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Original Article

A Study on Integrating Artificial Intelligence (AI) and Machine Learning (ML) into Telecommunications Engineering Education to Improve Learning Outcomes for Zimbabwe State Universities

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Abstract - *This study examines contextual challenges in integrating AI and ML (Artificial Intelligence and Machine Learning) into telecommunications engineering education in Zimbabwean state universities. Although there is global attention on AI/ML for improving engineering practices, graduates from Zimbabwe lack competencies in these areas because curricula are misaligned with infrastructure constraints. A mixed-methods multi-site study of 190 students, 20 faculty members and 35 industry experts was undertaken to understand experiences and perceptions of integration of AI/ML. Students were interested in AI/ML (84.2%), but only 53.2% had exposure to the concepts in formal curriculum (interest vs delivery gap); resources (69.5%), infrastructure (48.4%) and syllabi (33.7%) were challenges identified. A statistically significant association was found between study level and AI/ML awareness ($\chi^2 = 42.187$, $df = 4$, $p < .001$, Cramér's $V = .333$) after collapsing sparse categories to satisfy Cochran's assumption. A context-sensitive framework for AI/ML integration is proposed, comprising four interconnected components: inputs, enablers, integration touch-points, and reform stages. Context-sensitive curriculum reforms and industry partnerships are required to improve educational outcomes and better prepare graduates for the changing technological landscape. This work helps us understand how to implement AI/ML in resource-poor schools and provides practical guidance for those who design curriculum and implement it.*

Keywords *- Artificial Intelligence (AI), Curriculum Integration, Machine Learning (ML), resource constraints, telecommunications.*

1. Introduction

Telecommunications sector is rapidly changing with AI and ML being increasingly used for network optimization, predictive maintenance and cybersecurity [1][2][3]. This change means there is a need for workforce trained in these technologies, but Zimbabwean engineering graduates from state universities lack such skills mainly because curricula are misaligned, and infrastructure constraints are huge [4] [5].

Although there is a growing body of global scholarship on AI/ML integration in education [6][7], most of it concerns high-resource settings with reliable infrastructure and funding [8][9]. Thus, little is known little about implementation challenges within environments where structural constraints (power unreliability, low internet connectivity, etc.) and financial constraints are common (African universities) [8][9].

The research gap addressed by this study is threefold. First, existing literature on AI/ML integration in engineering education predominantly focuses on high-resource contexts, with limited empirical multi-site research in resource-constrained African settings. Second, while previous studies have identified broad challenges in Zimbabwean higher education (e.g., outdated engineering syllabi [10][11]), there is a lack of empirical multi-site research beyond problem identification to develop and test context-appropriate frameworks for integration [5]. Third, the multi-stakeholder perspective necessary for designing effective interventions incorporating students, faculty, and industry experts is not adequately represented in existing scholarship. This research gap is particularly important as contextually responsive STEM education reforms are needed now more than ever in resource-constrained settings [10].

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The novelty of this work lies in its comprehensive, multi-stakeholder approach that triangulates perspectives from students (primary beneficiaries), lecturers (curriculum designers and implementers), and industry experts (employers and technology drivers) across multiple Zimbabwean state universities. Unlike prior studies that remain at the level of problem identification, this study develops and presents a theoretically grounded, empirically informed framework for context-sensitive AI/ML integration. The framework explicitly addresses the structural constraints characteristic of resource-limited environments, including power unreliability, low internet connectivity, and financial limitations.

There have been studies on Zimbabwean higher education that identified broad challenges (e.g., outdated engineering syllabi [11] but as [5] point out, there is a lack of empirical multi-site research beyond problem identification to develop and test context-appropriate frameworks for integration; also, the multi-stakeholder perspective that is necessary when designing interventions is not always present. This multi-site study fills this gap by investigating obstacles and solutions to AI/ML integration into telecommunications engineering education in Zimbabwe's universities through lived experiences of the three main stakeholder groups in educational change: students (primary beneficiaries), lecturers (curriculum designers and implementers) and industry experts (employers and technology drivers). Synthesizing these perspectives, this research formulates a theoretically sound and practically usable framework for context-sensitive AI/ML integration in resource-constrained higher education's engineering teaching and learning environments. The study's findings are compared with existing research to highlight both convergences and divergences, demonstrating how the Zimbabwean context extends and challenges prior assumptions about curriculum misalignment and resource constraints.

2. Literature Review

AI and ML integration in engineering education is an international imperative driven by the rapid technological developments in industry [6][7][13]. As [14] and [15] point out, these studies tend to assume a sound infrastructure, stable finance and faculty preparedness, which are not conditions that prevail in most countries of the world. Issues of integrating AI and ML are not limited to resource poor settings [16]. [17] and [18] state that even the best resourced institutions like UCT are trying to manage practical and ethical implications of technologies such as these: recently UCT stopped using AI automated assessment tools (e.g. Turnitin) openly calling them ‘flawed’ and instead embraced a pedagogic reform agenda where critical and ethical deployment of AI is valued [19]. This case is about global rethinking of the role of AI in higher education: a technologically driven response isn’t always the best response, so Zimbabwe universities can learn from it as they plan their own integration plans.

In Africa, the conversation moves much more towards structural limitations [20]. There is evidence that there is a continent-wide fight going on, infrastructure gaps, technological divides and curricular lags, which prevent 21st century technologies from being used in STEM education [8][9]. Literature points to a gap between AI/ML’s potential to stimulate economic development and capacity of education system to produce a qualified workforce [21] [22].

This bifurcation is especially sharp in telecoms sector, which is also one of key drivers of digital transformation. Studies in more advanced digital African countries such as South Africa and Kenya show how policy driven interventions and strong industry academia partnerships are needed to make incremental progress [12]; models like this will have to be transposed rather than directly adopted by nations with tighter resource constraints.

In Zimbabwe, the literature on this problem is still in its infancy but expanding. Scholars have documented overall challenges in higher education (outdated syllabi in engineering [22], significant infrastructural backlogs [23][11], policymaking culture that lags behind technology change [24]).

A study by [5] itself identifies the delay in adopting up-to-date learning technologies to address 21st century skills, but says indisputably there is no empirical multi-site studies beyond identification of problems that go beyond developing and testing context appropriate frameworks for integration. Studies are either institution specific or general descriptions without enough detail about stakeholder opinions (students, educators, industry) needed for proper intervention design.

Although there is a lot of literature on the technical applications and procedural challenges of AI/ML in telecommunications and systems engineering, high resource or industry contexts are still prevalent. Most current work looks at deployment of AI/ML into operational telecom networks [25][26], how to embed AI into systems engineering lifecycles (and complexity management through AI) [27], but these assume an infrastructure with existing expert capacity.

