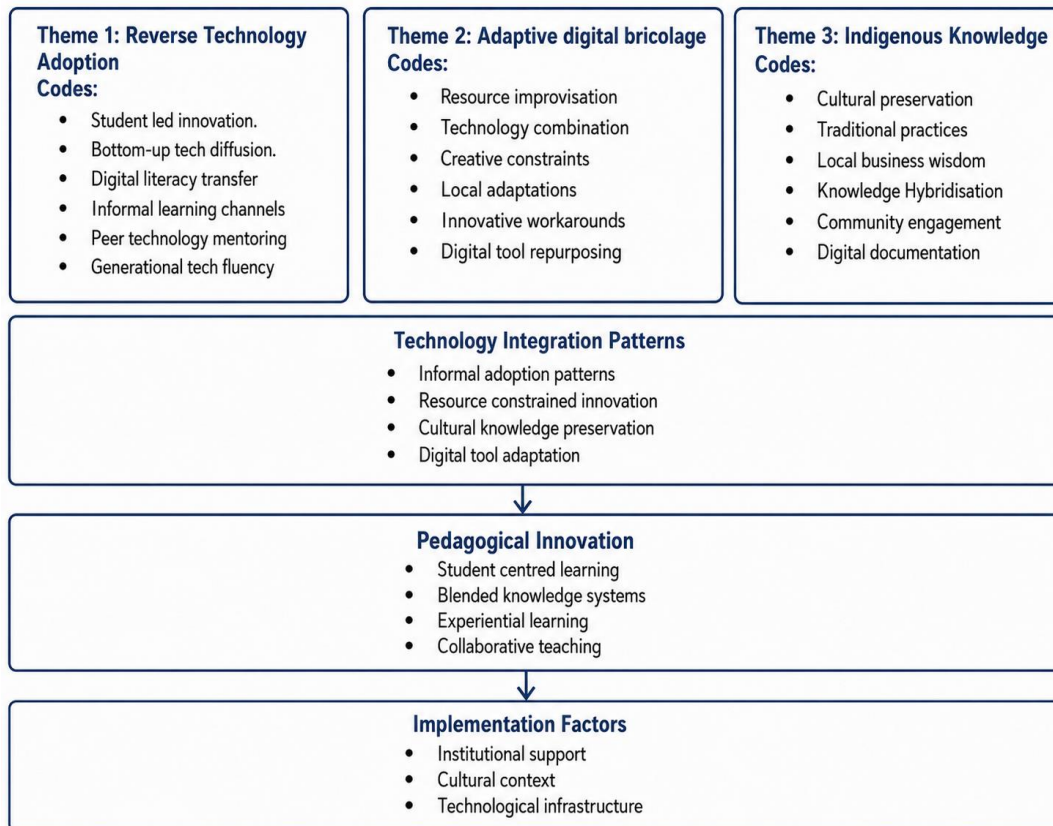
- In second-phase interviews, we presented our emerging concepts to participants using their own language.

- We asked: “We’ve noticed that students sometimes teach faculty about technology tools. Does this match your experience?”
- 22 of 25 participants confirmed these patterns aligned with their experiences.

This methodology enabled systematic exploration of technology integration in EE while remaining sensitive to cultural contexts and resource constraints. The two-phase approach allowed for both depth and temporal insight, revealing how resource-constrained institutions adapt and evolve their technology integration practices over time. The emergent themes challenge existing theoretical frameworks while suggesting new directions for understanding technology adoption in developing world contexts.

After generating the codes from both phases, a comprehensive code framework was developed as presented in Table 2.

Table 2. Code framework derived from data collection.



Source: Illustrated by the authors

5. Findings

Our analysis of semi-structured interviews revealed a transformative narrative of how resource constraints and cultural contexts are reshaping technology integration in EE. As previously indicated, our analysis of participant narratives identified three interconnected themes that challenge conventional wisdom: reverse technology adoption, adaptive digital bricolage and indigenous knowledge integration. These findings not only extend existing theoretical frameworks but also highlight the unique innovative potential of resource-constrained environments.

