Sustainable Futures 10 (2025) 100828

Contents lists available at ScienceDirect

Sustainable Futures

journal homepage: www.sciencedirect.com/journal/sustainable-futures

Enhancing sustainable academic course delivery using AI in technical universities: An empirical analysis using adaptive learning theory

Emmanuel S. Adabor [a,*], Elizabeth Addy [b], Nana Assyne [a], Emmanuel Antwi-Boasiako [a]

[a] Ghana Institute of Management and Public Administration, Accra, Ghana
[b] Koforidua Technical University, P. O. Box 981, Koforidua, Ghana

ARTICLE INFO

Keywords:
Artificial intelligence
Education
Course delivery
Structural equation modelling
Adaptive learning theory

ABSTRACT

The educational landscape is undergoing a significant transformation driven by the rapid advancements in Artificial Intelligence (AI) that hold immense potential for enhancing sustainable academic course delivery, fostering deeper understanding, and improving student-learning outcomes. However, while AI applications promise individualized learning experiences and more efficient instructional methods, their integration into Technical Universities, particularly in developing countries, remains limited. Few studies address the unique challenges and opportunities of deploying AI in this context, leaving educators and policymakers without clear, empirically-backed strategies for implementation. This study seeks to bridge this gap by analyzing the impact of AI integration on academic course delivery in Technical Universities, guided by Adaptive Learning Theory. A mixed-method approach was adopted, combining qualitative interviews with 8 students and 8 lecturers and structured surveys from 124 randomly selected students and lecturers, achieving an 81 % response rate. Structural equation modeling was employed to examine the relationships between AI-driven parameters and academic course delivery. It was found that personalized learning, natural language processing, intelligent tutoring systems, and data-driven insights significantly enhance course delivery, while virtual and augmented reality showed limited impact in this setting. The results highlight AI's potential to transform course design and delivery in Technical Universities, leading to improved learning outcomes. The study presents exciting possibilities that AI presents for educators and policymakers.

1. Introduction

The application of Artificial Intelligence (AI) across various industries has significantly enhanced operational processes and improved outcomes. In manufacturing, for instance, AI has been instrumental in improving decision-making and process efficiency [1], while also enabling predictive maintenance and autonomous operations [2]. Similarly, the rapid adoption of AI is reshaping the workforce landscape, creating both opportunities and challenges that demand urgent upskilling and reskilling initiatives to future-proof sectors such as education and technical training [3]. These industry-wide transformations underscore the growing relevance of AI in enabling adaptive and sustainable systems, making its application in academic course delivery, especially within Technical Universities, both timely and critical. In education, AI-driven tools such as natural language processing (NLP), intelligent tutoring systems (ITS), data-driven insights (DDI), and virtual/augmented reality (VR/AR) have demonstrated their potential to improve learning experiences and instructional delivery [4–7]. However, concerns persist among educators regarding data privacy, algorithmic bias, and the potential for AI to undermine students' critical and analytical thinking skills [8,9]. Despite these concerns, research has highlighted AI's capacity to enhance learner-instructor interactions, underscoring the need for further investigation into its role in academic course delivery, particularly in Technical Universities [5,10,11]

A thorough analysis of AI in Education (AIED) revealed that AI has the potential to transform hybrid education by improving the independence of both students and instructors, while creating a more dynamic and participatory learning atmosphere [12]. AIEd has been extensively adopted and used in the educational settings of many universities in developed countries [5,13–16]. However, these studies do not cover specialized applications to Technical Universities (TUs) and other intrinsic challenges that such institutions of developing countries ought to overcome for complete adoption and integration in academic course delivery.

* Corresponding author.
E-mail address: healmes@gmail.com (E.S. Adabor).

https://doi.org/10.1016/j.sftr.2025.100828
Received 29 October 2024; Received in revised form 16 May 2025; Accepted 7 June 2025
Available online 8 June 2025

As Technical Universities in developing countries strive to improve educational quality and accessibility, the integration of Artificial Intelligence (AI) offers transformative potential for academic course delivery. AI applications in personalized learning, natural language processing, intelligent tutoring systems, and data-driven insights hold the promise of individualized learning experiences, enhanced instructional methods, and more efficient resource allocation. Despite the growing potential of AI-driven tools in education, the adoption of Virtual and Augmented Reality (VR/AR) remains a challenge, particularly in resource-limited settings. The integration of VR/AR requires specialized hardware, high-bandwidth internet, and significant institutional investment, which can be prohibitive for many Technical Universities. For instance, institutions often struggle with the high costs of headsets and other equipment, as well as limited budgets to support such investments [17]. Additionally, factors such as accessibility, cost, and technical expertise hinder widespread implementation. Faculty members frequently lack sufficient training to effectively integrate VR/AR into curricula, while students face challenges in mastering the required digital literacy skills [18]. These barriers make VR/AR less immediately impactful compared to other AI-driven tools such as Natural Language Processing (NLP) and Intelligent Tutoring Systems (ITS), which are more scalable and accessible in constrained environments. Understanding these limitations is crucial for designing more inclusive AI adoption strategies in education. Further, the adoption of AI in education has been limited, particularly in the technical higher education sector of developing nations. Existing studies focus predominantly on AI's general benefits in broader educational contexts, with little attention to how these technologies can be harnessed specifically within Technical Universities, where practical and hands-on learning are crucial.

The lack of empirical studies on AI's impact in this setting creates a significant knowledge gap, leaving educators, policymakers, and administrators without clear evidence or frameworks for implementing AI effectively. Additionally, the unique needs, constraints, and opportunities presented by Technical Universities in developing countries (such as resource limitations, specific skill requirements, and diverse student demographics) necessitate tailored approaches to AI integration.

This study seeks to address these gaps by examining the impact of AI tools on academic course delivery within Technical Universities, using Adaptive Learning Theory (ALT) as a guiding framework. The ALT is a methodology for teaching and learning that attempts to personalize lessons, readings, practice activities, and assessments for individual students based on their current skills and performance [19]. The justification for choosing this theory is founded evidence that it is useful for providing immediate and specific problem-solving techniques, and adopting learning contents specific to student skill proficiency [14,20,21]. Through a mixed-method approach, this study integrates qualitative insights from interviews and quantitative survey data to provide a comprehensive understanding of AI's role in academic course delivery. This directly addresses the study's research questions:

1. How do students and lecturers perceive the role of AI in enhancing course delivery?
2. Which AI-driven tools significantly influence academic course delivery in Technical Universities?
3. What are the key barriers to adopting AI technologies, particularly Virtual and Augmented Reality (VR/AR), in Technical Universities?

Moreover, this the study fills the gap in literature characterised by the a noticeable lack of studies that use factor analysis and partial least squares structural equation model in examining the enhanced academic course delivery using AI as a tool. The study provides empirical evidence for informed decisions by stakeholders, ultimately contributing to improved learning outcomes and educational quality in the technical higher education sector.

2. Literature review

2.1. Theoretical foundation: adaptive learning theory

The theoretical foundation of this study is based on the adaptive learning theory. The adaptive learning theory in the educational space provides a flexible learning environment for learners and facilitators [22]. The idea of learning within the adaptive learning module creates an alleyway for the development of learning content as part of the learning support tool [23]. It is widely acknowledged that adaptive learning is a type of learning that offers a suitable environment for learning, ultimately, through the discovery and summarization of learners themselves during learning, creates theories, and is able to work out issues on their own. Adaptive learning is predicated on individual differences in learners' knowledge background, learning attitude, learning style, and learning ability. From the educators' perspectives, adaptive learning has been defined as the use of adaptive learning systems as instructional tools to gather and evaluate data, plan lessons, comprehend the learning state, assess, and promptly modify the curriculum to match students' evolving needs.

In the context of TUs, adaptive learning could provide an intelligent and dynamic modification of learning materials, activities, and content to match the particular requirements and preferences of individual students using AI. Adaptive learning theory was used for this study because it provides tailored learning experiences, raises students' engagement, maximising and allowing flexibility in course content delivery by tutors and facilitators [22,24–26]. It allowed the researchers to explore the effect of AI capabilities for optimising learners and educators' outcomes for enhanced academic course delivery.

2.2. Technical universities and artificial intelligence

Technical Universities (TUs) were established in Ghana per the Technical Universities Act 2016 (Act 922) to train students in the technical, vocational, professional, research and innovation fields. Therefore, transformations in the development of curriculum and course content delivery using AI are crucial for the TUs considering the changing academic environment. AI in education provides new opportunities, potentials and challenges for educational innovations. Change to personalized learning, stimulating the instructor's role and the development of complex educational system have been enhanced [27,28]. AI techniques such as natural language processing, artificial neural networks, machine learning, deep learning, and genetic algorithm have been implemented to create intelligent learning environments for behaviour detection, model building, learning recommendation, among others [29,30]. Wang and coworkers [15] have considered the relevance of AI applications such as ChatGPT and Large Language models (LLM) by teachers in the school settings. On the hindsight, AI adoption can be associated with academic integrity, infrastructure and a potential for job displacement [31,32]. Ethical AI policies, transformative frameworks, PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis), six thinking hats framework and ABCD listing frameworks have been developed as theoretical frameworks for AI [15,33–35].