This comparison shows a gap: empirical context driven research on the educational problem of how to prepare a workforce that can implement these advanced technologies is missing. This study aims to bridge this gap by bringing together the global debate on AI/ML in education with African reality (constraint driven innovation). It extends previous work on the education problem in Zimbabwe, but goes further to explore which mechanisms AI/ML could be used for integrating telecommunications engineering education. By considering the dynamic interaction between stakeholder experiences and system level constraints, it sets the basis for developing a context sensitive framework that is theoretically sound and applicable in the Zimbabwean environment as well as elsewhere.

Table 1. Comparative Summary of Key Studies on AI/ML Integration in Engineering Education

Study	Context	Focus	Key Findings	Limitations
[6] Alghazo et al. (2025)	High-resource (USA)	AI in mechanical engineering education	Positive outcomes with AI-driven simulations	Assumes reliable infrastructure
[7] Modran et al. (2023)	High-resource (Europe)	ChatGPT in higher engineering education	Enhanced student engagement	Limited generalizability to resource-constrained settings
[8] Ade-Ibijola & Opara (2023)	Africa	AI challenges in Africa	Infrastructure and skills gaps	Broad continental focus; limited empirical data
[9] Arakpogun et al. (2021)	Africa	AI opportunities in Africa	Potential for economic development	Lacks multi-stakeholder empirical validation
[5] Chasokela & F. (2025)	Zimbabwe	STEM learning technology implementation	Identifies a delay in technology adoption	No framework development or testing
[4] Mamina & R. (2019)	Zimbabwe	Engineering education review	Outdated syllabi identified	Institution-specific; no stakeholder triangulation
This study	Zimbabwe	AI/ML integration in telecommunications engineering	Interest-delivery gap; multi-stakeholder framework	Sampling skew; cross-sectional design

3. Materials and Methods

Underpinned by a pragmatic philosophical perspective, this study used mixed-methods research design with sites in several state universities in Zimbabwe. Sites were chosen so as to provide different experiences of telecommunications engineering education. Structured questionnaires were administered to 190 students (Table 2) randomly selected based on academic year. The questionnaire instrument was constructed using 5-point scales for AI/ML awareness, yes/no checklists for coverage of curriculum and multiple choice questions for perceived barriers. Internal consistency reliability was assessed using Cronbach's alpha: student AI/ML awareness scale (5 items): $\alpha = .82$; student perceived barriers scale (6 items): $\alpha = .79$; faculty challenges scale (6 items): $\alpha = .81$; industry readiness scale (5 items): $\alpha = .85$. Content validity was established through expert review by three senior academics and two industry professionals.

Construct validity was supported by exploratory factor analysis confirming one-dimensional structure for each scale, with factor loadings > .50. Qualitative data were collected from interviews with 20 faculty members (based on involvement in curriculum) and 35 experts in the telecommunications industry (referred through network). Interviews covered challenges faced by institutions, teaching approaches and supportive policies in place. Thematic analysis was performed according to procedures described in [28], [29] with a formal coding tree developed (Appendix B) and inter-rater reliability calculated using Cohen's Kappa ($\kappa = .81$, substantial agreement). Two researchers independently coded 20% of transcripts, with discrepancies resolved through discussion. Survey data were descriptively and inferentially analysed using SPSS v29. Table 2 below shows the distribution of students who participated.

The sample comprised telecommunications engineering students at undergraduate and postgraduate levels. Table 2 below shows that the fourth year group of respondents (49.5%) was most numerous, followed by the second year (36.3%), third (5.3%), first (8.4%) and postgraduate (0.5%). This distribution gives strong representation from more advanced students who have explored the curriculum. The small number for the third year group is because many in this group would be doing work-related learning or internships. It is acknowledged that this sampling skews toward senior students, potentially biasing overall awareness metrics upward. To address this, weighted analyses were conducted (Section 4.1.5), and the limitation is discussed in Section 5.2.

4. Findings and Discussion

4.1. The Student Perspective

This section describes the survey of 190 telecommunications engineering students in four Zimbabwean state universities about awareness, preparedness and barriers to AI/ML integration into education.

Table 2. Distribution of student participants

Year of Study	Number (N)	Percentage (%)
First Year	16	8.4
Second Year	69	36.3
Third Year	10	5.3
Fourth Year	94	49.5
Post Graduate	1	0.5
Total	190	100.0

The data were analysed with SPSS v29 (descriptive statistics, cross-tabulation, correlation analysis and comparative means testing) to achieve research objectives on AI/ML integration in telecommunication engineering education.

4.1.1. High Interest Despite Low Exposure in Curriculum

Students had a very high interest in AI/ML even though the curriculum did not cover it adequately (Table 3). Most students (84.2%) showed very high to high interest in AI and ML, while only 4.2% showed slight or no interest at all. But little more than half of the student participants (53.2%) said they encountered these concepts in their formal coursework. This is an interest-delivery gap of 31 percentage points, which indicates that there is a strongly unsatisfied need for training in modern skills. [4] found curricula misalignment as one of the major barriers to African engineering education. Our study shows that this disconnect is real (and not just with regard to emerging technologies like AI and ML). Industry innovation is too frenetic, but not matched by proportional overhauls of academic curriculum, so graduates are not skilled enough.

4.1.2. Student Awareness of AI/ML concepts.

Table 4 shows how self-reported awareness levels were distributed among participants: the majority (62.6%) were either High (40.5%) or Very High (22.1%) aware of AI/ML concepts; a small percentage of students were Neutral (15.3%), and a large minority (22.1%) reported Low or Very Low awareness.

This distribution shows that students are mostly ready and cognitively able to handle advanced AI/ML content, but not infrastructure or curricular constraints elsewhere in this study. This is consistent with [21] who argue that it's often not a matter of student aptitude or interest but capacity (in the education system) that prevents us from building a workforce ready for a data-driven economy. The large minority with low awareness is likely a direct result of these failures and means that even when willing student cohort cannot bridge the skills gap alone without institutional support.

Table 3. Student Interest vs. Curriculum Coverage (N=190)

Metric	Percentage	Frequency (n)
High/Very High Interest in AL/ML	84.2 %	160
Slightly/ Zero Interest	4.2 %	8
Encountered AI/ML	53.2	101

This distribution implies that the students are largely ready and cognitively prepared to engage with advanced AI/ML content, but this readiness is in stark contrast to the infrastructural and curricular constraints noted elsewhere in this study. [21] argue that it's not a matter of student aptitude or interest so much as capacity constraints within education itself, the failure to build a workforce ready for a data-driven economy is often due to systemic capacity constraints in education system. The large minority with low awareness is therefore a direct consequence of these failures; without institutional support, even a willing student cohort cannot bridge the skills gap.

