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AI Use and Academic Persistence among Undergraduate Students in Tanzania

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Research Article

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Abstract

The use of Artificial Intelligence (AI) tools such as ChatGPT and Google Gemini has become a routine part of student life in higher education worldwide, yet very little is known about how students in Sub-Saharan Africa actually experience these tools, or how that experience relates to whether they stay in or leave their studies. This qualitative study examines how undergraduate students at the Tanzania Institute of Accountancy (TIA) use AI in their learning, how AI helps them understand difficult material, how AI-supported learning relates to their intentions to persist in or withdraw from their studies, and what challenges they encounter along the way. Data were generated from 104 undergraduate students in the Bachelor of Public Sector Accounting and Finance (BPSAF) and Bachelor of Human Resources Management (BHRM) programmes through a semi-structured, Swahili-language interview guide, and analysed using Braun and Clarke's six-phase thematic analysis framework. Students described active, often critical engagement with AI tools across three distinct patterns of use, and identified four specific ways AI helped them understand difficult content, including two mechanisms - bilingual Swahili-English explanation and unlimited, judgement-free follow-up - that extend the existing literature on AI in higher education. Most students (86%) said AI made learning easier, and most (68%) had never considered withdrawing from their studies; among those who had, AI was frequently described as a reason they stayed. At the same time, a smaller group of students described AI use as undermining rather than supporting their learning, including cases of examination failure linked to uncritical reliance on AI-generated answers. Five categories of challenge were identified: AI inaccuracy, unreliable or unaffordable internet access, subscription paywalls, cognitive over-reliance, and a newly identified category of direct academic harm. This study offers one of the first qualitative accounts of AI use and academic persistence from a Tanzanian higher education setting, and contributes context-specific evidence to a literature that has so far drawn almost entirely on research from outside Africa.

1. Introduction

1.1 Background

The public release of ChatGPT in November 2022 changed how many university students study, and it did so very quickly [1, 2]. Within about two years the tool had attracted more than 100 million users, a large share of them students using it to explain concepts, work through problems, draft assignments and prepare for examinations [3]. Research on artificial intelligence in higher education (AIEd HE) has grown just as quickly: Crompton and Burke's systematic review of 138 peer-reviewed studies published between 2016 and 2022 found publication rates roughly doubling or tripling in 2021 and 2022 alone [4].

That review also found a striking imbalance in where this research is being done. Asia accounted for 41% of the studies, Europe 30%, and North America 21%; Africa, home to over 1.4 billion people and some of the fastest-growing university systems in the world, accounted for only 2% [4]. In practical terms, this means institutions like the Tanzania Institute of Accountancy (TIA) are making decisions

about AI in an almost complete evidence vacuum: there is little empirical basis for understanding how AI is shaping what their students learn, how well they understand it, or whether they stay enrolled.

Student persistence and dropout have long been central concerns in higher education research and policy [5, 6]. In a setting where completing a degree can change the economic trajectory of a student and their family, the factors that support or undermine persistence carry real weight. If AI tools are becoming part of how students cope with academic difficulty, as early evidence from other regions suggests, then understanding that relationship from students' own point of view is both an academic and a practical priority.

This study takes that starting point seriously. Rather than asking what institutions could do with AI to predict or prevent dropout, it asks students directly what they experience when they turn to AI for help - how it feels, what it makes possible, what it risks, and how it fits into their relationship with their studies. These are questions that call for a qualitative approach, answered in students' own words rather than through prediction models or rating scales.

1.2 Problem Statement and Objectives

Because so little published research exists on AI use in African higher education specifically, and none that we are aware of has examined the relationship between AI use and academic persistence among Tanzanian undergraduates, this study set out to describe and interpret that relationship directly, using data from TIA students themselves. The overarching research question was: how do undergraduate students at TIA experience and understand AI tools in their learning, and how does that experience relate to their intentions to remain in or withdraw from their studies? Four objectives guided the study:

Objective 1: To investigate the nature and patterns of AI tool use among undergraduate students at TIA, including the tools they use, how they use them, and what motivates that use.

Objective 2: To examine the pedagogical mechanisms through which AI tools help undergraduate students at TIA understand difficult academic concepts.

Objective 3: To explore the relationship between AI-supported learning and students' academic persistence, including their self-efficacy, their experience of learning ease, and their intentions to continue or withdraw.

Objective 4: To identify and examine the challenges undergraduate students at TIA encounter when using AI tools for academic purposes.