While this study focuses on Technical Universities (TUs) in Ghana, it is important to place the discussion within a broader global context. Various TUs and applied sciences universities worldwide have successfully integrated AI with a sustainability lens, offering valuable insights. For instance, Germany's universities of applied sciences have leveraged AI in smart manufacturing and green technology education, optimizing energy use and resource efficiency [36]. Similarly, Finland's technical institutions employ AI-driven adaptive learning systems to enhance sustainability in education [37]. However, the adoption of AI in TUs across different regions presents unique challenges, particularly in resource-constrained settings like Ghana. Limited access to high-performance computing, unreliable internet connectivity, and the high costs of AI adoption can hinder full-scale implementation. Therefore, AI solutions in these contexts must be designed to optimize energy efficiency, leverage cost-effective cloud-based technologies, and align with institutional sustainability goals. Integrating these global perspectives highlights the potential for AI-driven educational models tailored to different socio-economic and infrastructural realities.

2.3. Barriers to AI integration in technical universities in developing countries

While the integration of Artificial Intelligence (AI) into education holds immense potential, its adoption in Technical Universities (TUs) within developing countries is often met with significant challenges. One major barrier is the high implementation cost associated with AI technologies [38]. The financial investment required for acquiring, implementing, and maintaining AI systems often exceeds the budgets of many Technical Universities (TUs) in developing countries. These institutions frequently prioritize other critical needs, leaving minimal funding for advanced technologies [38]. Furthermore, the ongoing expenses for updates, maintenance, and scaling exacerbate the financial burden.

Another significant challenge is the lack of adequate training and technical expertise. Effective use of AI tools requires instructors and administrative staff to have sufficient knowledge and skills [39]. However, training programs tailored to the specific needs of AI in education are often unavailable or insufficient in developing countries. As a result, many educators feel unprepared to adopt AI, and the steep learning curve further discourages widespread usage [40].

Ethical and privacy concerns pose significant barriers to AI adoption in education [18]. The use of AI involves collecting and processing personal data, raising critical issues related to data security and privacy [18]. In developing countries, where data protection laws are often weak or poorly enforced, there is a heightened risk of data misuse and potential algorithmic discrimination.

Infrastructure limitations present another substantial hurdle. Many Technical Universities in developing countries, particularly in low-bandwidth and rural settings, lack the necessary technological infrastructure, such as reliable internet connectivity, modern hardware, and adequate IT support. These deficiencies make it challenging to implement and sustain AI-driven adaptive learning tools, significantly hindering their effectiveness and accessibility [41].

Finally, resistance to change within educational institutions slows down AI adoption. Traditional teaching methods are deeply rooted in the culture and practices of many Technical Universities (TUs). Educators and administrators may be skeptical about the benefits of AI, leading to reluctance in embracing these advancements [40]. This resistance often stems from skill gaps and a lack of understanding of AI's potential. In developing countries, the challenges are compounded by infrastructural limitations and the need for strategic navigation between technological potential and effective implementation [40].

Addressing these barriers requires a comprehensive approach that includes increasing investments in infrastructure, making AI tools more affordable, providing capacity-building initiatives for faculty and students, and establishing ethical guidelines to ensure fair and secure use of AI. Besides, institutions can explore lightweight AI models that function offline or in hybrid learning environments. Additionally, partnerships with industry stakeholders can facilitate access to cost-effective AI solutions tailored to low-resource settings. By overcoming these challenges, Technical Universities in developing countries can unlock the full potential of AI to enhance sustainable education and improve learning outcomes.

2.4. Conceptual framework and research scope

The conceptual framework for this study is grounded in constructs from Adaptive Learning Theory (ALT) and focuses on specific AI-driven technologies that enhance academic course delivery in Technical Universities (TUs). As illustrated in Fig. 1, the framework identifies five core AI components: Personalized Learning (PL), Natural Language Processing (NLP), Intelligent Tutoring Systems (ITS), Data-Driven Insights (DDI), and Virtual and Augmented Reality (VR/AR). These components represent the operational definition of AI in this study. Each componeny is conceptualized as follows:

- **PL** refers to AI systems that adapt content to individual learning styles and progress.
- **NLP** involves AI tools that support language understanding, communication, and academic writing.
- **ITS** are systems that offer automated, interactive learning support and feedback.
- **DDI** encompasses the use of AI analytics to inform teaching and learning decisions.
- **VR/AR** refers to immersive technologies that simulate real-world scenarios to enhance engagement and comprehension.

Together, these components form the technological configuration of AI under investigation, establishing clear boundaries for the study's focus and ensuring alignment with ALT. This framework guides both the data collection and analysis phases and supports the examination of AI's pedagogical, practical, and sustainability-related impacts.

3. Methodology and data collections

3.1. Research approach

This study adopted a mixed-method approach to leverage the strengths of both qualitative and quantitative research. Data collection and analysis integrated qualitative insights and statistical examination to provide a comprehensive understanding of AI-driven course delivery in Technical Universities. A technical route design diagram for this study, outlining the sequential steps followed through the study is presented in Fig. 2. Considering the complex nature of the adaptive learning system and AI, a qualitative inductive approach was employed in the first phase of the study.

3.2. Qualitative phase

Qualitative interviews of eight (8) students and eight (8) lecturers, two focus group discussion (FDGs) and cross-sectional survey were employed for the study. The manual coding strategy was employed, following an inductive approach in which data from participants was categorized without fitting it into a predetermined coding frame. This ensured that analysis was driven by the collected data rather than imposed structures. Thematic analysis was conducted in two stages: descriptive (summarizing participant responses) and interpretative (identifying deeper patterns and meanings).

Transcription of the data initially yielded 51 distinct issues from students and lecturers. Further analysis consolidated these into 33 categories, which were further refined into 20 thematic categories such as Real-Time Feedback, Learning Style Adaptation, Predictive Student Success Modeling, and AI-Based Course Content Optimization. A final review of the transcripts and highlighted quotations led to further thematic consolidation into five overarching themes: Personalized Learning Paths, Natural Language Processing, Intelligent Tutorial Systems, Data-Driven Insights, and Virtual and Augmented Reality. To ensure reliability and consistency, a rigorous iterative review process was conducted, where the authors revisited the data multiple times to refine categories and validate emerging themes. While no automated thematic analysis software was used, intercoder agreement was established through discussion and consensus among researchers to enhance validity. Specifically, two researchers independently coded the data and then met to compare their initial codes. Differences were discussed

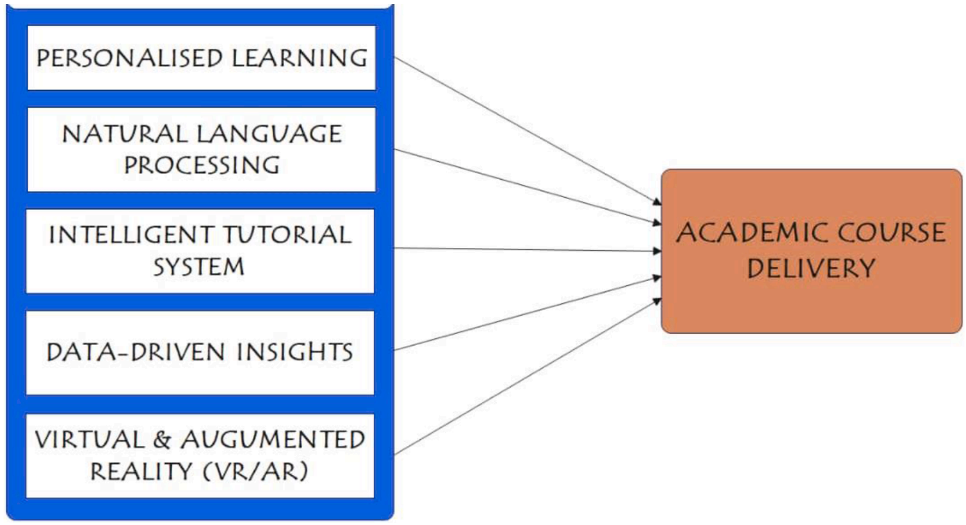

Fig. 1. Conceptual framework.
Source(s) Authors' Construct (June 2024)

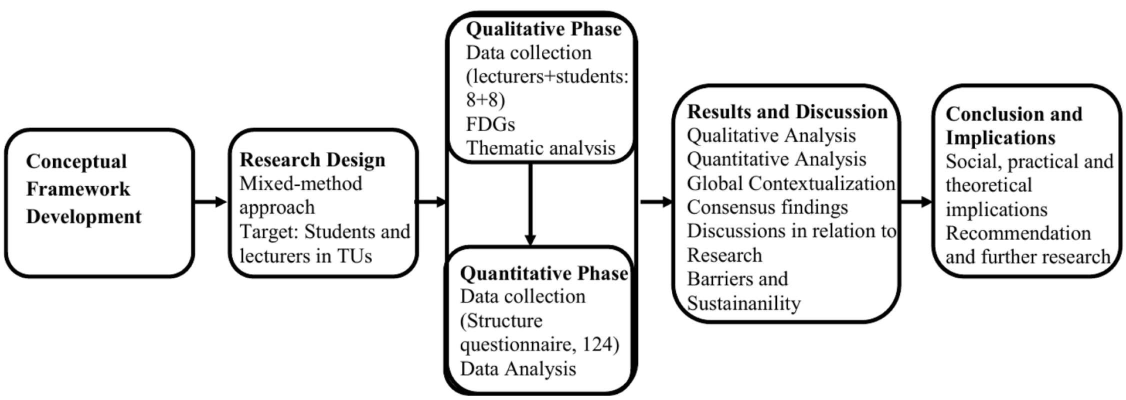

Fig. 2. Technical route design diagram for the study.

systematically until consensus was reached for each theme. This iterative process ensured that the themes were grounded in the data and reflected a shared interpretation. This consensus approach provided methodological rigor consistent with qualitative research standards. Microsoft Excel was used to support data organization. Particularly, Excel functions such as sorting, filtering, and grouping were employed to organize and review code frequencies and patterns. This facilitated the aggregation of codes into broader categories and the refinement of themes into the thematic areas.