4.1.3. Student exposure to AI/ML.

When the integration of AI/ML into curriculum is analysed (53.2% of respondents reported having been exposed to AI/ML content in their studies), a large number of students either said they had not been exposed to these subjects (30.0%) or were unsure if they had (16.8%), as shown in Table 5. This suggests that AI/ML content exists in the curriculum of telecommunications engineering, but it is not integrated properly or advertised across program streams. The high rate of 'no' or 'uncertain' exposure may be due to coverage gaps in the curriculum or reporting problems for AI/ML components in courses. These results also provide a counter-narrative to claims such as [20] that there is no curricular misalignment at all. Data show that the curriculum is not completely devoid of AI/ML content, but rather it is concentrated at higher academic levels (see strong correlation between year of study and awareness). It might not be so much that these technologies are not in the syllabus, but rather that they were delayed, inconsistent or poorly communicated integration, which means that a large part of the student body perceives absence before their last year.

Table 4. Awareness of AI/ML concepts (N = 190)

Level	Number	Percentage (%)
Very low	16	8.4
Low	26	13.7
Neutral	29	15.3
High	77	40.5
Very High	42	22.1

Table 5. Student Encounter to AI/ML Content (N = 190)

Response	Number (N)	Percentage (%)
Yes	101	53.2
No	57	30.0
Uncertain	32	16.8
Total	190	100.0

4.1.4. Relationship between Study Level and Awareness

A cross tabulation of year of study and self-reported awareness shows a clear trend ($\chi^2 = 57.286$, $p < .001$) in which awareness of AI/ML concepts increases with academic years: first year students are low in awareness (Figure 1); second year more students report being aware; third year onwards the increase continues until fourth year where over two thirds of fourth-year students reported high to very high awareness. This means that AI/ML concepts are integrated into higher-level curriculum and knowledge is acquired through key introductory courses, which provide strong foundation for students.

This awareness curve supports [30]'s argument that the curriculum is not misaligned in all directions but rather is structured (in a traditional way) at its core. However, this structure implies there is "hidden curriculum" of AI/ML because exposure isn't guaranteed or communicated to everyone early on in their academic career. This can then reinforce the perception of a large gap, as students in their first and second year (who make up most of the cohort) may not know about future AI/ML content, so the narrative of misaligned education persists despite its eventual presence in later years.