2. Theoretical Framework

Three theoretical strands inform how this study interprets its findings. The first is Vygotsky's concept of the Zone of Proximal Development (ZPD): the space between what a learner can do alone and what they can do with the right kind of assistance [7]. Scaffolded support within that space - hints, structured

steps, prompts adjusted to where the learner currently stands - is what allows new understanding to take hold. This framework is used here to interpret the mechanisms through which students describe AI helping them understand difficult material.

The second is self-efficacy theory: a person's belief in their own ability to succeed at a given task, and one of the most consistently identified predictors of whether students persist with or withdraw from study [8, 9]. Students who believe they can master difficult material tend to keep going; students who do not tend to disengage. This framework is used to interpret how AI use relates to students' sense of their own academic capability, including cases where that relationship runs in the opposite direction.

The third is cognitive load theory, which holds that working memory has a limited capacity, and that processing information in a non-dominant language imposes an additional load that competes directly with the effort needed to understand the content itself [10, 11]. For students studying in English while thinking in Kiswahili, this additional burden is not incidental; it is a standing feature of daily academic life. This framework is used to interpret the study's finding on bilingual AI use.

These three strands connect to a fourth, more applied idea that runs through the discussion: Tinto's account of academic persistence, which holds that students who feel academically capable and connected to their institution are more likely to remain enrolled, and that persistence is undermined when that sense of capability or connection breaks down [5, 6]. Read together, these frameworks suggest a pathway worth testing empirically: if AI genuinely narrows the ZPD gap and builds self-efficacy, and does so without adding unmanageable cognitive load, it should be associated with stronger, not weaker, persistence. Whether that is what TIA students actually describe is the question this study investigates.

3. AI in Higher Education: Global and Regional Evidence

Artificial intelligence, understood broadly as computing systems capable of learning, adapting and performing tasks that would ordinarily require human judgement [12, 13], has moved from the margins of educational technology discussion to its centre. That shift accelerated once large language model chatbots demonstrated they could hold coherent, personalised, subject-relevant conversations with users on virtually any topic [14, 2]. Unlike earlier institution-built AI systems, today's chatbots are freely available to individual students on their own devices, which makes AI use in higher education largely a student-driven phenomenon rather than an institutionally managed one.

Crompton and Burke's review identified five principal functions of AI in higher education: assessment and evaluation, predicting outcomes such as dropout risk, AI assistants providing chatbot-style support, intelligent tutoring systems, and managing student learning through analytics [4]. Seventy-two percent of the studies they reviewed focused on undergraduate students, the same population examined here. Singh and Hiran add texture to this picture, describing how adaptive learning technologies let students study at any time and place, and how AI teaching assistants can offer instant, personalised responses that supplement - and in some settings approach the quality of - human instruction [15]. In institutions

with high student-to-staff ratios, of which TIA is one, this affordance matters in a very concrete way: when a student cannot get a question answered in class, AI fills a gap that would otherwise stay unfilled. Ouyang, Zheng and Jiao's review of online higher education research from 2011 to 2020 and Zawacki-Richter and colleagues' earlier review covering 2007 to 2018 both arrive at a similar set of dominant functions - prediction, assessment, adaptive systems and intelligent tutoring - establishing a reasonably stable picture of what AI does in higher education globally, even as the geographic base of that evidence remains narrow [16, 17].

A smaller body of work has looked specifically at AI's relationship to student persistence. Bond and colleagues, in a meta-systematic review calling for greater ethical rigour in this research area, note growing evidence that AI can support engagement and performance, while cautioning that its psychosocial effects remain poorly understood [18]. Gao and colleagues found that students who consulted ChatGPT before seeking help from a teacher reported greater confidence in the human interaction that followed, suggesting AI can function as a step before, rather than a replacement for, human support [19]. The most theoretically developed study on this question is Crawford and colleagues' structural equation model of 387 students across Australia, the United Kingdom and the United States, which found no direct effect of AI use on retention, but a significant indirect negative effect operating through social support: students who used AI as a substitute for human social connection reported reduced belonging and greater intention to leave [1]. Building on this, Pani, Crawford and Allen raise a related theoretical concern - that short-term comprehension gains from AI use may come at the cost of the deeper cognitive engagement that builds lasting competence [20].