Insights from the qualitative interviews played a fundamental role in shaping the questionnaire used to measure the constructs in the Adaptive Learning Theory (ALT). The interview data were analyzed inductively to identify key themes related to students' experiences and lecturers' usage of AI in science, engineering, and humanities course delivery. These themes were systematically mapped onto the survey constructs. For instance, discussions on AI-driven personalized learning experiences led to the development of scale items measuring Personalized Learning (PL), while feedback on AI-powered content optimization and analytics informed items related to Data-Driven Insights (DDI). Similarly, lecturers' perceptions of AI-facilitated student engagement and real-time assistance contributed to the development of items assessing Intelligent Tutoring Systems (ITS). Moreover, concerns about VR/AR accessibility and cost, which emerged as major discussion points, guided the inclusion of items assessing the challenges of AI adoption in Technical Universities. This approach ensured that the questionnaire was directly grounded in empirical qualitative insights, enhancing its validity and relevance to the study context.

The quantitative survey surveyed the students and lecturers' perceptions. The analysis identified potential impact of AI in enhancing course delivery and balanced perspective that considers both the benefits and impacts of AI integration in course delivery in TUs.

Accordingly, purposive sampling was used to select final-year students from the science, engineering, and humanities disciplines, as well as lecturers, for data collection for the qualitative analysis. This approach was appropriate because it enabled the selection of individuals with relevant experience and exposure to AI tools in academic settings, ensuring rich and targeted insights. As affirmed by Creswell [42] and Yin [43], purposive sampling is suitable when information is required from individuals with expertise and contextual knowledge of the phenomenon under study.

An interview guide was used for the interviews, which lasted between 30 min and 60 min. The triangulation methods to coding of the qualitative data and cross section analyses in the various disciplines were employed for the study.

3.3. Quantitative phase

On the other hand, the sample for the quantitative study was randomly sampled to ensure a fair representation of both students and lecturers. In the quantitative phase, the ALT was used to develop the questionnaires involving the impact of using AI on course delivery.

A total of 124 questionnaires were distributed, targeting final-year students and lecturers across different disciplines. The response rate of 81 % (100 responses) reflects the combined feedback from both groups. Additionally, the 10-times rule [44], which suggests that the minimum sample size should be at least 10 times the largest number of indicators in any construct or the largest number of structural paths directed at any latent variable, a criterion that our sample meets. The questionnaires were distributed in a hybrid form through Google Form link created and shared with students randomly and in-person in the universities between April and June 2024.

To ensure representativeness, the random sampling process involved stratification by role, where the population was divided into two distinct groups: students and lecturers. This approach ensured that both categories were proportionally represented in the study. Within each stratum, respondents were randomly selected to avoid selection bias and to provide a balanced dataset for analysis. In order to mitigate other potential biases that could arise because of AI exposure and adoption across disciplines, efforts were made to engage participants from all targeted disciplines and ensure balanced representation across roles

Additionally, the distribution of questionnaires was carried out across multiple disciplines to capture diverse perspectives on AI-driven course delivery. This method allowed for a more comprehensive understanding of the varying experiences and insights from both students and lecturers regarding the integration of AI tools in education.

The questionnaire used the five-point Likert Scale, ranging from 1, strongly disagree to 5, strongly agree. The use of the Likert scale enabled accurate ordinal measurements of variables considered in this study. The questionnaire was pre-tested on six students in the three disciplines and two lecturers before actual distribution. This paved the way for assessing the validity of the questions, and correcting errors to improve the collection of appropriate data for analysis. A sample questionnaire is provided as Supplementary Material.

3.4. Data analysis

Quantitative data analysis was performed using partial least squares structural equation modelling (PLS-SEM) version 4. This enabled assessments of validity and reliability of the study. PLS-SEM was chosen for this study due to its suitability for analyzing complex models with relatively small sample sizes and its prediction-oriented approach [45]. PLS-SEM focuses on maximizing explained variance in endogenous constructs, making it particularly effective for exploratory and applied research settings. One key reason for adopting PLS-SEM is the study's sample size, which aligns with best practices recommending PLS-SEM for studies with smaller datasets, especially when assessing complex relationships among latent variables [46]. Given our sample size, we employed bootstrapping (5000 resamples) to improve statistical reliability and mitigate over-fitting concerns

Additionally, PLS-SEM does not assume normal data distributions, making it a robust choice for datasets where normality cannot be assumed [45]. To ensure the robustness of the model estimation, key model fit indices were assessed. The Standardized Root Mean Square Residual (SRMR) of 0.079 obtained for the model falls within acceptable thresholds (≤ 0.08), indicating a good model fit. Other metric values squared Euclidean distance (3.254) and geodesic distance (3.1) values further confirm model adequacy, as they are within acceptable bounds for assessing model discrepancy.

Focusing on AI's impact on academic course delivery in Technical Universities, PLS-SEM was the most appropriate choice as it allows for evaluating complex relationships between AI-driven parameters and academic outcomes, even with a relatively small sample [47]. This approach ensures that the model effectively captures relevant relationships and practical implications, making it highly relevant to this study.

3.5. Statement of informed consent

All participants were informed about the purpose and scope of this study, including the collection and usage of their data to evaluate the impact of AI tools on academic course delivery in Technical Universities. Participants were notified that their involvement was voluntary and that they could withdraw from the study at any time without penalty. They were assured of the confidentiality and anonymity of their responses, with all identifying information removed or anonymized in the reporting process. Consent was obtained from each participant prior to data collection, with an understanding that the results would be used strictly for academic research and publication purposes.

4. Results

4.1. Results of qualitative analysis

The results were corroborated with qualitative interviews and FGDs and participants revealed their familiarity with some AI tools which they mostly use daily and a few weekly for academic learning using the ALT. They indicated their familiarity with tools such as quillbot, perplexity ai, reo, lamda, chatGPT, gemini, grammarly, consensus apps, plaito and jupiter among others for academic learning. Participants in the FGDs 1 confirmed that some AI tools have been used as:

> We are in a global world and we are aware that AI is the way to go for our academic work. It is very important we familiarise ourselves with the use of AI tools in this digital technology era. The digital devices such as laptops and smart phones with access to internet enable us to access and explore the AI tools. It enables us to compete intellectually with our counterparts in the intellectual global space (Focus Group Discussion 1).

The implication of these results revealed that the participants made a conscious and deliberate effort to use the AI tools to enhance their academic work, and these had consequences on the academic course delivery. While many indicate that AI has been introduced in some of their courses of study such as software development with python, programming, project work and java script, web programming, data structures and algorithms for the science and engineering participants, little awareness existed among participants in the humanities.

Several participants indicated that the AI usage was very beneficial to them and had a significant positive impact on their academic work and learning. It was alarming for first time users of AI. They initially used it for their private studies and social activities before they explored the AI tools to assist them to understand some of their courses. Many of the participants use the AI for personalised learning and most of the time refers to the AI tools to solve some of their assignments and course work for them.

One participant stated:

> I find it sometimes difficult to comprehend some of the courses our lecturers teach us. We have seen the potential of the AI to assist us understand our courses better from different perspectives and make useful contribution during the course delivery. Though it is fast and reliable tool for academic course delivery, it requires that students become cautious in its usage since it could make one lazy (Student 5)

However, some participants raised concerns about academic integrity, particularly regarding students relying on AI to generate assignments rather than engaging in critical thinking. There were also discussions about data privacy risks, as many AI tools require personal data input, raising fears about how this information is stored and used. These concerns are particularly relevant in the context of Ghana's Data Protection Act, 2012 (Act 843), which regulates the collection, use, and disclosure of personal data. Although many AI tools operate outside local jurisdiction, participants' apprehensions reflect a growing awareness of the need for stronger safeguards and digital literacy in line with national data protection policies. Another key concern was the potential over-reliance on AI, which, according to some lecturers, might hinder students from developing independent problem-solving skills. One participant noted that while AI provides quick answers, it does not always encourage deep learning, making it essential for students to use AI responsibly.

Apart from personalised learning, it was observed from the interviews and FGDS that participants used the AI tools to facilitate their language learning and understanding of course content and delivery. It also increases their accessibility in the language processing and minimizes the language barriers in the course content. Different explanations and perspectives are demonstrated using the AI tools.