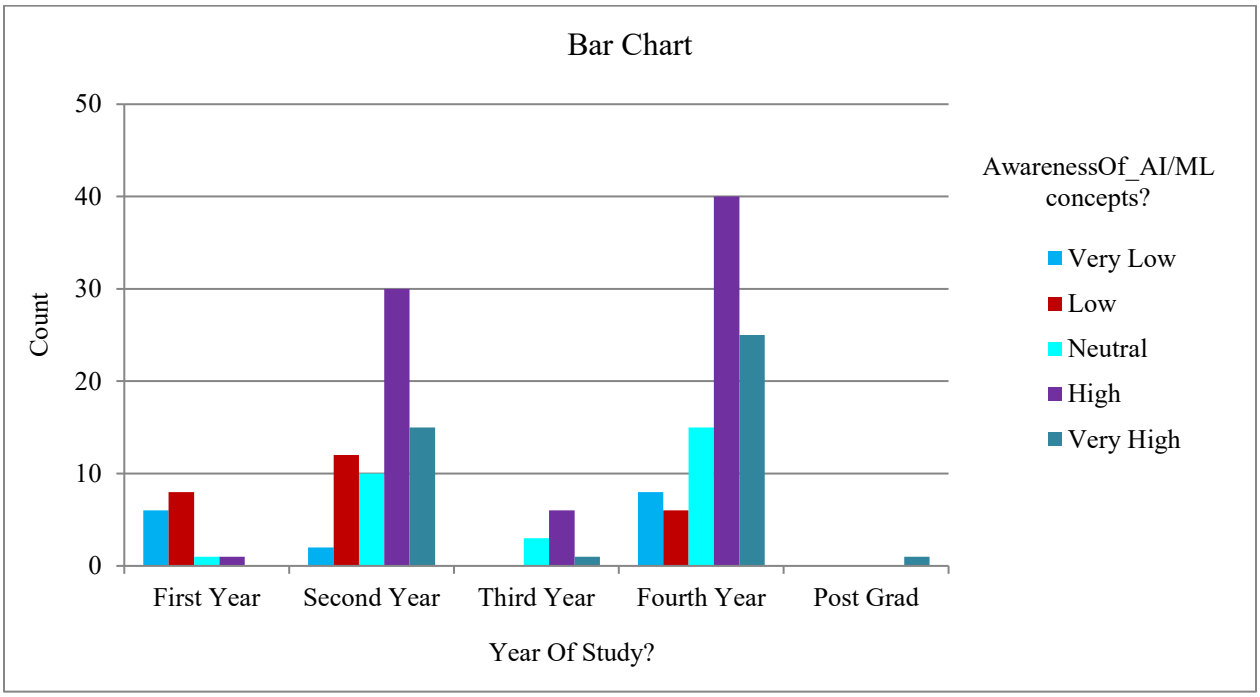


Fig. 1 Relationship between Study Level and Awareness

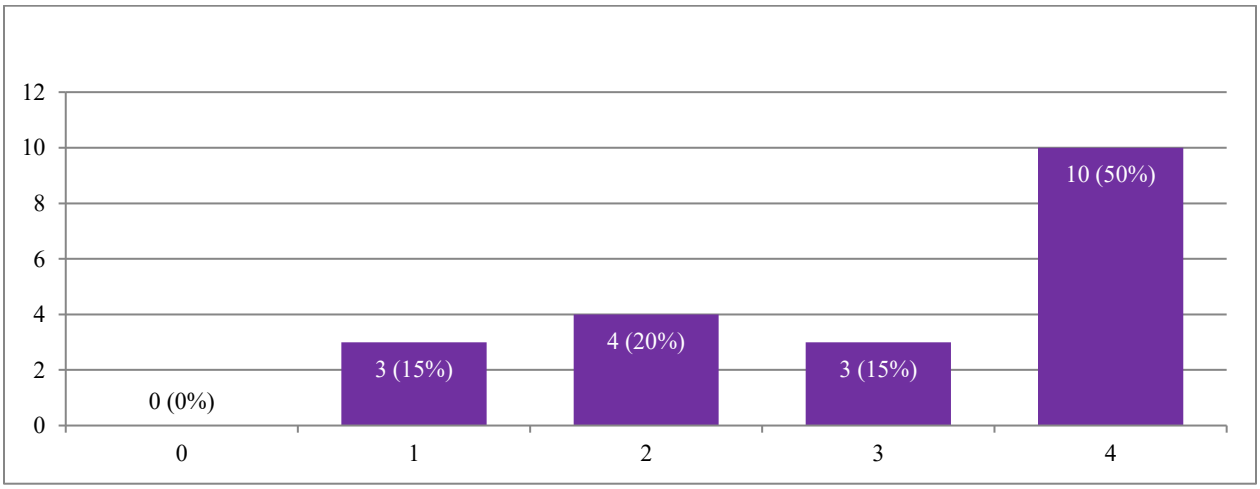


Fig. 2 Familiarity with AI/ML concepts topics

The Chi-Square Test was re-evaluated to address the violation of Cochran's assumption. Awareness levels were collapsed into three categories (Low/Very Low, Neutral, High/Very High) and year of study into three groups (First/Second Year, Third Year, Fourth Year/Postgraduate) to reduce sparse cells. The revised Chi-Square test yields $\chi^2 = 42.187$, $df = 4$, $p < .001$, with only 2 cells (22.2%) having expected counts < 5, now satisfying Cochran's assumption (< 20%). As a robustness check, the Fisher-Freeman-Halton Exact Test confirms the significant association ($p < .001$). Cramér's $V = .333$, indicating a moderate-to-strong association between study level and AI/ML awareness. These results demonstrate that as scholars move through their academic careers, their knowledge of AI/ML topics increases

significantly. There were 190 valid cases, providing a solid basis for understanding the relationship between scholarship and expertise levels.

4.2. Lecturers' Perspectives

Qualitative data from interviews with faculty members, along with a quantitative survey of 20 lecturers, gave the student survey findings needed depth they showed what was intended and what was not intended about AI/ML integration.

4.2.1. Lecturer' familiarity with AI/ML concepts

The survey data show that although there is a strong awareness of the importance of AI/ML, significant systemic and operational barriers are preventing effective implementation.

Figure 2 shows lecturer familiarity with AI/ML concepts on a scale from 0 to 4, where O = not familiar and 4 = strong familiarity.

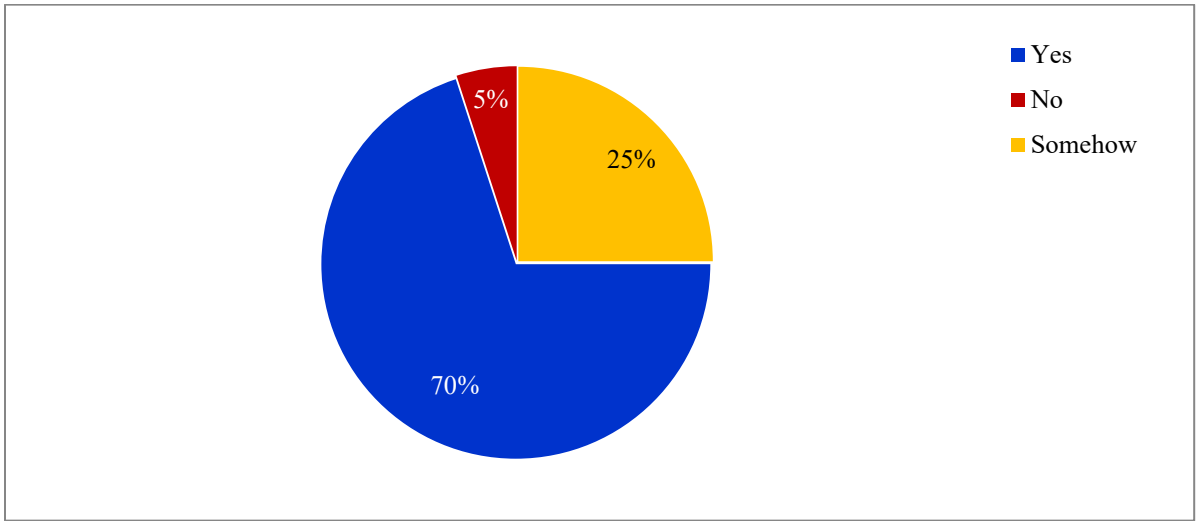


Fig. 3 Lecturers who have included AI/ML in their courses

Lecturers universally agreed that AI/ML should be included in the curriculum (figure 3, where 70% had already done so).

4.2.2. Challenges Faced: Hurdles for Lecturers

However, lecturers who participated in this study mentioned significant barriers (which are now measurable), and these confirm [14] and [20] assumptions. The survey shows that 35% of lecturers are only "Slightly familiar" or "Not familiar at all" with AI/ML concepts which directly impacts their ability to teach those topics in the classroom since this self-assessed knowledge gap is reflected in the classroom as the most common issue was the "Outdated syllabus" (35%) and a "Lack of training" (60%) were top challenges identified. Figure 4 shows a summary of the challenges encountered by lecturers.