Whether these findings transfer to a setting like TIA is an open question worth asking directly rather than assuming either way. Crawford and colleagues' study was conducted in institutions with well-resourced advising services, accessible faculty and dense peer networks, where turning to AI instead of a librarian or advisor represents a genuine substitution of one support option for another. Kuleto and colleagues, studying AI adoption in Serbian higher education, note that infrastructure and resource constraints in lower-income settings shape how AI is used in ways that higher-income-country research does not capture [21]. At TIA, where access to faculty outside scheduled teaching hours is limited and formal advising and wellbeing services are thin, the more relevant comparison for many students may not be AI versus available human support, but AI versus no support at all - a distinction this study returns to in the Discussion.

On the specific question of how AI supports comprehension, evidence from intelligent tutoring systems is instructive. de Chiusole and colleagues' Stat-Knowlab system, which uses competence-based knowledge mapping to build personalised, step-by-step learning paths in statistics, produced measurable improvements in student performance [22]. Kim and Bennekin documented a comparable effect with the Alex AI system in an online mathematics course, built explicitly around supporting student persistence through staged, goal-oriented scaffolding [23]. Chen and colleagues found that AI classroom assistants increased student responsiveness and engagement [24], and Eager and Brunton report early evidence that AI-augmented teaching support outperformed instructor-only support in some

settings [25]. None of this literature, however, addresses students learning in a second language - a gap directly relevant to TIA, where most students study in English while thinking primarily in Kiswahili, and where cognitive load theory suggests that this everyday translation work competes with the effort available for actually understanding the material [10, 11].

The benefits documented above come with acknowledged costs. Crawford and colleagues' concern about AI displacing human connection is echoed by Xie, Pentina and Hancock, who found that prolonged chatbot use could lead to psychological dependency, particularly among already socially isolated students [26], and by Hu, Mao and Kim, who found that students with social anxiety were the most likely to develop problematic AI use patterns [27]. At the level of academic integrity, Cotton and colleagues document the risk of students submitting AI-generated work as their own [14], a pattern Ivanov describes as part of the "dark side" of AI in higher education, and one Perkins argues has challenged assessment design at a fairly basic level [28, 29]. Kuleto and colleagues identify connectivity and device access as the primary barrier to AI adoption in lower- and middle-income countries [21], a barrier that, within a single institution, can create real inequality between students who can afford reliable data and premium subscriptions and those who cannot. It is against this backdrop of documented benefit and documented risk - almost entirely from research conducted outside Africa - that the present study examines what TIA students actually report.

4. Methods

4.1 Research Design and Philosophical Stance

This study adopts an interpretive qualitative approach, on the premise that human experience is best understood through the perspectives of the people living it [30, 31]. That stance suits the aim here: not to measure AI use or predict outcomes from it, but to understand what using AI actually means to TIA students - how they make sense of it, and how it connects to decisions about their studies. A qualitative approach allows the nuance and, at times, the contradictions in participants' accounts to come through in a way that a survey instrument would not [32, 33]. A purely qualitative design was also the more defensible choice given the state of the field: there is no existing body of Tanzanian evidence on this question against which hypotheses could meaningfully be tested, so description and interpretation needed to come before measurement.

4.2 Study Setting and Participants

The study was conducted at the Tanzania Institute of Accountancy (TIA), Dar es Salaam. A total of 104 undergraduate students took part, drawn from the Bachelor of Public Sector Accounting and Finance (BPSAF, n = 86, 83%) and the Bachelor of Human Resources Management (BHRM, n = 15, 14%) programmes, with a further three participants (3%) from other programmes. Most participants were Year 2 students (n = 84, 81%), with Year 3 students making up 15% (n = 16) of the sample.

4.3 Sampling Strategy

Purposive sampling was used, consistent with standard qualitative practice, where the goal is to select participants able to speak meaningfully to the research questions rather than to achieve statistical representativeness [34]. Students were selected on the basis of being current AI users enrolled in technically demanding programmes where AI-supported study is particularly likely. This approach is appropriate for the exploratory aims of the study, though it means the findings are best read as theoretically rather than statistically generalisable.

4.4 Research Instrument and Data Collection

Data were generated using a semi-structured interview guide developed specifically for this study, titled Mwongozo wa Usaili (Interview Guide) and written in everyday Swahili rather than academic language, to encourage natural, unguarded responses [35]. The guide comprised 13 questions across six sections, moving from background information, through AI use and its motivations, to how AI assists comprehension, its effect on confidence and learning ease, its relationship to withdrawal considerations, and finally the challenges students encounter and their broader views on AI in university education. Each section was designed to speak directly to one of the study's four objectives. The instrument was piloted with five students before full data collection, leading to minor wording adjustments, and was reviewed by a senior academic colleague familiar with TIA's student population for cultural and contextual fit.