5.1 Theme 1: Reverse technology adoption – Inverting hierarchies of knowledge transfer

Our analysis revealed three interconnected themes that redefine technology adoption in resource-constrained EE contexts. Below, we present these findings alongside participant perspectives and critically examine their implications for existing theoretical frameworks. Contrary to traditional models of top-down technology diffusion, students emerged as key drivers of innovation, mentoring faculty in digital tool adoption. For instance, ES3 described informing faculty on AI tools: *“I showed my lecturer the art of prompt engineering to generate culturally relevant business scenarios. Now, she uses these in class discussions.”* Furthermore, faculty acknowledged this dynamic, with FM2 noting: *“Students introduced me to apps like Elicit, Canva and Notion among others, tools I now use daily. Their fluency with technology is reshaping how I prepare my lectures.”*

Theoretical Implications

While UTAUT emphasises “social influence” as a determinant of technology adoption (Venkatesh et al., 2003), our findings invert its traditional application. Thus, UTAUT typically frames social influence as peer-to-peer or institutional pressure (e.g., faculty mandating tools). In our case, “reverse adoption” introduces a bottom-up model where students’ digital literacy redefines power dynamics. This challenges UTAUT’s assumption that adoption is driven by superiors or peers of equal status suggesting the need to incorporate “intergenerational influence” as a distinct construct. Therefore, future iterations of UTAUT must account for contexts where students, not educators, act as change agents.

5.2 Theme 2: Adaptive digital bricolage – Innovation born from constraints

Participants consistently repurposed basic tools to overcome resource limitations. FM5 detailed a low-cost simulation: *“We combined WhatsApp groups, Google Docs and free AI analytics to mimic a startup ecosystem. Students role-played as CEOs and investors and it cost nothing but sparked deep learning.”* Similarly, ES7 highlighted improvisation: *“We used TikTok to pitch ideas and Instagram polls for market research. Our lecturers never taught this, but it worked!”*

Theoretical Implications

TPACK emphasises the interplay of technological, pedagogical and content knowledge (Mishra & Koehler, 2006). However, TPACK assumes access to formal technologies, neglecting contexts where educators combine informal tools to achieve pedagogical goals. Our concept of “adaptive bricolage” extends TPACK by demonstrating how resource constraints force educators to prioritise creativity over technological sophistication. This challenges TPACK’s implicit bias toward well-resourced environments and introduces “constraint-driven TPACK” as a framework for low-infrastructure settings.

5.3 Theme 3: Indigenous knowledge integration – Digital tools as cultural amplifiers

Our findings revealed that digital tools were leveraged to preserve, rather than erode, local entrepreneurial traditions. FM7 explained: *“There are some trained AI models that can document elders’ trading practices in isiZulu and Sesotho. Now, students access this wisdom digitally as it bridges generations.”*

Students like ES9 blended tradition with technology: *“Using VR, we recreated a traditional spaza shop negotiation. It taught us modern marketing without losing our cultural roots.”*

Theoretical Implications

This theme disrupts the “digital colonialism” narrative (Kwet, 2019) by positioning technology as a vehicle for cultural preservation. While TAM focuses on perceived usefulness of tools (Davis, 1989), our findings revealed a dimension absent in traditional models, that is “cultural relevance” as a driver of adoption. When tools align with indigenous values (e.g., communal knowledge sharing), they gain legitimacy beyond mere functionality. This necessitates revising TAM to include cultural alignment as a core determinant of perceived usefulness in non-Western contexts.

These insights demand a paradigm shift in how we conceptualise digital transformation. Rather than viewing resource constraints as barriers, our study positions them as catalysts for context-driven innovation, a framework where local knowledge, student agency and improvisation redefine technological “best practices.”

5. Limitations of the Study

This study’s findings must be interpreted within the context of several key methodological and conceptual limitations that shape both their applicability and generalisability.

Methodological Constraints. Our single institution focusses at UNISA allowed for deep contextual insights although it presents significant limitations for generalisability. Despite UNISA’s prominence in South African higher education, the unique characteristics of its entrepreneurship program and institutional culture may not reflect the broader landscape of EE in other developing economies or institutions. This limitation is particularly salient given the heterogeneous nature of African HEIs and entrepreneurial ecosystems. The sample size of 25 participants, though reaching theoretical saturation within our specific context, limits the breadth of perspectives captured. While this aligns with qualitative research principles, it may not fully represent the diversity of experiences within EE, particularly regarding technology integration. The exclusive focus on the entrepreneurship department provides disciplinary depth while potentially overlooking valuable interdisciplinary insights that could have enriched our understanding of technology integration across different academic contexts.