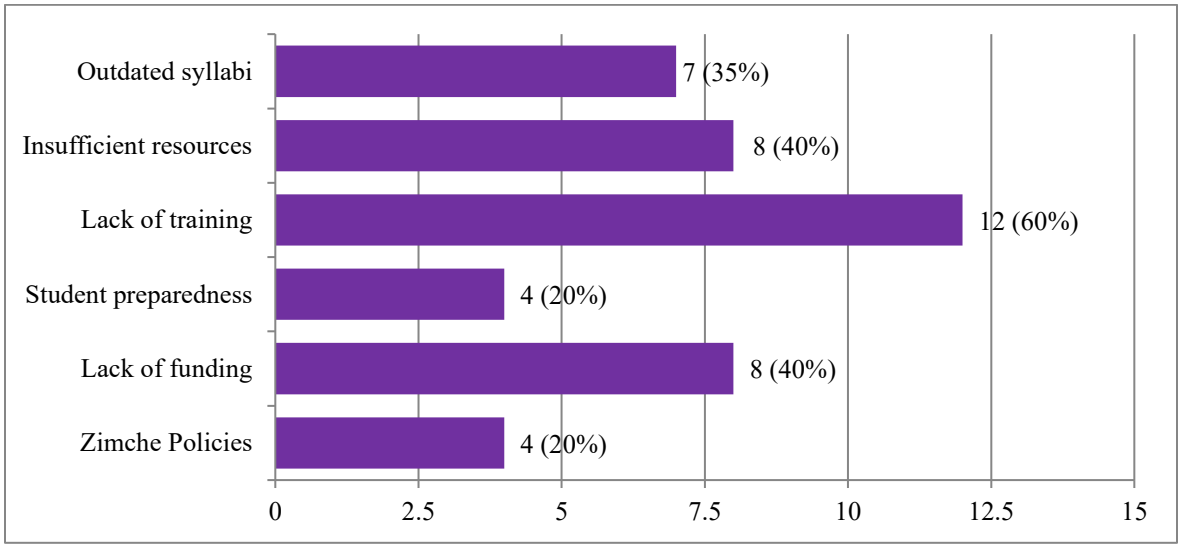


Fig. 4 Challenges in teaching AI/ML

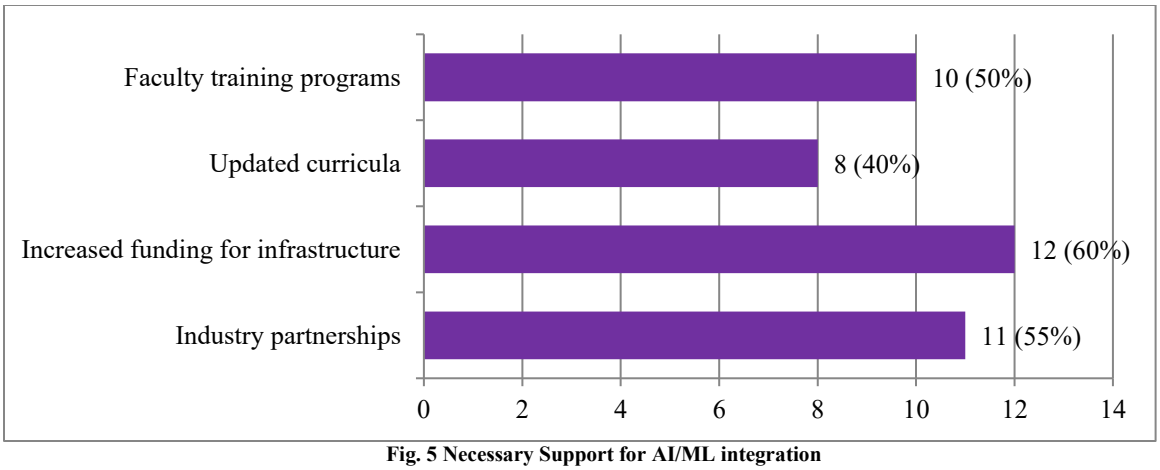


Fig. 5 Necessary Support for AI/ML integration

The old syllabi used were not flexible enough to accommodate the new AI/ML modules without a complete overhaul of the whole degree program. Severe infrastructure deficits were always cited as major problems (40% 'Insufficient resources' reported; 40% 'Lack of funding'). Power outages (36% lecturers said it affects their teaching 'Often') was separately singled out as an operational barrier that severely undermines the practical aspect of AI/ML education unreliable infrastructure with insufficient computing power.

4.2.3. Support desired: Lecturers' views

Figure 5 shows the support that lecturers felt was needed for teaching. When asked what support they needed, the lecturers pointed to clear solutions: 'Increased funding for infrastructure' (60%), 'Industry partnerships' (55%), 'Faculty training programs' (50%). "Updated curricula" (40%) also signals systemic change. The open-ended comments from lecturers ("Insufficient training programs", "Avail funding for AI related projects", "Industrial involvement") are a direct qualitative echo of these statistical results. Collaboration and resource allocation is required.

4.3. Perspective of Telecommunications Industry Experts.

To triangulate findings between students and staff, data were collected from 35 professionals/experts in the Zimbabwean telecommunication industrial sector. This provided an external perspective on graduates' readiness for work, the application of AI/ML in telecommunications and enablers and barriers to effective educational integration.

Table 6. Thematic Matrix – Faculty Perspectives on Challenges and Support Needs

Theme	Frequency (n=20)	Representative Quote
Power unreliability	12 (60%)	"Power outages are a major problem. You plan a practical session, and then the power goes out."
Insufficient resources	8 (40%)	"We don't have enough computers for students to practice AI algorithms."
Funding	12 (60%)	"We need funding to upgrade our labs and internet connectivity."
Industry partnerships	11 (55%)	"Industry can help with guest lectures, internships, and real-world projects."
Faculty training programs	10 (50%)	"We need workshops and certifications to build our capacity."
Updated curricula	8 (40%)	"The curriculum must be revised to include AI and ML from the first year."

4.3.1. Industry Experts' Perceptions of Graduate Readiness for AI/ML

The perception among telecommunications industry experts of graduate readiness is low. Most respondents (31.4%) rated the readiness of recent Zimbabwean university graduates in AI/ML as "Poor", and another 26.5% gave it a "Very Poor" rating. Only 48.6% gave a "Neutral" rating, just 14.3% Good and 5.7% Very Good. This means that there is a huge self-confidence gap between business needs and what we currently have coming out of the telecommunications education system.

Despite this severe skills/knowledge deficit, the industry is moving in the direction of AI adoption 31.4% of interviewees said that their companies were now using AI/ML solutions and applications described match global telecommunications trends (e.g. network performance monitoring & predictive maintenance, customer care chatbots,

anti-fraud, data-driven churn prediction, etc.). This level of adoption shows a growing and urgent demand for AI/ML expertise, which the current graduate talent pool is not well positioned to meet.