The guide was administered as an open-ended written questionnaire through Google Forms between 7 and 8 June 2026. Questions were posed in Swahili so that language itself would not be a barrier to honest expression, and participants were free to respond in Swahili or English as they preferred. Written, open-ended responses of this kind generate the reflective, considered data that thematic analysis is well suited to working with [32]. All participants gave informed consent before taking part, and confidentiality was maintained throughout.

4.5 Data Analysis

Data were analysed using Braun and Clarke's six-phase thematic analysis framework [32, 36]. All 104 response sets were first read repeatedly in their original Swahili to build familiarity with the data. Meaningful units of text were then coded systematically, using in vivo coding where possible to keep codes anchored in participants' own language [37]. Related codes were grouped into candidate themes organised around the four research objectives, then reviewed against the full dataset to check that each theme was internally coherent and clearly distinct from the others, before being finalised, named and written up with supporting participant quotations.

Trustworthiness was addressed using Lincoln and Guba's four criteria: credibility, through sustained engagement with the data and the use of direct quotations; transferability, through detailed description of the research setting and participants; dependability, through systematic documentation of the analytic process; and confirmability, through grounding interpretation in participants' own language and keeping data and interpretation visibly separate [38]. Participant responses were collected in Swahili and English as participants chose, and all quotations presented in the findings are given here in English translation, prepared by the researcher, who is fluent in both languages; frequency terms such as "approximately

80% of respondents" are used throughout as indicative guides to how common a theme was across the dataset, not as statistically precise figures.

4.6 Ethical Considerations

The protocol was approved by the Institute Research Committee (IRC) of the Tanzania Institute of Accountancy (TIA) in accordance with the Tanzania Institute of Accountancy (TIA) Research Policy and other applicable national research guidelines. Ethical clearance and permission to conduct the study were obtained prior to data collection. All participants were informed of the study's purpose, its voluntary nature, and the confidentiality safeguards in place, and gave informed consent before taking part; participants were free to withdraw at any stage without penalty. Identities were anonymised using participant codes throughout data storage, analysis and reporting.

5. Findings

The findings below are organised around the study's four objectives. To protect participant identity, illustrative quotations are attributed to anonymised codes (Participant 01, Participant 02, and so on) rather than to any name, year of study or programme. Each theme is illustrated with participant quotations, presented here in English translation, followed by interpretation and connection to the relevant literature.

5.1 Objective 1: How TIA Students Use AI, and Why

Active and varied use. AI use among TIA students is neither passive nor incidental. Students described purposeful, self-directed engagement with a range of tools: ChatGPT was cited by roughly 64% of respondents and Google Gemini by 49%, with smaller numbers of students using DeepSeek, Meta AI, Microsoft Copilot, Claude, Kimi and Perplexity. This is a student population that has largely found and adopted these tools on its own, without formal institutional guidance.

A number of students went further, deliberately cross-checking answers across two or more AI tools when accuracy mattered:

“I photograph questions, get answers, then compare them because AI does not always give correct answers - that is why I use all of them to get the right answer.” — Participant 01

This kind of cross-checking is exactly the sort of critical AI literacy that researchers in this field call for [4, 14]: a refusal to take AI output at face value, checked instead against a second source. That it emerged without any instruction from the institution suggests a degree of metacognitive care that studies framing student AI use as inherently uncritical may be underestimating.

Three patterns of use. Responses to the question of how students use AI clustered into three distinct patterns. The most common was remedial use - AI as a last resort, turned to only once other options had been exhausted:

“Whenever I get stuck on a section, I use AI as the last resort helper.” — Participant 02

A second, smaller group used AI proactively, before lectures or group discussions, to build a general picture of the topic in advance:

“Before attending sessions or group discussions, I use AI to go through the relevant topic and get an overall picture - it makes me confident enough to contribute ideas in class.” — Participant 03

A third, smaller still, group treated AI as an ongoing intellectual partner - asking follow-up questions, challenging its answers, and checking its output against textbooks:

“I never accept everything as it is - I must verify or compare it against textbooks or what the lecturer has explained.” — Participant 04

These three patterns echo broader accounts of how learners engage with technology in the education literature [39], extended here to AI specifically. Where Crompton and Burke's AI Assistant category captures what students use AI for, this pattern taxonomy captures something slightly different: how they relate to it as a source of knowledge [4].