One FGDs 2 member reiterated that:

> Some of the courses delivered by our lecturers are very technical and difficult to comprehend. However, with the use of the AI, I have been able to understand many of the courses I had challenges. Technical languages are no more a barrier as explanations and different perspectives are available through AI. (Focus Group Discussion 2).

Beyond academic support, participants acknowledged AI's potential in sustainable resource management, such as optimizing learning materials and reducing reliance on printed textbooks through digital tools. Some also noted how AI-driven language translation and accessibility features promote inclusivity, enabling students from diverse linguistic backgrounds to engage with course content more effectively. Additionally, participants expressed optimism about AI enhancing future employability, as exposure to AI tools prepares them for technology-driven job markets and fosters essential digital skills.

The qualitative data disclosed that many of the participants have experienced adaptive learning to enhance their academic progress. Critical thinking skills, intellectual discourse and quality of content and relevant courses have been improved. Again, data driven insights have been acquired using the AI tools.

One participant interviewed stated:

I do acknowledge the potential benefits of the AI tools in sharpening my thinking skills and helping to be innovative and thinking outside the box. I have observed that since I started using the AI my academic performance has improved and I am able to follow the course being taught in class (Student 8).

The AI concept is catching up with the TUs because programmes and courses in AI are being introduced and the AI tools are being used for academic learning. The virtual reality and augmented reality do exist for the TUs to take advantage of it. It was noticed that though the AI concepts are being adopted in the TUs context, a policy guideline of its usage is required to obtain the maximum benefits and impact in the course delivery. It can be adopted and applied to all courses for a better understanding of students' academic work and provide a robust course content and delivery.

A lecturer interviewed claimed this:

> As a University, we cannot assume that AI tool usage is the prerogative of students to explore. We want to see our lecturers embedding this AI concept and tools usage in every aspect of our academic course and delivery. This will enhance our thinking and innovative skills. Our curriculum design and instructional strategies should be practically guided by current AI tools for more self-innovative teaching and learning as it is done in developed countries. We are far behind and must catch up quickly. It seems to me that more lecturers are becoming aware that we should develop the curriculum for our students to adopt modern technological trends (Lecturer 1).

In order to systematically present the qualitative insights, Table 1 categorizes participants' responses into key themes, highlighting their perspectives on AI integration in academic course delivery.

Table 1
Qualitative Findings on AI integration on Academic Course Delivery.

Theme	Key findings	Representative quotes
AI familiarity and usage	Most students and lecturers are familiar with AI tools such as ChatGPT, Quillbot, Gemini, and Grammarly.	"We are in a global world, and we are aware that AI is the way to go for our academic work." (FGD 1)
Benefits of AI in Learning	AI enhances personalized learning, aids in understanding complex topics, and provides multiple perspectives.	"I find it sometimes difficult to comprehend some courses. We have seen the potential of the AI to assist us understand our courses better" (Student 5)
Language Processing and Accessibility	AI tools help students overcome language barriers, improving comprehension.	"Technical languages are no more a barrier as explanations and perspectives are available through AI." (FGD 2)
Impact on Critical Thinking	AI supports intellectual discourse, improves reasoning, and enhances content quality.	"Since I started using AI, my academic performance has improved." (Student 8)
Challenges in AI Adoption	Limited awareness in humanities, lack of institutional policy guidelines, and concerns over-reliance.	"A policy guideline on AI usage is required to maximize its impact." (Lecturer 1)
Need for Curriculum Integration	AI should be embedded in all courses for better academic delivery.	"Our curriculum design and 362instructional strategies should be practically guided by current AI tools for more self-innovative teaching and learning as it is done in developed countries." (Lecturer 1)

4.2. Results of quantitative analysis

4.2.1. Demographic characteristics

The cross-section demographic composition of the study is in Table 2, which displays the ages, sex, programme and field of study for students and lecturers' respondents. The highest ages of respondents ranged from 19–29 years, representing 53 % and the least of 40 years and above represented 10 %. The respondents were predominantly males, making up to 69 % (69) of the sample according to the demographic parameters used in the study. The level of programmes of study and teaching the respondents were mainly Bachelor of Technology (B. Tech) 52 % (52). This is followed by the Higher National Diploma (HND) programmes 30 (30 %) in the Technical Universities. Only a small percentage 14 % and 4 % of the respondents respectively were studying and teaching non-tertiary and masters' students. The field of study and teaching of respondents were predominantly science and engineering representing 43 % and 42 respectively.

Table 2
Demographic Characteristics of Respondents.

Variables	Frequencies	Percentages
	$n = 100$	100 %
Age		
19–29	53	53.2
30–39	37	36.7
40–49	9	8.9
50+	1	1.2
Sex		
Male	69	69.4
Female	31	30.6
Programme		
Non-Tertiary	14	14.1
HND	30	30.2
BTech	52	52.1
Masters	4	3.6
Field of Study/Teaching		
Sciences	43	43.2
Engineering	42	41.5
Humanities	15	15.3

Source (s) Field Survey, June 2024.

4.2.2. Impact of AI on academic course delivery

Analysing the data using structural equation modelling enabled the assessment of the load of item on every factor considered for the study. We found satisfactory loadings on each of the factors personalized learning, natural language processing, intelligence tutorial system, data driven insights, virtual and augmented reality, and the measures of academic course delivery. The satisfaction of these loadings emanates from the high loading values that ranged between 0.7 and 1.0. Besides, the constructs presented in this study were assessed to empirically establish our assertion that by integrating AI into design and delivery of courses, educators would enhance course delivery in Technical Universities. It was found that AI measures such as natural language processing, intelligent tutorial system, data driven insights, and AI aids in personalized learning enhanced academic course delivery (Table 3). These were shown by the positive and statistically significant parameter or regression coefficients of the AI variables (Table 3). These findings are consistent with the findings of the qualitative analysis where respondents' consensus responses suggested that adopting AI enhanced course delivery. However, virtual and augmented reality was not statistically significant although it had a positive coefficient to suggest it could enhance academic course delivery (Table 3).

The statistically significant AI measures, natural language processing, intelligent tutoring systems, data-driven insights, and personalized learning, underscore the transformative potential of AI-driven education in Technical Universities. These findings suggest that AI integration not only enhances course delivery but also fosters sustainable educational development by improving learning efficiency, accessibility, and adaptability. In the context of sustainable development, these AI-driven improvements align with SDG 4 by ensuring inclusive and equitable learning experiences, particularly in resource-constrained environments. Moreover, the positive but non-significant effect of virtual and augmented reality highlights the need for further investment in infrastructure and digital capacity building within Technical Universities, ensuring that emerging AI technologies are both accessible and impactful in fostering long-term sustainability in education.

These results are further supported in the structural model (Fig. 3). All the factor loadings connecting every item to each variable were found to be statistical ($p = 0.000$). The model was deemed fit as 89 per cent of the variation in academic course delivery is explained by the model of the AI measures (R-square = 0.89, Adjusted R-square = 0.88). Intelligent tutorial system had 4 factor loadings and the greatest impact on academic course delivery compared to data driven insights, personalized learning, and natural language processing (Table 3). Among the variables that were statistically significant, Natural language processing had the least impact on academic course delivery (17.8 per cent). This was to be expected since natural language required more technical skills for its usage. We further assess the statistical adequacy of the study.

Further confirmation of validity of study instruments and quality of study using measures such as Cronbach alpha, composite reliability, and average variance extracted (AVE). Besides the natural language processing that could lead to a Cronbach's alpha of 77 per cent, the other variables related higher values ranging between 83 per cent and 95 per cent (Table 4). These higher values support acceptable internal consistency, demonstrating strong reliability of our measurements supporting the results for the study [48]. Furthermore, validity of our construct's reliability and validity instruments are supported with >50 per cent values for composite reliability and average variance extracted (Table 4).

Table 3
Statistical significance of AI parameters on course delivery.

AI Parameter	Coefficient	P-value
Personalized learning	0.203	0.001
Natural language processing	0.178	0.006
Intelligent tutorial system	0.376	0.000
Data driven insights	0.258	0.001
Virtual and augmented reality	0.084	0.330

The strong reliability and validity of the study instruments, as evidenced by high Cronbach's alpha (77 %–95 %), composite reliability, and average variance extracted (above 50 %), reinforce the robustness of the findings. In the context of sustainable development, these results ensure that AI-driven educational interventions are measured with precision and consistency, contributing to data-driven policy and decision-making in Technical Universities. Reliable measurement tools support the development of scalable and replicable AI-enhanced learning models, which are essential for achieving SDG 4 by promoting evidence-based improvements in teaching and learning. Furthermore, strong construct validity enhances confidence in AI's role in fostering innovation, skill development, and long-term sustainability in education.

Further, it must be mentioned clarified that the R-squared value of 0.89 indicates a strong explanatory power of the model, demonstrating that AI-driven tools significantly impact academic course delivery in Technical Universities. However, we acknowledge the potential concerns regarding overfitting, particularly given the relatively small sample size. Overfitting occurs when a model captures noise or specific patterns in the training data that may not generalize well to broader populations. Measures mitigate these risks including bootstrapping and the use of PLS-SEM, a method well-suited for predictive modeling in small sample sizes due to its ability to handle complex relationships while maintaining robustness, were employed. Additionally, model complexity was carefully managed to prevent excessive parameterization. Nonetheless, the constraints of data availability remain a limitation. Future studies with larger and more diverse datasets across multiple institutions would provide further validation and enhance the generalizability of our findings.