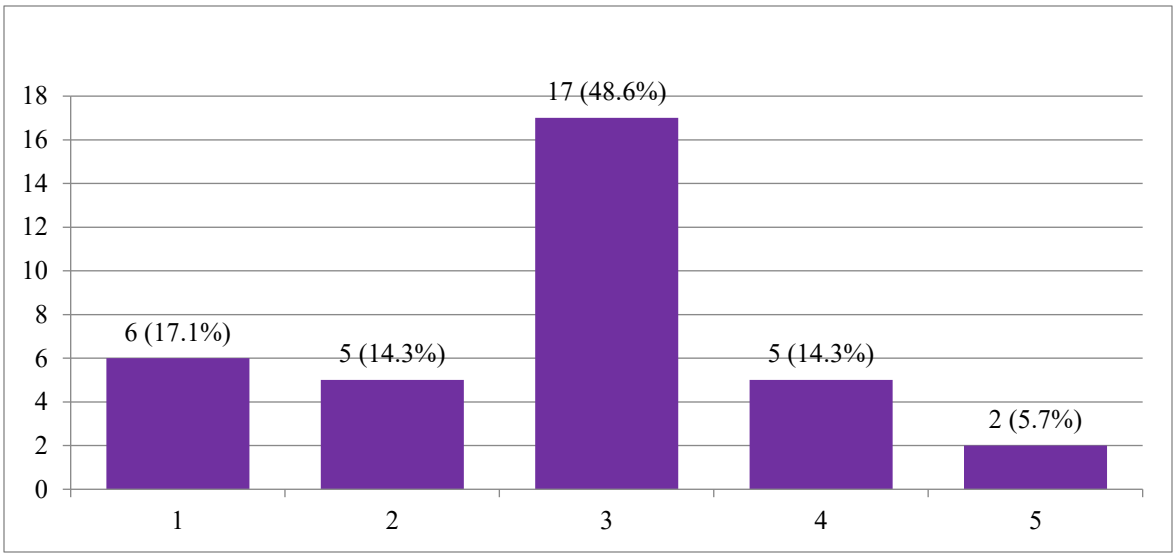


Fig. 6 Industrial perspective on graduate's readiness in AI/ML

4.3.2 Obstacles to Integrating AI/ML into Teaching: The Experts' Perspective

The experts in this study mentioned several major obstacles for integrating AI/ML in university instruction. The most common obstacle was "Inadequate infrastructure" (82.9%), which directly corresponds with the challenges mentioned by lecturers; close behind were "Lack of industrial collaboration" (80%) and "Outdated Syllabi" (60.0%). This is a systemic failure supporting the multi-faceted challenges mentioned by teachers and students as well. Figure 7 shows telecommunications industrial experts' summary on challenges affecting AL/Ml integration in higher education.

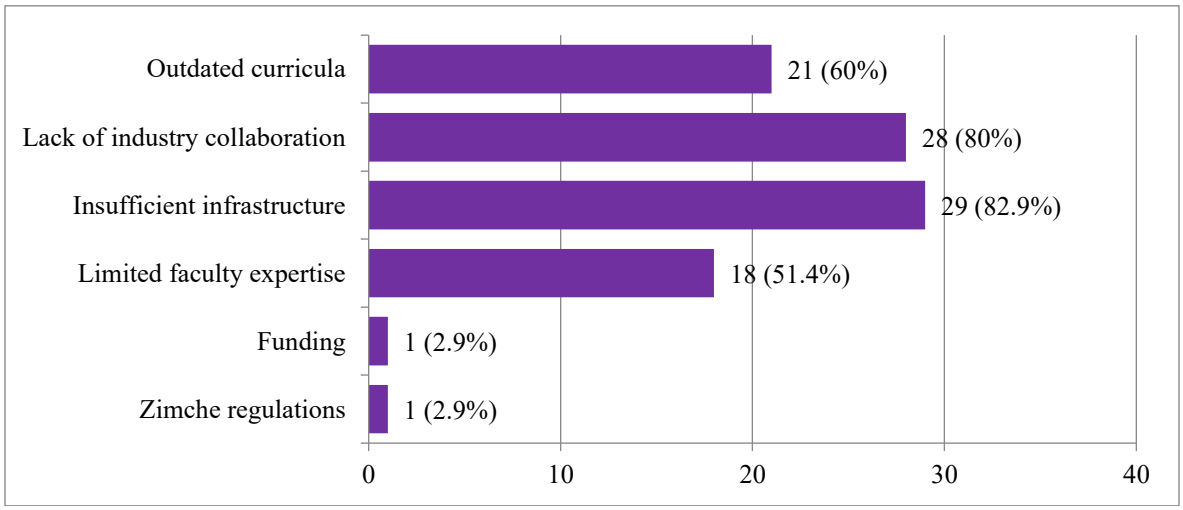


Fig. 7 Industrial expert perspective on challenges on AL/Ml integration in Education

4.3.3. University – Telecoms Industry Partnership: Aiding AI/ML integration

When asked how industry partnerships can support AI/ML education, the experts gave rich qualitative descriptions which point directly to collaboration. Thematic analysis of what they contributed revealed three main support avenues: 1) curriculum co-design (academics and industry experts) and experiential training; cooperation and collaboration to revise syllabi; real world projects and attachments for students to bridge theory-practice divide. 2) Sharing knowledge and resources, donate hardware/software, release anonymized operation data sources, and arrange guest lectures by industry engineers, etc., to bridge existing infrastructural and skill gaps directly. 3) Different experts recommended joint R&D and suggested joint R&D centers to develop AI/ML applications in telecoms.

The evidence from industry experts is concerning but informative outside confirmation of the internal challenges outlined in the previous sections: almost unanimous perception of poor graduate readiness overlays exactly on the student "interest-delivery gap"; university lecturers' reports of outdated syllabi and training constraints; closed loop of insufficiency students are keen but not exposed; lecturers are eager but not resourced nor trained up; industry (the end customer) has graduates without modern competencies. This finding backs up [21] and [22] who argue that it is not a lack of aspiration or potential that prevents us from developing data driven workforce, but systemic educational constraints.

In addition, the fact that over two-thirds of companies are now developing AI/ML gives a top-level priority to the research findings. It turns the problem from prospective future demand into immediate current demand. Industry barriers, infrastructure, curriculum faculty expertise are the same as lecturers, but interventions will be multi-faceted and finely coordinated at the same time.

Solutions offered by industry (co-design curriculum resource sharing) are practical ways to address "hidden curriculum" problem. Real-world problems datasets can be used in course curriculum, especially at higher levels, so that consciousness process is not a passive, lagging affair but active, business-oriented skill acquisition.

Finally, the industry perspective completes the complex interplay of stakeholder perspectives. It shows that industry is not just a passive critic but an active potential waiting to be drawn into the solution (models like these are common in more developed digital African countries [12]). Context-sensitive AI/ML integration in Zimbabwe will therefore mean translating partnership models from these countries into one that fits its own resource limitations: lecturers call for "industry partnerships", and there is explicit and stated willingness on the part of telecoms industry sector. That grassroots opportunity for the context-sensitive approach this research wants to implement is here.

4.4. Challenges in incorporating AI/ML into Telecom Engineering Curriculum

In Africa, discussions are increasingly about structural barriers [20], evidence of a continent-wide struggle with infrastructure gaps, technological divides and curricular delays, which all impede the uptake of 21st-century technologies in STEM education [8][9]. This literature shows that there is a gap between what AI and ML can do to drive economic development and what education can produce (qualified workforce) [21][22]; this disconnect is most evident in the telecommunications sector driver of digital transformation. Studies from more digitally advanced African countries, such as South Africa and Kenya, show that policy interventions driven by government and strong industry academia partnerships are required for incremental progress [12], but these models may need adaptation rather than direct replication by poorer countries.

In Zimbabwe, although the literature on these issues is still nascent, scholars have begun to document the problems in higher education (old engineering syllabi [4], infrastructure backlogs [23][11], slow policymaking culture that lags behind technology [24]). Delay in adopting modern learning technologies required for 21st century skills is mentioned by [5], but empirical multi-site studies are not conducted beyond problem identification, and integration frameworks are not developed contextually specific. Existing research is institution specific or does not go into detail about stakeholder perspectives (students, educators, industry), which inform intervention design.