Why students turn to AI. Two motivations came through particularly clearly. The first was patience - AI's willingness to answer the same question repeatedly without frustration:

“AI does not get tired even if I do not understand something 40 times - it still guides me when I ask about the same thing, unlike a human who gets frustrated and starts to belittle you.” — Participant 05

The second was access - simply not being able to reach a lecturer when a question came up:

“Getting face-to-face access to a lecturer is not easy, so many of my questions go unanswered.” — Participant 06

Singh and Hiran describe the same dynamic - AI filling gaps left by limited access to instructors - in more general terms [15]; what the TIA data add is the emotional register behind it: relief at having a resource that does not tire, judge, or turn a student away.

5.2 Objective 2: How AI Helps Students Understand Difficult Material

Asked which topics they found hardest, students' answers clustered around quantitative and applied professional content: Cost and Management Accounting (including process accounting, overhead absorption, and the distinction between marginal and absorption costing), Corporate and Advanced Finance (weighted average cost of capital, capital structure, bond valuation), Research Methodology, and Financial Mathematics and Statistics. BHRM students additionally named Labour Law and Project Management. This concentration in accounting and finance is itself notable: Crompton and Burke found that language learning, computer science and engineering dominate the existing evidence base on AI

and subject comprehension, with business and finance receiving comparatively little attention [4]; the TIA data begin to fill that gap.

Step-by-step explanation. The most widely described mechanism, mentioned by roughly 80% of respondents, was AI breaking a complex problem into manageable steps:

“AI makes it easy for me to understand how to do cost accounting questions in simple language and also provides detailed step-by-step examples.” — Participant 07

One student described asking AI to demonstrate the Overhead Absorption Rate, and being walked through the calculation step by step rather than simply given the formula - "that step-by-step approach made the topic easier than just reading the formula in my notes." This is close to a textbook description of Vygotsky's Zone of Proximal Development: the scaffolding that lets a student move from not understanding to understanding [7]. Purpose-built systems like de Chiusole and colleagues' Stat-Knowlab achieve the same effect in a controlled environment [22]; TIA students are getting there through general-purpose chatbots.

Real-life analogies. About 65% of respondents described AI placing abstract ideas into everyday, recognisable scenarios:

“I asked AI to explain Marginal Costing and Absorption Costing using the example of a bread-making factory - seeing those calculations illustrated with the example of bread helped me understand the difference between them very quickly.” — Participant 08

This mirrors long-standing findings in cognitive psychology on the power of concrete analogy for building deep understanding [40, 11]: an abstract distinction becomes usable once it is anchored to something the student can picture.

Explaining in Kiswahili. The most contextually specific finding of the study, reported by around 45% of respondents, was AI's use as a bilingual teaching aid - students asking for explanations in Kiswahili when the English version had not landed:

“AI has a great role in my education because it makes it easy for me to learn in difficult ways and also explains to me in both Swahili and English.” — Participant 09

Cognitive load theory explains why this matters [10, 11]: when a student is simultaneously processing unfamiliar content and doing so in a second language, the effort spent on translation competes directly with the effort needed to actually understand the material. AI's ability to remove the language burden on request - letting a student receive content in the language where their processing capacity is greatest - has no documented parallel in the AIEd literature we are aware of, and appears to be a contribution specific to multilingual African higher education settings.

Unlimited, judgement-free follow-up. Around 55% of students described the psychological side of AI interaction - being free to ask the same question repeatedly, admit confusion, and receive patient guidance without social cost:

"AI does not get tired even if I do not understand after 40 times - it still guides me when I ask about the same thing, unlike a human who gives up and starts looking down on you." — Participant 10

This speaks to the role of psychological safety in learning: students take greater intellectual risks and learn more deeply when they are not afraid of being judged for their confusion [41]. In a large lecture setting, where raising a hand to ask a "simple" question carries some social risk, AI removes that barrier entirely.

5.3 Objective 3: AI-Supported Learning and Academic Persistence

Confidence: a mixed picture. Self-efficacy - a person's belief in their own ability to succeed at a task - is one of the strongest known predictors of academic persistence [8, 9]. The TIA data show AI's effect on it is real but not uniform. About 44% of students said AI use had increased their academic confidence:

"It has increased my confidence because it has given me the ability to know various strategies for self-study and to deal with examination questions." — Participant 11

About 37% described AI as a useful reference tool with no particular effect on their confidence. More importantly, about 19% described the opposite effect - AI use undermining rather than building their confidence in their own thinking:

"It has affected me because I no longer trust my own thinking to answer questions until I have asked AI." — Participant 12

Kuleto and colleagues' evidence that AI enhances skills and collaborative learning fits the positive-confidence group [21]; Crawford and colleagues' and Pani and colleagues' concerns about AI dependency undermining genuine capability fit the negative-confidence group [1, 20]. What stands out in the TIA data is that both effects are present within the same student population, and that the negative effect is described not by outside researchers but by students reflecting on their own experience.