Temporal and Technological Limitations. The cross-sectional nature of our data collection presents a significant limitation in understanding the dynamic process of technology adoption and integration. As Børte et al. (2023), and Børte and Lillejord (2024) argue, technology acceptance and integration in higher education are evolutionary processes that unfold over time. Our snapshot approach, while providing valuable insights into current practices cannot capture the longitudinal developments in how faculty and students adapt to and integrate new technologies over time. Additionally, our focus on specific AI may have inadvertently overlooked other emerging technologies that could significantly impact EE. We note that the rapid pace of technological advancement means that any study of current technologies risks becoming quickly outdated. This limitation is particularly relevant given the emergence of new technologies like quantum computing and latest artificial generative intelligence models that could reshape EE in ways not captured by our study.

Methodological Self-reflection. The reliance on self-reported data through interviews introduced potential social desirability bias, as identified by Fisher (1993). Participants may have overstated their technology proficiency or understated their resistance to technology adoption. The absence of observational data or direct assessment of technology use in classroom settings limits our ability to verify reported behaviours against actual practices.

Stakeholder Representation. The exclusion of industry partners and entrepreneurs from our sample represents a missed opportunity to triangulate academic perspectives with real-world practitioners. It is important to align educational practices with industry needs, a dimension our study could not fully address. This limitation is particularly relevant given the applied nature of EE and its goal of preparing students for real-world business challenges.

6. Implications for Future Research

These limitations suggest several directions for future research:

- i. Multi-institutional studies spanning different African countries to capture broader patterns of technology integration in EE.
- ii. Longitudinal investigations tracking the evolution of technology adoption and its impact on learning outcomes.

- iii. Mixed - methods approaches incorporating classroom observations and quantitative metrics of technology use.
- iv. Comparative studies evaluating the effectiveness of different pedagogical approaches, both traditional and technology enhanced.
- v. Research incorporating industry perspectives and measuring the alignment between educational practices and market needs.

Understanding these limitations not only contextualises our findings but also provides a roadmap for future research that can address these gaps and advance our understanding of technology integration in EE within developing economies.

Theoretical Synthesis and Contributions. Our research makes three significant theoretical contributions that extend current understanding of technology integration in EE.

Reverse Technology Adoption Theory in Educational Settings. The discovery of bottom-up technology adoption pattern challenges traditional technology acceptance models. While existing frameworks like TAM and UTAUT assume a top-down diffusion of technology (Venkatesh et al., 2003), our findings suggest a need to reconceptualise these models to account for student-led technology adoption in educational settings. This extends Killen and Knight's, (2020) work on the role student partners play as digital change agents by identifying a novel mechanism where students become primary agents of technological change.

Resource-constrained Innovation Framework. Our identification of "adaptive digital bricolage" contributes a new theoretical construct to understanding technology integration in resource-limited EE contexts. This framework extends beyond simple adaptation to demonstrate how resource constraints can catalyse innovative pedagogical approaches. This challenges the dominant narrative in digital transformation literature that positions resource limitations as purely inhibitory factors (Hanelt et al., 2021).

Indigenous Digital Pedagogy Model. The study's findings on the integration of indigenous knowledge through digital means contributes to decolonial theory in education technology. This extends Kadhila and Nyambe's (2022) work by demonstrating how AI technologies can serve as tools for legitimising and preserving indigenous knowledge in formal educational settings rather than merely replacing it.

7. Conclusion

This study offers novel insights into how AI technologies can transform EE in resource-constrained settings. By examining the dynamics of technology adoption at a South African university, we identified three critical phenomena: reverse technology adoption, adaptive digital bricolage and indigenous knowledge integration. These findings challenge traditional assumptions about top-down technology diffusion and demonstrate the creative potential of resource-constrained environments. Theoretically, this study contributes to existing literature by extending the applicability of TAM, UTAUT and TPACK in developing world contexts. Specifically, it highlights the role of students as digital change agents, the innovative potential of constraints through bricolage, and the capacity of digital tools to preserve and enhance cultural knowledge. These insights expand the scope of technology acceptance and pedagogical frameworks, offering a more context-sensitive understanding of digital transformation in EE. Practically, this research underscores actionable strategies for HEIs operating in resource-constrained environments. Therefore, HEIs should formalise reverse mentoring programs enabling students to support faculty in adopting emerging technologies. Institutions can also establish innovation.