4.3. Contextualizing findings within the global trends in AI and education

The findings of this study aligns with global trends in Artificial Intelligence in Education. This emphasizes the transformative role of AI tools in enhancing personalized and adaptive learning experiences. The results show a significant trend of AI adoption among students for academic learning, aligning with global shifts in education. Students are actively using a variety of AI tools like QuillBot, Perplexity AI, and ChatGPT to enhance their understanding of course content, overcome language barriers, and personalize their learning experiences is consistent with global observations [49,50]. This reflects a broader move towards integrating AI to support learning and improve accessibility. The increased use of AI for personalized learning is also observed in the use of AI for assignments and coursework, which has resulted in improved academic performance and engagement among students.

However, the findings also underscore specific contextual challenges and opportunities for Technical Universities in developing countries. The conscious efforts of participants to use AI tools, despite limited institutional support, highlight a growing awareness of AI's educational value. Yet, the lack of structured curriculum integration and institutional policies for AI usage creates a gap compared to global benchmarks, where AI tools are deeply embedded in educational strategies.

Prior studies suggest that the integration of AI in educational curricula is still in its infancy, particularly in developing regions. For instance, it has been emphasized that the effectiveness of AI technology in learning is significantly influenced by infrastructure and organizational support, indicating that many institutions struggle with these foundational elements [51]. This gap in curriculum design reflects a broader trend where educational institutions fail to keep pace with technological advancements, resulting in a disconnect between students' learning experiences and the skills required in the global job market [52].

The call for policy guidelines, training, and curriculum redesign to incorporate AI tools reflects a pressing need to align universities with

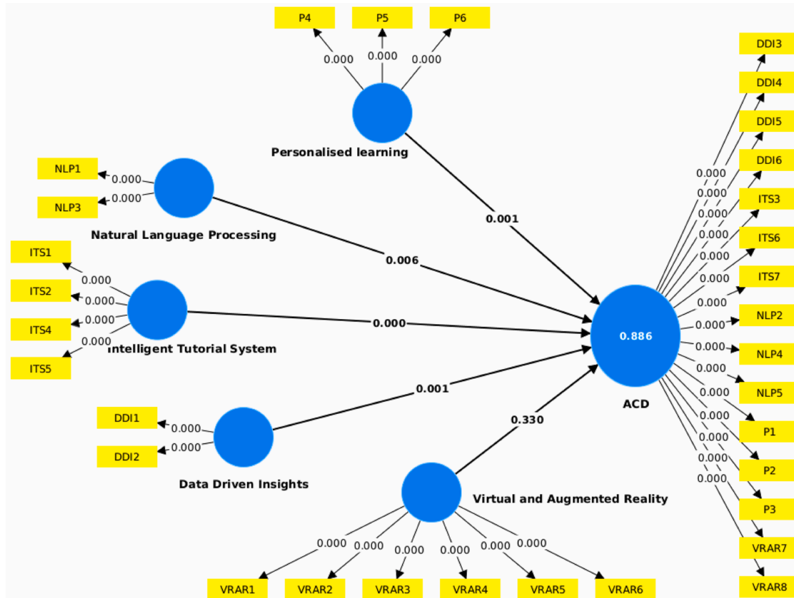

Fig. 3. Structural model of AI enhances academic course delivery (ACD). The significance of relationships is indicated by p-values on the arrows.

Table 4
Construct reliability and validity.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Academic Course Delivery	0.953	0.954	0.958	0.604
Data Driven Insights	0.832	0.84	0.922	0.856
Intelligent Tutorial System	0.891	0.891	0.925	0.754
Natural Language Processing	0.766	0.77	0.895	0.81
Personalised learning	0.899	0.903	0.937	0.832
Virtual and augmented reality	0.941	0.943	0.954	0.774

global trends which have been reported in other related studies [29,53]. By addressing these gaps and ensuring equitable access, Technical Universities can harness AI to not only improve academic course delivery but also position their students to compete in the global intellectual and technological space.

4.4. Consensus findings from qualitative and quantitative analysis

To enhance the linkage between qualitative and quantitative findings, we explicitly examined how themes identified from FGDs align with the statistical results obtained from PLS-SEM. The qualitative data revealed that faculty members and students widely acknowledged AI-driven tools as beneficial for academic course delivery, particularly in areas such as personalized learning and intelligent tutoring systems (ITS). These insights align with the statistically significant positive coefficients observed for AI measures such as natural language processing (NLP), intelligent tutoring systems (ITS), and data-driven insights (DDI). However, VR/AR emerged as a key point of divergence between qualitative and quantitative findings. While the statistical results showed that VR/AR had a non-significant effect, qualitative responses emphasized its potential benefits but also highlighted concerns regarding accessibility, infrastructure costs, and technical expertise required for effective adoption. This suggests that while VR/AR holds promise, its limited practical implementation and institutional readiness may have contributed to the observed statistical insignificance. These consensus findings emphasize the need for targeted institutional strategies to overcome implementation barriers and maximize AI's impact on academic course delivery. A summary of the alignment between qualitative and quantitative findings is presented in Table 5, highlighting points of convergence and divergence across the AI components examined.

5. Discussion

This study examined the impact of AI integration on academic course delivery in Technical Universities (TUs), guided by the following research questions:

1. How do students and lecturers perceive the role of AI in enhancing course delivery?

Table 5
Alignment of Qualitative Themes and Quantitative Results on AI Tools.

AI Component	Qualitative Insight	Quantitative Result	Alignment
Personalized Learning (PL)	Strongly perceived as enhancing learning flexibility and student engagement	Statistically significant positive effect ($p < 0.05$)	Aligned
Natural Language Processing (NLP)	Used to support academic writing, comprehension, and language processing	Statistically significant positive effect ($p < 0.05$)	Aligned
Intelligent Tutoring Systems (ITS)	Recognized for adaptive feedback, student support, and independent study	Statistically significant positive effect ($p < 0.05$)	Aligned
Data-Driven Insights (DDI)	Helps track student performance and inform learning strategies	Statistically significant positive effect ($p < 0.05$)	Aligned
Virtual and Augmented Reality (VR/AR)	Acknowledged potential benefits, but barriers noted: access, cost, lack of training	Statistically non-significant effect (positive coefficient)	Partial divergence

2. Which AI-driven tools significantly influence academic course delivery in TUs?
3. What are the key barriers to adopting AI technologies, particularly Virtual and Augmented Reality (VR/AR), in TUs?

Addressing Research Question 1, qualitative findings revealed that both students and lecturers recognize AI as a valuable tool in academic learning. Students highlighted AI's role in improving understanding of complex course content, while lecturers emphasized the urgency of integrating AI into curriculum development. These insights were reinforced by statistically significant relationships between AI parameters namely personalized learning (PL), natural language processing (NLP), intelligent tutoring systems (ITS), and data-driven insights (DDI), and course delivery ($P < 0.05$). This aligns with recent studies on AI in education that contextualize student learning, reduce teaching workload, and enable intelligent feedback systems [5,13,16,54,55].

In response to Research Question 2, participants reported frequent use of AI tools such as ChatGPT, Grammarly, Quillbot, Consensus AI, Gemini, and others. ChatGPT and Grammarly were most used (27 %), confirming trends in similar studies [56]. Although all respondents had access to AI tools, most used laptops (64 %) or smartphones (21 %), while inconsistent internet access remained a challenge. Our findings confirmed that PL significantly enhances academic delivery (Table 3), as AI systems tailor content to individual learner needs, consistent with Chaudhry and Kazim [57]. Likewise, NLP supported comprehension and linguistic accessibility [58,59], and ITS improved engagement through real-time feedback and adaptive learning [60–63]. DDI also enabled strategic decision-making through performance trend analysis [64,65], highlighting its relevance in resource-constrained TUs.

In relation to Research Question 3, while VR/AR showed a positive coefficient, it was not statistically significant (Table 3). Qualitative insights revealed four main barriers: lack of awareness and training, limited curricular integration, infrastructure costs, and institutional resistance. Many lecturers and students had not received adequate training on VR/AR, and the technology remained peripheral to the curriculum. Moreover, advanced hardware requirements and usability issues limited accessibility. Institutional resistance rooted in traditional teaching cultures further stalled adoption [66].

To address these barriers, TUs should implement structured training programs, develop course-specific VR/AR content in collaboration with industry, and embed VR/AR in core curricula. Cloud-based VR platforms may improve accessibility, while policies and budget allocations can incentivize adoption of immersive technologies.

Beyond academic delivery, the study emphasizes AI's role in fostering socioeconomic development. Tools like ITS and DDI nurture critical thinking and innovation skills vital for bridging workforce gaps in technology and engineering. AI-enabled education also supports entrepreneurial ecosystems by equipping students with self-directed learning capacities and creative problem-solving abilities. These outcomes align with global sustainability objectives, including SDGs on Quality Education, Decent Work and Economic Growth, and Industry, Innovation, and Infrastructure. This aligns with global best practices and ethical considerations as emphasized in UNESCO's Guidance for Generative AI in Education and Research [67].