Learning ease. Asked directly whether AI made learning easier or harder, 86% of respondents said easier, with almost no one describing it as making learning harder in any simple sense; even students who raised concerns about over-reliance still described genuine comprehension benefits alongside those concerns. This is broadly consistent with Alneyadi and Wardat's experimental finding that ChatGPT improved both test performance and students' own explanations of concepts [42], and responds directly to Bond and colleagues' call for more evidence on how AI affects the actual experience of learning, not just engagement metrics [18].

Staying enrolled. Sixty-eight percent of respondents said they had never considered withdrawing from their studies. Among the 16% (n = 17) who had, AI was frequently credited as part of why they stayed:

"Yes, I have thought about leaving university... but I have been looking for strategies and alternative tools to help me overcome that difficulty rather than give up. Its presence makes me see that studying is possible." — Participant 13

Several students who had never considered leaving offered, unprompted, that AI was part of the reason:

"No, I have never thought of leaving university because when I first arrived at university I encountered AI technology which has helped to make my studies easier." — Participant 14

Read together, these accounts describe a fairly coherent pathway: AI lowers the perceived difficulty of hard material, which reduces the frustration that can trigger thoughts of leaving, which supports continued enrolment. This tracks closely with Tinto's account of academic integration as a protective factor against dropout, and with Kahu and Nelson's emphasis on engagement as the mechanism linking conditions to outcomes [5, 6] - with the difference that here AI appears to be doing the work of academic integration specifically, by making content accessible, rather than functioning as a form of social integration.

A point of contrast with Crawford and colleagues. This largely positive picture sits in some tension with Crawford and colleagues' finding that AI use poses an indirect retention risk by displacing human social support [1]. That tension is worth sitting with rather than smoothing over. Their study was conducted in institutions with well-resourced advisors, peer mentoring and accessible faculty - contexts where choosing AI over a human alternative is a genuine substitution with a real cost. The relevant comparison at TIA looks different. When a student messages ChatGPT at eleven at night because a lecturer cannot be reached and the notes do not explain the concept clearly, they are less often choosing AI over a human option than using the only option available. Nguyen and colleagues make a related point about human-AI collaboration more generally: how it plays out depends heavily on the institutional resources and demographics of the setting it occurs in [43], which argues for exactly the kind of context-specific evidence this study is trying to provide.

Where it goes wrong. The most consequential finding in this section is that, for a minority of students, the same reliance that helps most students appears to work against them - particularly where AI output is accepted uncritically and treated as a final answer rather than a starting point. The clearest evidence of this is a confirmed case of examination failure:

"I trusted AI and failed my examination - it helped me with solving and I used it as the final answer; overall I failed that subject badly and received a supplementary examination because of AI's answers." — Participant 15

This is not an abstract worry about cognitive dependency; it is a specific, documented academic outcome. Pani, Crawford and Allen theorise that short-term AI benefits can invert over time as students

substitute AI output for their own reasoning [20]; this account shows that inversion happening within a single assessment cycle. Ivanov's description of AI's "dark side" in higher education is not abstract here either - it has a specific consequence attached to it [28]. The practical implication is that the useful institutional question is not simply whether students should use AI, but under what conditions AI use supports rather than undermines academic development.

5.4 Objective 4: Challenges Students Encounter

Getting it wrong. The most widely reported challenge, cited by around 75% of respondents, was AI producing inconsistent or confidently wrong answers - felt most sharply in calculation-heavy subjects:

“If you are not careful it can deceive you by teaching you something that is not what you asked.” — Participant 16

Crompton and Burke's caution that AI-generated content always needs verification is directly relevant here [4], and Rudolph and colleagues' description of AI's capacity to produce fluent but wrong output captures something students clearly recognise from their own experience [2]. In accounting and finance, where one wrong step in a calculation cascades through an entire answer, this is not a minor inconvenience.

Data and connectivity. About 40% of students raised the cost or unreliability of internet access - referred to repeatedly by the Swahili word bando, colloquial for mobile data - as a barrier that excludes some students from AI's benefits entirely:

“When I do not have data/internet I cannot ask questions.” — Participant 17

Kuleto and colleagues identify connectivity as the primary barrier to AI adoption in lower-income settings [21]; the TIA data put a specific, everyday word to that barrier, and point toward a fairly direct institutional response - some form of campus-based AI access that does not depend on individual data purchases.