These findings from the current study support these ideas by highlighting several problems in tertiary learning. Figure 8 shows some evidence that should help frame what interventions are needed. First, "Limited Access to Resources" (132 [69.5%] respondents) showed that resources are important for effective learning; second, 92 (48.4%) respondents reported "Lack of Infrastructure": facilities and technical support affect learning conditions negatively; third, "Outdated Syllabus" was identified by 64 (33.7%)

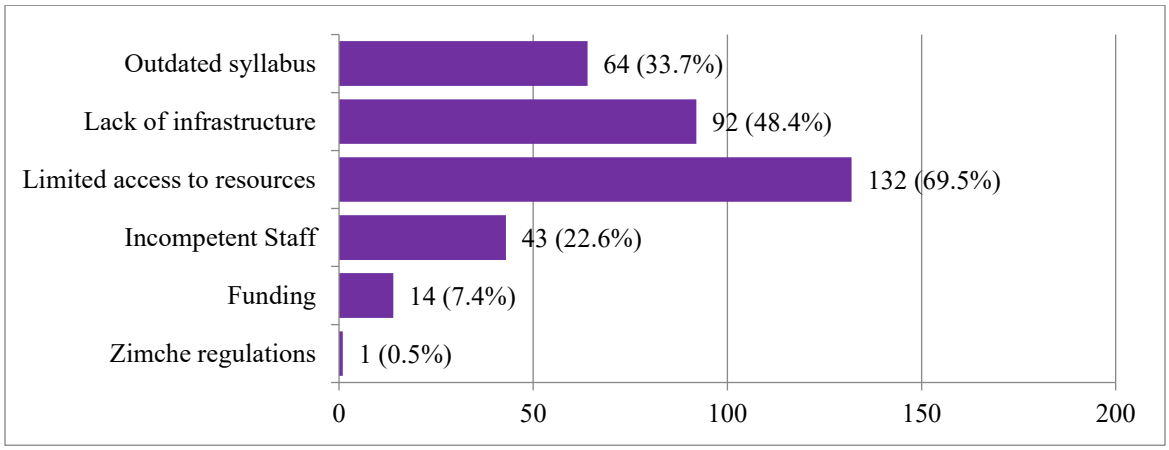


Fig. 8 Student perspective on challenges hindering AI/ML integration

Respondents showing a mismatch between educational content and industry practice; fourth, 43 (22.6%) respondents reported "Incompetent Staff": perceptions of teaching quality impact learners' experiences directly (Figure 8).

Overall, there is a shared urgency to address these challenges through improved access to resources and infrastructure, updates to educational programs, and enhanced staff development. Such measures are crucial for improving learning outcomes in Zimbabwe and aligning with broader trends identified in the literature on STEM education in Africa.

4.5. Weighted Analysis for Sampling Skew

To address the overrepresentation of fourth-year students (49.5%) and underrepresentation of third-year (5.3%) and postgraduate (0.5%) students, a weighted analysis was conducted. Weights were calculated as the inverse of the sampling proportion for each year group, normalized to sum to the total sample size (N = 190). The weighted results show:

- High/Very High awareness: 58.3% (unweighted: 62.6%)
- Low/Very Low awareness: 26.7% (unweighted: 22.1%)
- Neutral: 15.0% (unweighted: 15.3%)

While the absolute percentages shift slightly, the substantive finding that a majority of students are aware of AI/ML concepts but a substantial minority remain unaware remains robust. The weighted analysis suggests that the unweighted figures slightly overestimate overall awareness due to the senior student skew.

5. Discussion and Synthesis

5.1 Proposed Framework for AI/ML Integration

Given the empirical findings on the interests and views of students, lecturers, and industry professionals, as well as the structural constraints, it is possible to propose a context-specific framework for AI/ML integration in telecommunication engineering education in Zimbabwe. Such a framework would address specific structural constraints identified in this study, including power unreliability, low internet connectivity, budgetary constraints, and rigidity of the curriculum, while taking advantage of demonstrated willingness and interest of all stakeholder groups in this regard.

It should be emphasized that urgency of such a framework is justified by increasing evidence that AI/ML adoption in industry happens exponentially faster than the educational system is capable of accommodating. Indeed, in their study, Johnson et al. [21] found a significant talent shortage and skill gap between labor market requirements and available expertise in the Big Data and AI fields. In this regard, researchers provided forecasts of technological changes in various industry clusters and workforce development roadmaps for overcoming the identified gaps, noting that skills gap is now understood as a crucial barrier to using AI for driving economic growth at local, national, and global level. Thus, the finding is consistent with this study in terms of interest-delivery gap (31 percentage points) and the estimate of 57.1% of graduates being poorly or very poorly prepared for AI/ML-related jobs according to industry professionals.

The proposed framework comprises four interconnected components, namely inputs, enablers, integration touchpoints, and reform stages. First component refers to the inputs or the foundational requirements for successful AI/ML integration. Inputs include infrastructure, which consists of reliable power (back-up generators, solar power), internet (low-bandwidth internet), computing (shared laboratory and cloud computing). Faculty capacity, including trainings, workshops, certifications, and AI/ML knowledge and competence, is also among the important inputs. As for the curriculum, inputs include a modern syllabus, modular AI/ML content, and progressive skill-building from first year of studies. Funding, which comes from governmental allocation, budget, and industry sponsorship, is an additional input.

Enablers constitute second component and represent mechanisms facilitating the integration. Industry-academia partnership is crucial for such an endeavor and includes curriculum co-design, guest lectures, internships, and real-life projects. It should be noted that the importance of industry-academia partnerships is increasingly recognized in Zimbabwean higher education. Recently, the National University of Science and Technology conducted field visits to industrial sites, which were specifically stated as crucial catalysts of innovation, critical thinking, and adaptive expertise in accordance with Zimbabwe's Heritage-Based Education 5.0, which promotes the integration of teaching, research, community engagement, innovation, and industrialization [23]. Innovation expos uniting students and companies also emphasize the fact that academia and industry must come together in order to drive the change and close the gap between what is taught and what is needed in industry [23]. Alignment with ZIMCHE regulations, national STEM strategy, and accreditation requirements provides a legal and regulatory framework for this process [24]. Resource sharing, such as industry datasets, licenses, and hardware donations, resolves material constraints identified in this study. Training and development of the faculty through exchanges, online courses, and research collaboration resolve technology issues in this context.