Appendix

A.1 Initial Interview Guide (24 Questions)

Section 1: Technology Integration Experiences (6 questions)

1. What AI technologies are you currently using in your entrepreneurship education (learning/teaching)?
2. How did you first learn about or become aware of these AI tools?
3. Can you describe a specific instance where you successfully used AI technology in your entrepreneurship studies/teaching?
4. What challenges have you encountered when trying to use AI tools in entrepreneurship education?
5. What factors have made it easier for you to adopt and use these technologies?
6. How do you perceive the role of AI technology in entrepreneurship learning/teaching?

Section 2: Resource Context and Adaptation (7 questions)

7. What technological resources does your institution provide for entrepreneurship education?
8. What technological resources or infrastructure do you feel are lacking?
9. How do you work around or compensate for limited technological resources?
10. Can you describe any creative approaches you have used to achieve educational goals despite resource limitations?
11. Do you collaborate with others (students/colleagues) when using AI technology? If so, how?
12. How do cost considerations influence your choice of AI tools?
13. What role does internet connectivity and device availability play in your AI technology use?

Section 3: Cultural and Knowledge Dynamics (6 questions)

14. How do you integrate local or indigenous entrepreneurial knowledge into your studies/teaching?
15. Do you see any conflicts between using AI technology and preserving cultural knowledge? Please explain.
16. Can you describe ways in which technology has helped (or could help) preserve or share indigenous business practices?
17. How important is cultural relevance when selecting or using educational technologies?
18. Do the AI tools you use reflect or accommodate South African/African entrepreneurial contexts?
19. How do you balance modern technological approaches with traditional entrepreneurial wisdom?

Section 4: Learning and Teaching Relationships (5 questions)

20. How would you describe the typical pattern of AI technology adoption in your department (who leads, who follows)?
21. Have you ever taught or learned about AI technology from a student/lecturer? Please describe.
22. How have AI technology tools changed the way you interact with faculty/students?
23. What role do students play in introducing new AI technologies to the learning environment?
24. How has the use of AI technology affected traditional teacher-student relationships or hierarchies?

A.2 Refined Interview Guide Post-Pilot Testing (18 Questions)

Section 1: Technology Integration Experiences (5 questions)

1. Can you describe any AI tools or technologies you have used or seen used in entrepreneurship learning, whether individually or in groups?
2. How did you first discover or learn about these AI tools? Who introduced them to you?
3. Could you share a specific example of when using AI technology helped you achieve a learning or teaching goal?
4. What challenges have you or your colleagues faced when trying to use AI tools and how have you worked around these challenges?
5. What do you think makes it easier or harder to start using new AI technologies in entrepreneurship education?

Section 2: Resource Context and Adaptation (5 questions)

6. What AI technological resources are available to you for entrepreneurship education at this institution?
7. When you need a AI technology tool that is not available or is too expensive, what do you do?
8. Can you describe a time when you combined different AI basic tools to create something more advanced for your learning/teaching?
9. How do you and your classmates/colleagues work together when using AI technology?
10. How do factors like data costs, device access and internet connectivity affect your use of AI tools?

Section 3: Cultural and Knowledge Dynamics (4 questions)

11. How do you bring local entrepreneurial knowledge, stories or practices from your community into your entrepreneurship studies/teaching?
12. Have you used any AI or digital tools to preserve, document or share indigenous or local business practices? Please describe.
13. When choosing AI technology tools, how important is it that they reflect African or South African business contexts?
14. Do you think AI technology supports or threatens the preservation of local entrepreneurial knowledge? Why?

Section 4: Learning and Teaching Relationships (4 questions)

15. In your experience, who typically introduces new AI technologies first, students, lecturers or the institution?
16. Have you ever shown a lecturer/student how to use an AI technology tool? What was that experience like?
17. How has the use of AI tools changed the way you communicate or collaborate with your lecturers/students?
18. Has AI technology use affected the traditional roles of teacher and student in any way? Please explain.

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Data availability statement. The data that support the findings of this study are available from the corresponding author, F.I Mugunzva, upon reasonable request.

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