The cost of the good version. About 25% of respondents described subscription fees for premium AI features as beyond their reach:

“To get more detailed explanations you must pay in dollars to upgrade AI so it works properly.” — Participant 18

This compounds the connectivity issue in an awkward way: the students who most need detailed, reliable explanations - those struggling with technically demanding material - are often the ones least able to pay for the tier of AI that provides them.

Naming their own risk. Perhaps the most striking finding in this section is how often students raised concerns about their own over-reliance on AI without being asked directly about it - about 36% did so unprompted:

“AI makes learning easy but it can also become a dependency and make students lazy in their thinking.” — Participant 19

Where Crawford and colleagues document AI-induced dependency from a researcher's vantage point [1], TIA students are describing it from the inside, in their own words, unprompted. That level of self-awareness suggests a student population reasonably well placed to respond to AI-literacy guidance, since the concern it would need to build on is already there.

When it costs them a grade. A smaller group, around 10% of respondents, described direct academic harm - examination failure, supplementary assessments or grade penalties - resulting from submitting AI-generated answers without adequate checking. This goes beyond the general concern about dependency into a specific, documented outcome, and appears to be a category not much discussed in the wider qualitative literature on AI in higher education. Ivanov discusses AI's darker consequences at a systemic level and Cotton and colleagues document academic integrity concerns in general terms [28, 14]; what the TIA data add is a first-person account of what that looks like in practice, with direct implications for assessment design and AI-literacy provision before students meet these risks in a high-stakes setting.

Conditional enthusiasm. Asked for their broader view of AI in university education, around 93% of students expressed support, almost always with a condition attached:

“AI should be like a second teacher, not a shortcut to passing examinations without studying.” — Participant 20

“Let us not kill our minds by depending too much on AI - sometimes our own minds produce better ideas than AI itself.” — Participant 21

These are, more or less, the same principles that AI-ethics researchers advocate for: AI as a supplement rather than a replacement, alongside a real concern for protecting one's own thinking [18, 19]. That students arrived at this position on their own, without being prompted or taught it, suggests the institutional conversation about responsible AI use at TIA can start from a position of existing student understanding rather than student ignorance.

6. Discussion

6.1 AI as Scaffolding, Not Substitution

The comprehension findings in Section 5.2 line up closely with the theoretical framework set out in Section 2. Step-by-step explanation, real-life analogy, bilingual accessibility and judgement-free follow-up all function, in different ways, as scaffolding within the Zone of Proximal Development [7] - support that lets a student cross from not understanding to understanding, without doing the understanding for them. The bilingual mechanism is the clearest illustration of cognitive load theory in action [10, 11]: removing

the translation burden appears to free up processing capacity that can then go toward the content itself, a pattern that has not, as far as we are aware, been documented in the AIEd literature to date.

6.2 A Persistence Pathway Consistent with Tinto's Model

The finding that most students experienced AI as reducing academic difficulty, and that a meaningful subset credited AI with helping them stay enrolled, is consistent with Tinto's account of academic integration as protective against dropout, and with the self-efficacy literature more broadly [5, 8]. What this study adds is a plausible mechanism: AI appears to be supporting academic, rather than social, integration - making content accessible rather than building peer or institutional belonging - which is a distinction the existing literature has not drawn out clearly for a setting like this one.

6.3 Why the TIA Findings Differ from Crawford et al.

The apparent tension with Crawford and colleagues' finding that AI use is an indirect retention risk [1] is best explained by context rather than contradiction. Their finding depends on AI functioning as a substitute for available, resourced human support; at TIA, where that kind of support is comparatively thin, AI more often appears to be filling a gap than displacing an alternative. This matters beyond this single study: it suggests that findings on AI and persistence from well-resourced institutions should not be assumed to generalise to institutions with different support infrastructure, and that context-specific research of the kind conducted here is necessary rather than optional [43].

6.4 The Bifurcation Finding

The clearest caution in this study's findings is that AI's relationship to persistence is not uniformly positive. For a minority of students, uncritical reliance on AI - accepting its output as final rather than provisional - produced measurable academic harm, up to and including examination failure. This is consistent with Pani, Crawford and Allen's theoretical concern that short-term AI benefits can invert into longer-term cost [20], and with Ivanov's account of AI's darker institutional consequences [28]. The practical implication is that institutional policy needs to move past the binary question of whether AI use should be allowed, toward the more specific question of what conditions - verification habits, assessment design, AI-literacy training - determine whether AI use helps or harms a given student.