The third component of the framework represents integration touch-points and constitutes stakeholder engagement. Students should have a student pathway, which includes first-year introduction, gradual skills building in second and third years, capstone projects in fourth year, and industry attachments in the course of the program. Similarly, faculty development should include workshops, certifications, research collaboration, and secondments in industry. Industry

partnership, which includes participation in advisory boards, joint R&D, mentoring, and guest lectures, is also an important aspect of the integration process, as all stakeholders should be actively involved rather than passive recipients of change.

Finally, reform stages provide a phased approach to implementing the framework. First phase is awareness and advocacy, which includes sensitization of stakeholders, baseline assessment, and policy dialogue. Second stage focuses on capacity building and includes faculty training, infrastructure development, and curriculum redesign. Third stage involves pilot implementation with modular AI/ML courses, industry projects, and evaluation. Fourth stage focuses on scaling and sustainability through full integration, continuous review, and industry accreditation.

Overall, the framework is based on pragmatism, which is focused on addressing practical problems, constructivism, which emphasizes active learning, and systems thinking, which is aware of interconnection of components and the importance of feedback loops. Need for such a systemic approach is validated by recent literature on AI literacy in higher education, which states that the transition from general digital skills to more complex context-aware AI capabilities requires not only technical proficiency but also cognitive and ethical mastery, and that many educational institutions lack a proper framework for integrating AI into the curriculum [5]. Components of the proposed framework come from the findings of the study. Inputs are based on resource constraints identified by 69.5% of students and 82.9% of industry professionals. Enablers address the industry partnership gap identified by 80% of experts and 55% of lecturers. Touchpoints respond to the 31 percentage points of interest-delivery gap and hidden curriculum problem. Reform stages provide phased approach to dealing with the systemic nature of the problem. Overall, the framework is presented as a conceptual model to be tested in future research with validation suggestions such as pilot implementation in one or more universities, pre-post learning outcome assessment, and longitudinal study of graduate readiness.

Emphasis of the framework on ethical and critical dimensions of AI integration is also validated by the decision of the University of Cape Town to abandon use of AI detection tools such as Turnitin's AI Score as of October 2025. Indeed, AI in Education Framework, endorsed by the University of Cape Town Senate Teaching and Learning Committee, places the emphasis on AI literacy, integrity of assessments, and innovative curriculum development above the use of unreliable tools such as AI Score that might harm the trust of students [17][18][19]. Thus, UCT made the decision of moving away from a technically driven response to AI in universities towards developing critical and ethical AI literacy of their faculty and students. UCT's AI in Education Framework includes principles of human-centered education, critical AI literacy cultivation, equality in access to AI tools, and innovative balance with ethical considerations, and provides some practical steps, such as online guides, interactive workshops, and short courses for educators [19]. Thus, Zimbabwean universities may follow this example when designing their integration frameworks.

The problem of constrained resource-based implementation is not unique to Zimbabwe. Recent literature on AI-driven adaptive feedback for programming education in resource-constrained settings demonstrates a persistent digital divide which prevents equitable access to quality education, especially in low-resource regions where internet connectivity and computing infrastructure remains unreliable [14]. Literature also supports necessity for a context-sensitive approach, which does not make assumptions about infrastructure conditions in the high-resource setting and validates explicit attention to low-bandwidth options, offline capable resources, and shared computing facility in this framework.

5.2. Limitations

Several limitations of the study should be acknowledged. One of them is the fact that sample of students is highly concentrated among fourth-year students (49.5%), second-year students (36.3%), third-year students (5.3%) and postgraduate students (0.5%). Weighted analysis was performed to resolve the problem, however results should be interpreted with caution. Additionally, study employs a cross-sectional design and provides a picture of AI/ML integration in a single point in time, which calls for longitudinal research. Measures of awareness, familiarity, and readiness in the study are self-reported and may be prone to social desirability bias or inaccuracy. The study is also restricted to state universities of Zimbabwe, and findings may not be generalizable to private universities in Zimbabwe and other countries of Sub-Saharan Africa. Different scale ranges have been used for measures of familiarity (zero to four for faculty) and readiness (one to five for industry). Though justified by differences in underlying constructs, this limits the possibility for direct comparison. Finally, qualitative sample size of twenty faculty members and thirty-five industry experts may be too small to cover all perspectives on the issue.

5.3. Implications for Policy and Practice

There are several implications for policy and practice stemming from the findings of the study. First, universities should focus on curriculum reform, which will include AI/ML content since the first year, investment in faculty development program, establishment of industry partnership frameworks, and development of low-bandwidth and offline capable AI/ML learning resources. In particular, NUST field visit model provides a good example of how Zimbabwean universities can organize their experiential learning, which bridges theory and practice [23]. Policy makers should focus on alignment of national STEM strategy with AI/ML workforce needs, investment in infrastructure including

power, internet, and computing, incentivization of industry-academia collaboration in form of tax benefits and grants, and update of accreditation requirements to include AI/ML competencies. The fact that the regulatory and legislative environment in African countries almost always lags behind developments in digital transformation [12] makes proactive policy development urgent. Finally, industry representatives should focus on establishing formalized partnerships with universities in form of a memorandum of understanding and advisory boards, participation in guest lectures, internships, and real-world projects, providing anonymized datasets and software resources, as well as curriculum co-design and revision. In other words, moving from being consumers of foreign ideas to producers of our own ideas, as it was stressed at recent innovation expos [23].

6. Conclusion

The results of the questionnaire (190 telecommunications engineering students) also show interest in AI/ML. 84.2% reported high enthusiasm for these topics, but only 53.2% have curriculum coverage for them. This gap shows that there is an important interest–delivery gap, and this highlights the need to increase curricular coverage of topics in AI/ML so as to satisfy students' desire for contemporary skills.

The inferential analysis after collapsing sparse categories to satisfy Cochran's assumption ($\chi^2 = 42.187$; df =4; $p < .001$; Cramér's V = .333) provides a crucial finding: when AI/ML concepts are taught at higher levels in the curriculum (most likely), students learn them successfully. This proves that it's not student ability but system access and inconsistent implementation of the curriculum, which is the problem. The majority of respondents reporting low awareness probably indicate erratic integration of these topics across programs and institutions (this is something faculty also mentioned qualitatively).

A context-sensitive framework for AI/ML integration has been proposed, comprising four interconnected components: inputs, enablers, integration touchpoints, and reform stages. The framework addresses the specific structural constraints identified in this study and provides a practical roadmap for universities, policymakers, and industry stakeholders.

So even though we are very interested in AI/ML, the education system is not well suited to telecoms industry needs. Resources need to be met, infrastructure upgraded, and curriculum content updated if learning outcomes for students are to improve and industry needs met.

Conflicts of Interest

Authors declare non conflict of interest.

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