Ultimately, by integrating AI in teaching and learning, TUs can act as catalysts for socioeconomic transformation, creating inclusive, innovation-driven ecosystems where education and technology intersect. This study thus reinforces existing AIEd research while offering local insights that inform broader implementation strategies. Overall, the findings of this study not only align with and reinforce existing research in AI and education but also offer new context-specific insights for Technical Universities in developing countries, thereby contributing to the global discourse on AI integration in sustainable and inclusive academic delivery.

5.1. Social, practical and theoretical implications

Education policymakers should unreservedly embrace the use of AI tools for enhancing education, especially in Africa. Rigorous utilisation of AI in Technical Universities (TUs) across all courses and programmes will boost the technological drive for innovation in these emerging universities [68–70]. Practically, this will encourage more applied research in this area by TUs. The use of AI could also enhance entrepreneurship education in the TUs [71–73]. Consequently, the integration of AI in course design and delivery will improve knowledge transfer through personalised learning for students and educators alike. This will enable both groups to explore and better understand Natural Language Processing (NLP), Intelligent Tutoring Systems (ITS), Data-Driven Insights (DDI), and Personalised Learning (PL), which can drive innovation and improve learning outcomes.

However, the successful integration of AI in education requires targeted policy measures and a collaborative approach involving government, institutional governance, and industry stakeholders. Governments should develop clear policy frameworks that support the integration of AI tools in education, prioritizing equitable access to the required digital infrastructure, such as internet connectivity and devices like smartphones, laptops, and desktops [74–76]. Institutional governance within TUs must adopt strategies to embed AI into curricula while promoting responsible and ethical AI use. This includes capacity-building initiatives for faculty members to integrate AI-driven teaching tools and ensuring that students are educated on the ethical implications of AI usage.

Furthermore, fostering industry collaboration is crucial to accelerate AI adoption. Partnerships with tech companies can ensure that cutting-edge AI tools are accessible and tailored to the specific educational needs of TUs. These collaborations can also provide opportunities for research, internships, and skills improvement, enabling students to contribute meaningfully to the workforce and innovation ecosystems. By leveraging such partnerships, TUs can align with global best practices in AI integration and position themselves as key players in the knowledge economy.

To ensure the systematic and sustainable integration of AI in Technical Universities, institutions can adopt best practices from established frameworks such as UNESCO's guidelines on AI in education and the IEEE's Ethically Aligned Design for AI. UNESCO's guidance emphasizes human agency, inclusion, equity, and ethical governance, providing foundational policies for responsible AI implementation in education [67]. The IEEE framework advocates embedding ethical considerations into AI systems from their inception, prioritizing transparency, human well-being, and accountability (Shahriari and [77]). Technical Universities can align their AI strategies with national digital transformation policies, leveraging governance models that emphasize inclusive education and long-term resource efficiency. For instance, Singapore's Institute of Technical Education (ITE) has implemented AI-driven educational models through collaborations like its AI Lab with Microsoft, equipping students with responsible AI skills [78]. Furthermore, Technical Universities can look to models such as India's AI for All program, which integrates AI literacy at multiple education levels and fosters industry-academia collaboration [79]. Establishing clear institutional policies, faculty training programs, and AI ethics committees can further support responsible and structured AI adoption in technical universities.

Graduates trained in AI from Technical Universities (TUs) play a critical role in addressing local and national development goals by driving technological innovation, improving productivity, and fostering digital transformation in key industries. In Ghana, AI expertise aligns with government initiatives such as the National Digital Transformation Agenda, which emphasizes the use of emerging technologies to enhance education, healthcare, and industrial processes [80]. Graduates skilled in AI can contribute by optimizing agricultural processes through predictive analytics, enhancing financial inclusion via AI-driven fintech solutions, and supporting smart city initiatives for efficient urban planning. By leveraging such frameworks, Ghanaian TUs can develop structured AI curricula that are industry-aligned, government-supported, and locally relevant, ensuring that AI adoption contributes meaningfully to sustainable development

5.2. Implications on global sustainability agenda

The integration of AI in education, particularly in Technical Universities (TUs), holds substantial potential to contribute to recognized sustainability frameworks, such as the United Nations Sustainable Development Goals (SDGs). AI-enhanced academic course delivery aligns closely with SDG 4, which emphasizes inclusive and equitable quality education and lifelong learning opportunities for all. By personalizing learning experiences, AI can bridge learning gaps, promote equity, and ensure that diverse student populations, including those in underserved and resource-constrained communities, have access to tailored, high-quality education. This fosters the development of skills needed for sustainable economic growth and innovation, as outlined in SDG 8.

Further, AI tools enable data-driven insights, which empower educators and institutions to optimize resource allocation, reduce inefficiencies, and promote sustainability within their operational structures. For instance, by leveraging intelligent tutorial systems and virtual platforms, TUs can minimize dependence on physical infrastructure and traditional methods, reducing environmental footprints. This contributes to SDG 9, which advocates for innovation, infrastructure development, and sustainable industrialization.

The broader implications of AI-enhanced education also support SDG 17, which emphasizes partnerships for sustainable development. AI integration facilitates global collaboration by enabling students and educators to access shared knowledge, collaborate across borders, and adopt best practices in technology-driven education. In this way, the study's findings on AI's role in improving academic course delivery can be positioned as a pathway toward achieving sustainability by building resilient, adaptive, and equitable educational ecosystems. By embedding AI into the core of educational delivery in TUs, institutions can foster sustainability not only in their academic outcomes but also in their contributions to societal and environmental resilience.

To embed AI in pedagogically efficient, sustainable, and ethically responsible ways, TUs should adopt a structured AI integration framework guided by key principles such as transparency, accountability, and equitable access. To begin with, policy frameworks should be developed to ensure AI applications align with institutional and national education goals while mitigating risks such as data privacy concerns and algorithmic bias. Furthermore, faculty and student training programs should be prioritized to build digital literacy and ethical awareness regarding AI's role in education. In addition, industry collaborations with AI firms and policymakers can facilitate the development of contextually relevant AI solutions tailored to the needs of TUs. It is further suggested that AI integration should be continuously monitored through impact assessments and feedback loops, ensuring that the technology remains a tool for inclusion and not exclusion. By aligning AI-driven education with global sustainability initiatives, TUs can create a transformative learning ecosystem.

6. Conclusion

A conceptual framework based on ALT was developed for the study, which established that AI enhanced academic course delivery. The study confirmed the relationships between AI-inspired tools involving PL, NLP, ITS, DDI and VRAR and improving academic course delivery. The study bridges the theoretical gap of how the interaction between PL, NLP, ITS, DDI and VRAR is pivotal in defining AI tools. The study showed that AI (parameterized by PL, NLP, ITS, DDI) positively influences academic course delivery for effective academic performance with the exception of VRAR whose effect is not statistically significant. Nevertheless, qualitative analysis of FGDs provided general support that using AI enhanced academic course delivery and learning outcomes. Therefore, the study provides an empirical support to the preposition that the integration AI in academic course delivery in TUs improve learning outcome. This sets the basis for other future works.

Future research could explore how Technical Universities (TUs) can systematically integrate AI solutions to align with sustainability goals, such as optimizing energy consumption, minimizing resource wastage, and fostering economic resilience. For instance, AI-driven systems could enhance efficiency by reducing redundant administrative processes, enabling smart resource allocation, and supporting energy-efficient digital learning environments. Additionally, AI applications in education could contribute to socio-economic development by improving workforce readiness, fostering innovation ecosystems, and promoting equitable access to learning resources. Further, a potential future study could employ longitudinal studies to assess AI's sustained impact on student performance, retention, and engagement over multiple semesters or years. Additionally, for long-term integration, Technical Universities must establish clear policies and structured training modules that equip lecturers with the skills to embed AI-driven approaches consistently across curricula, ensuring both pedagogical effectiveness and sustainability. Examining these synergies will provide valuable insights for policymakers and institutions seeking to balance technological advancement with sustainable development objectives.

7. Limitation and future research

One limitation of this study is the sample size, consisting of qualitative interviews with 8 students and 8 lecturers, along with structured responses from 124 randomly selected students, resulting in an 81 % response rate. While the sample size may appear modest, it was selected to ensure a manageable yet insightful balance of perspectives, considering the study's specific context in Technical Universities within a developing country. The qualitative component allowed for in-depth understanding of participant experiences with AI-driven course delivery, while the quantitative survey provided statistically relevant insights that reflect broader trends in student perceptions and learning outcomes. However, this sample size may limit the generalizability of the findings across diverse educational institutions or regions. Larger samples could potentially capture a wider range of experiences and further validate the findings. Future studies with expanded participant pools could build on these results, helping to confirm or refine the identified relationships between AI tools and academic course delivery outcomes.

Besides, the limited use of AI tools significantly restricts the potential benefits that AI could bring to educational practices. Future research should investigate how a more comprehensive and widespread integration of AI could enhance academic course delivery. Second, the study focused exclusively on technical education, which, while important, does not account for the variety of subjects and learning styles found in a broader educational curriculum. It would be useful to explore the application of AI tools across different educational fields to determine if the findings are consistent across a wider range of subjects. Furthermore, future studies should replicate this research in various emerging countries to provide a more comprehensive understanding of how AI can be integrated into diverse educational systems. Moreover, the focus on one geographical area and one type of education highlights the need for broader studies that consider different views and educational levels.