6.5 Equity and Institutional Response

The challenges documented in Section 5.4 - unreliable connectivity, unaffordable premium subscriptions, and uneven access to a resource that many students describe as central to their learning - are consistent with Kuleto and colleagues' identification of infrastructure as the primary constraint on AI adoption in lower-income settings [21]. Within a single institution, these constraints translate into a within-institution AI divide: students with reliable data and the means to pay for a premium subscription have access to a materially better version of the same tool than their classmates without either. This is squarely an equity issue, and one that institutional infrastructure investment - rather than individual student behaviour - is best placed to address.

7. Conclusion and Recommendations

This study set out to understand something the global literature had not yet examined directly: what it actually looks like, from the inside, for undergraduate students at a Tanzanian accounting and human resources institution to use AI in their studies. Drawing on thematic analysis of 104 student accounts, four things stand out. First, TIA students are neither passive nor uncritical AI users; a meaningful share of them cross-check AI output against other sources as a matter of course. Second, AI supports comprehension of difficult, quantitative material through four identifiable mechanisms, two of which - bilingual explanation and unlimited, judgement-free follow-up - appear to be original contributions to the wider literature on AI in higher education, particularly relevant to multilingual African settings. Third, the relationship between AI use and persistence is, for most students, positive, and appears to work through academic rather than social integration, in a way that contrasts with findings from better-resourced institutions elsewhere - a difference that is best read as a matter of context rather than contradiction. Fourth, this is not a uniformly positive story: a minority of students experience real academic harm from uncritical AI reliance, and structural barriers of cost and connectivity limit who gets to benefit from AI in the first place.

Taken together, these findings respond directly to Crompton and Burke's identification of Africa as the most underrepresented region in the global AIEd literature [4]. They also suggest that the practical question for institutions like TIA is not whether to allow AI, since students are already using it, but how to shape the conditions under which that use happens.

7.1 Recommendations for Practice and Policy

TIA should develop a formal AI use policy that distinguishes clearly between legitimate assistance and academic dishonesty, sets out verification expectations for AI-assisted work, and gives students and staff practical guidance across different types of assessment.

AI literacy should be built into first-year orientation, giving students the skills to evaluate, verify and productively use AI tools before they encounter high-stakes assessment situations where the consequences of not doing so are real.

TIA should explore campus-level AI infrastructure - such as institutionally provided access that does not depend on individual data purchases - to reduce the connectivity divide documented in this study.

Faculty teaching quantitative subjects should build explicit AI-verification exercises into coursework, asking students to check AI output against authoritative sources and explain their reasoning, as a direct way of building the habits that protect against the academic risk documented here.

A follow-up study linking AI use patterns to actual academic performance and withdrawal records would help establish whether the persistence pathway described here by students themselves also shows up in TIA's institutional data.

7.2 Limitations and Future Research

This study has several limitations worth noting. Data were collected through an open-ended written questionnaire rather than face-to-face interviews, which may have limited the depth achievable in a live conversation. The sample was drawn predominantly from BPSAF (83%), so some findings may speak more directly to accounting and finance students than to the wider TIA population. The frequency figures reported throughout are indicative guides to how common a theme was, not statistically precise proportions, and should be read that way. The study captures a single point in time and cannot speak to how AI use or persistence intentions change over the course of a degree. Finally, although participant responses in Swahili were translated as carefully as possible by the researcher, who is fluent in both languages, translation always involves some interpretive choice, and a bilingual research team would strengthen future work of this kind. A longitudinal or mixed-methods follow-up, linking the qualitative pathway identified here to actual academic outcomes, would be a natural next step.

Declarations

Funding: Not applicable. No external funding was received for this research; the study was solely developed and written by the author.

Competing interests: Not applicable.

Ethical approval: The protocol was approved by the Institute Research Committee (IRC) of the Tanzania Institute of Accountancy (TIA) in accordance with the Tanzania Institute of Accountancy (TIA) Research Policy and other applicable national research guidelines. The study protocol was approved prior to data collection.

Consent to participate: All participants provided informed consent prior to their involvement in the study, and confidentiality was maintained throughout data collection and analysis through anonymised participant coding.

Consent to publish: Not applicable — the manuscript contains no individually identifiable participant data, images or case details.

Data availability: The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

Author contributions: Henry Estomihi Nkya conceived the study, developed the research instrument, collected and analysed the data, and wrote the manuscript.

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