CRediT authorship contribution statement

Emmanuel S. Adabor: Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Elizabeth Addy:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Nana Assyne:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Emmanuel Antwi-Boasiako:** Writing – review & editing, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

the authors would like to thank participants from the Technical Universities that participated in the study.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sftr.2025.100828.

Data availability

Data is included in submission as supplementary material

References

[1] R.S. Peres, X. Jia, J. Lee, K. Sun, A.W. Colombo, J. Barata, Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook, IEEE Access 8 (2020) 220121–220139.
[2] I. Ahmed, G. Jeon, F. Piccialli, From artificial intelligence to explainable artificial intelligence in industry 4.0: a survey on what, how, and where, IEEE Trans. Industr. Inform. 18 (8) (2022) 5031–5042.
[3] D. Santandreu Calonge, F. Kamalov, P. Medina Aguerrebere, L. Hassock, L. Smail, D. Yousef, D.R. Thadani, T. Kwong, N. Abdulla, Upskilling and reskilling in the United Arab Emirates: future-proofing careers with AI skills, J. Adult Contin. Educ. 0 (0) (2025), https://doi.org/10.1177/14779714251315288.
[4] C. Beaulac, J.S. Rosenthal, Predicting university students' academic success and major using random forests, Res. High. Educ. 60 (2019) 1048–1064, https://doi.org/10.1007/s11162-019-09546-y.
[5] X. Chen, D. Zou, H. Xie, G. Cheng, C. Liu, Two decades of artificial intelligence in education, Educ. Technol. Soc. 25 (1) (2022) 28–47.
[6] P.T. Hultberg, D. Santandreu Calonge, F. Kamalov, L. Smail, Comparing and assessing four AI chatbots' competence in economics, PLoS ONE 19 (5) (2024) e0297804, https://doi.org/10.1371/journal.pone.0297804.
[7] X. Xu, J. Wang, H. Peng, R. Wu, Prediction of academic performance associated with internet usage behaviors using machine learning algorithms, Comput. Human. Behav. 98 (2019) 166–173, https://doi.org/10.1016/j.chb.2019.04.015.
[8] K. Crawford, R. Calo, There is a blind spot in AI research, Nature 538 (7625) (2016) 311–313.
[9] R. Luckin, Towards artificial intelligence-based assessment systems, Nat. Hum. Behav. 1 (3) (2017) 1–3.
[10] M. Chassignol, A. Khoroshavin, A. Klimova, A. Bilyatdinova, Artificial Intelligence trends in education: a narrative overview, Procedia Comput. Sci. 136 (2018) 16–24.
[11] G.J. Hwang, H. Xie, B.W. Wah, D. Gašević, Vision, challenges, roles and research issues of Artificial Intelligence in Education, Comput. Educ. 1 (2020) 100001.
[12] A. Almusaed, A. Almssad, I. Yitmen, R.Z. Homod, Enhancing student engagement: harnessing "AIED"'s power in hybrid education—a review analysis, Educ. Sci. 13 (7) (2023) 632.
[13] A. Bhutoria, Personalized education and artificial intelligence in the United States, China, and India: a systematic review using a human-in-the-loop model, Comput. Educ. 3 (2022) 100068.
[14] S. Minn, AI-assisted knowledge assessment techniques for adaptive learning environments, Comput. Educ. 3 (2022) 100050.
[15] T. Wang, B.D. Lund, A. Marengo, A. Pagano, N.R. Mannuru, Z.A. Teel, J. Pange, Exploring the potential impact of artificial intelligence (AI) on international students in higher education: generative AI, chatbots, analytics, and international student success, Appl. Sci. 13 (11) (2023) 6716.
[16] B. Williamson, J. Komljenovic, K. Gulson (Eds.), World Yearbook of Education 2024: Digitalisation of Education in the Era of algorithms, Automation and Artificial Intelligence, Taylor & Francis, 2023.
[17] L. Evans, Barriers to VR use in HE, in: J. Hudson, R. Kerton (Eds.), Proceedings of the Virtual and Augmented Reality to Enhance Learning and Teaching in Higher Education Conference 2018, IM Publications Open, Chichester, 2019, pp. 3–13.
[18] M.P.-C. Lin, A.L. Liu, E. Poitras, M. Chang, D.H Chang, An exploratory study on the efficacy and inclusivity of AI technologies in diverse learning environments, Sustainability 16 (20) (2024) 8992, https://doi.org/10.3390/su16208992.
[19] R. McGuire, What is Adaptive Learning and How Does It Work to Promote Equity in Higher Education, Every Learner Everywhere, 2021. https://www.everylearnereverywhere.org/blog/what-is-adaptive-learning-and-how-does-it-work-to-promote-equity-in-higher-education/. Last accessed date: April 3, 2025.
[20] R.S. Baker, Artificial Intelligence in Education: Bringing it All together. Digital Education Outlook: Pushing the Frontiers with AI, blockchain, and Robots, 2021, pp. 43–54.
[21] M.C. Desmarais, R.S.D. Baker, A review of recent advances in learner and skill modeling in intelligent learning environments, User. Model. User-adapt. Interact. 22 (2012) 9–38.
[22] F. Li, Y. He, Q. Xue, Progress, challenges and countermeasures of adaptive learning, Educ. Technol. Soc. 24 (3) (2021) 238–255.
[23] P.J. Durlach, A.M. Lesgold, Adaptive Technologies for Training and Education, Cambridge University Press., A. M., Cambridge, United Kingdom, 2012.
[24] A. Ezzaim, A. Dahbi, A. Aqqal, A. Haidine, AI-based learning style detection in adaptive learning systems: a systematic literature review, J. Comput. Educ. (2024) 1–39.
[25] I. Gligorea, M. Cioca, R. Oancea, A.T. Gorski, H. Gorski, P. Tudorache, Adaptive learning using artificial intelligence in e-learning: a literature review, Educ. Sci. 13 (12) (2023) 1216.
[26] T. Kabudi, I. Pappas, D.H. Olsen, AI-enabled adaptive learning systems: a systematic mapping of the literature, Comput. Educ. 2 (2021) 100017.
[27] R.S. Baker, Challenges for the future of educational data mining: the Baker learning analytics prizes, J. Educ. Data Mining 11 (1) (2019) 1–17.
[28] A.I. Starcic, Human learning and learning analytics in the age of artificial intelligence, Br. J. Educ. Technol. 50 (6) (2019) 2974–2976.
[29] L. Chen, P. Chen, Z. Lin, Artificial intelligence in education: a review, IEEE Access 8 (2020) 75264–75278.
[30] M. Rowe, Shaping our algorithms before they shape us, in: J. Knox, Y. Wang, M. Gallagher (Eds.), Artificial Intelligence and Inclusive Education: Speculative Futures and Emerging Practices, Springer Nature, Singapore, 2019, pp. 151–163.
[31] G. Saidakhror, The impact of artificial intelligence on higher education and the economics of information technology, Int. J. Law Policy 2 (3) (2024) 1–6.
[32] X. Zhai, X. Chu, C.S. Chai, M.S.Y. Jong, A. Istenic, M. Spector, Y. Li, A Review of Artificial Intelligence (AI) in Education from 2010 to 2020, Complexity 2021 (1) (2021) 8812542.
[33] S. Aithal, P.S. Aithal, Effects of AI-based ChatGPT on higher education libraries, Int. J. Manag. Technol. Soc. Sci. 8 (2) (2023) 95–108.
[34] H. Crompton, D. Burke, Artificial intelligence in higher education: the state of the field, Int. J. Educ. Technol. High. Educ. 20 (1) (2023) 22.
[35] A. Ghimire, J. Edwards, From guidelines to governance: a study of ai policies in education, in: International Conference on Artificial Intelligence in Education, Springer Nature Switzerland, 2024, pp. 299–307.
[36] R. Schmidt, J. Müller, A. Hartmann, AI-enhanced smart manufacturing: educational approaches in German Universities, J. Manuf. Technol. Manag. 32 (2) (2021) 451–464, https://doi.org/10.1108/JMTM-07-2020-0278.
[37] A. Alamäki, C. Nyberg, A. Kimberley, A.O. Salonen, Artificial intelligence literacy in sustainable development: a learning experiment in higher education, Front. Educ. 9 (2024) 1343406, https://doi.org/10.3389/feduc.2024.1343406.
[38] G. Anzoline, N. Haraguchi, A.P.N. De Sousa, A. Savrasov, J. Reis, Bridging the AI divide: empowering developing countries through manufacturing, UNIDO, 2012. https://www.unido.org/sites/default/files/unido-publications/2024-07/IID%20Policy%20Brief%2012.pdf (Accessed 22 January 2025).
[39] F. Pedro, M. Subosa, A. Rivas, P. Valverde, Artificial Intelligence in Education: Challenges and Opportunities For Sustainable Development, UNESCO, 2019 url, https://unesdoc.unesco.org/ark:/48223/pf0000366994 (Accessed 22 January 2025).
[40] A.O. Aderibigbe, P.E. Ohenhen, N.K. Nwaobia, J.O. Gidiagba, E.C. Ani, Artificial intelligence in developing countries: bridging he gap between potential and implementation, Comput. Sci. IT Res. J. 4 (3) (2023) 185–199.
[41] C.G. Demartini, L. Sciascia, A. Bosso, F. Manuri, Artificial intelligence bringing improvements to adaptive learning in education: a case study, Sustainability 16 (3) (2024) 1347, https://doi.org/10.3390/su16031347.
[42] J.W. Creswell, A Concise Introduction to Mixed Methods Research, SAGE Publications, 2021.
[43] R.K. Yin, Case Study methods: Design and Methods, 6th ed., Sage, Thousand Oaks, CA, 2018.
[44] J.F. Hair, C.E. Ringle, M. Sarstedt, PLS-SEM: indeed a silver bullet, J. Market. Theory Pract. 19 (2) (2011) 139–152.
[45] J. Hair, A. Alamer, Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: guidelines using an applied example, Res. Methods Appl. Linguist. 1 (2022) (2022) 100027.
[46] M.A. Fauzi, Partial least square structural equation modelling (PLS-SEM) in knowledge management studies: knowledge sharing in virtual communities, Knowl. Manag. E-Learn. 14 (1) (2022) 103–124, https://doi.org/10.34105/j.kmel.2022.14.007.
[47] J.F. Hair, J.J. Risher, M. Sarstedt, C.M. Ringle, When to use and how to report the results of PLS-SEM, Eur. Bus. Rev. 31 (1) (2019) 2–24, https://doi.org/10.1108/EBR-11-2018-0203.
[48] J.F. Hair Jr, L.M. Matthews, R.L. Matthews, M. Sarstedt, PLS-SEM or CB-SEM: updated guidelines on which method to use, Int. J. Multivar. Data Anal. 1 (2) (2017) 107–123, https://doi.org/10.1504/ijmda.2017.10008574.
[49] D.L. Johnson, C.G. Davis, Bridging the gap for underserved populations: personalized ai solutions for college access and learning support, New Direct. High. Educ. 2024 (207) (2024) 47–62, https://doi.org/10.1002/he.20511.

[50] A.S.M. Selim, The transformative impact of ai-powered tools on academic writing: perspectives of efl university students, Int. J. Engl. Linguist. 14 (1) (2024) 14, https://doi.org/10.5539/ijel.v14n1p14.
[51] F. Alenezi, Artificial intelligence versus arab universities: an enquiry into the Saudi context, Human. Manag. Sci. (2023) 1–7, https://doi.org/10.37575/h/edu/220038.
[52] R. Salhab, Ai literacy across curriculum design: investigating college instructor's perspectives, Online Learn. 28 (2) (2024), https://doi.org/10.24059/olj.v28i2.4426.
[53] K.S. Tarisayi, Strategic leadership for responsible artificial intelligence adoption in higher education, CTE Workshop Proc. 11 (2024) 4–14, https://doi.org/10.55056/cte.616.
[54] A.C. Borges Monteiro, R. Padilha França, R. Arthur, Y. Iano, A look at artificial intelligence on the perspective of application in the modern education, Comput. Intell. Bus. Anal. (2021) 171–189.
[55] F. Ouyang, P. Jiao, Artificial intelligence in education: the three paradigms, Comput. Educ. 2 (2021) 100020.
[56] T.N. Fitria, Artificial intelligence (AI) in education: using AI tools for teaching and learning process, Prosiding Seminar Nasional & Call for Paper STIE AAS 4 (1) (2021) 134–147.
[57] M.A. Chaudhry, E. Kazim, Artificial Intelligence in Education (AIEd): a high-level academic and industry note 2021, AI Ethics 2 (2022) 157–165, https://doi.org/10.1007/s43681-021-00074-z.
[58] M. Mejeh, M. Rehm, Taking adaptive learning in educational settings to the next level: leveraging natural language processing for improved personalization. Educational Technology Research and Development, 2024, pp. 1–25.
[59] N.S.F. Putri, P. Widiharso, A.B.P. Utama, M.C. Shakti, U. Ghosh, Natural language processing in higher education, Bull. Soc. Inform. Theory Appl. 6 (1) (2022) 90–101.
[60] M.S. Alam, S. Kumar, Z. Khursheed, H.K. Mahato, S. Bashar, A. Suman, Designing an AI driven intelligent Tutorial System, in: 2024 5th International Conference on Recent Trends in Computer Science and Technology (ICRTCST), IEEE, 2024, pp. 585–588.
[61] L. Alfaro, C. Rivera, E. Castaneda, J. Zuniga-Cueva, M. Rivera-Chavez, F. Fialho, A review of intelligent tutorial systems in computer and web based education, Int. J. Adv. Comput. Sci. Appl. 11 (2) (2020) 755–763.
[62] N.T. Heffernan, C.L. Heffernan, The ASSISTments Ecosystem: building a platform that brings scientists and teachers together for minimally invasive research on human learning and teaching, Int. J. Artif. Intell. Educ. 24 (2014) (2014) 470–497.
[63] C. Walkington, M.L. Bernacki, Personalizing algebra to students' individual interests in an intelligent tutoring system: moderators of impact, Int. J. Artif. Intell. Educ. 29 (1) (2019) 58–88, https://doi.org/10.1007/s40593-018-0168-1.
[64] L.W. Balling, O. Townend, L.L. Mølgaard, C.B. Jespersen, W. Switalski, AI-driven insights from AI-driven data, Hear. Rev. 28 (01) (2021) 27–29.
[65] M. Moinuddin, M. Usman, R. Khan, Strategic insights in a data-driven era: maximizing business potential with analytics and AI, Rev. Espan. Document. Cient. 18 (02) (2024) 117–133.
[66] N. Alalwan, L.K. Cheng, H. Al-Samarraie, R. Yousef, A.I. Alzahrani, S.M. Sarsam, Challenges and prospects of virtual reality and augmented reality utilization among primary school teachers: a developing country perspective, Stud. Educ. Eval. 66 (2020) 100876, https://doi.org/10.1016/j.stueduc.2020.100876.
[67] UNESCO, Guidance For Generative AI in Education and Research, United Nations Educational, Scientific and Cultural Organization, 2023, https://doi.org/10.54675/EWZM9535 (Accessed 28 March 2025).
[68] O.A. Farayola, A.A. Abdul, B.O. Irabor, E.C. Okeleke, Innovative business models driven by ai technologies: a review, Comput. Sci. IT Res. J. 4 (2) (2023) 85–110.
[69] M.M. Mariani, I. Machado, V. Magrelli, Y.K. Dwivedi, Artificial intelligence in innovation research: a systematic review, conceptual framework, and future research directions, Technovation 122 (2023) 102623.
[70] Z. Tekic, J. Füller, Managing innovation in the era of AI, Technol Soc. 73 (2023) 102254.
[71] M. Alqahtani, Artificial intelligence and entrepreneurship education: a paradigm in Qatari higher education institutions after COVID-19 pandemic, Int. J. Data Netw. Sci. 7 (2) (2023) 695–706.
[72] R. Bell, H. Bell, Entrepreneurship education in the era of generative artificial intelligence, Entrepren. Educ. 6 (3) (2023) 229–244.
[73] N. Otis, R.P. Clarke, S. Delecourt, D. Holtz, & R. Koning, (2024). The uneven impact of generative AI on entrepreneurial performance. Available at SSRN: https://ssrn.com/abstract=4671369 or https://doi.org/10.2139/ssrn.4671369 (Accessed 1 June 2024).
[74] A. Badshah, A. Ghani, A. Daud, A. Jalal, M. Bilal, J. Crowcroft, Towards smart education through internet of things: a survey, ACM Comput. Surv. 56 (2) (2023) 1–33.
[75] J.W. Cortada, Living with Computers: The Digital World of Today and Tomorrow, Springer Nature, 2020.
[76] A.S. Reddy, J.S. Likhitha, Y.R. Alla, S.R. Reeja, AI-powered laptop companions: bridging the human-machine gap, in: 2024 4th International Conference on Data Engineering and Communication Systems (ICDECS), IEEE, 2024, pp. 1–6.
[77] K. Shahriari, M. Shahriari, M, IEEE standard review: ethically aligned design: a vision for prioritizing human wellbeing with artificial intelligence and autonomous systems, in: 2017 IEEE Canada International Humanitarian Technology Conference (IHTC), Toronto, ON, Canada 2017, 2017, pp. 197–201, https://doi.org/10.1109/IHTC.2017.8058187.
[78] Microsoft, ITE and Microsoft Collaborate to Equip over 4000 Students with Responsible AI Skills, 2022. https://news.microsoft.com/en-sg/2022/05/28/ite-and-microsoft-collaborate-to-equip-over-4000-students-with-responsible-ai-skills/ (Accessed 28 March 2025).
[79] Central Board of Secondary Education, India, AI For All Information Manual, 2021. https://cbseacademic.nic.in/web_material/Circulars/2021/56_Circular_2021.pdf.
[80] Ministry of Communication and Digitisation, Ghana, Republic of Ghana National Artificial Intelligence Strategy: 2023-2033, 2022. https://aighana.net/ghana-national-ai-strategy/ (Accessed 28 March 2025).