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Adoption of Sustainable and Human-Centered Explainable AI in Higher Education. An Extended UTAUT Perspective

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ABSTRACT

As Artificial Intelligence permeates higher education, concerns regarding its "black-box" nature, ethical implications and environmental sustainability have intensified. This study develops and empirically validates an Extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework to investigate the factors influencing AI adoption among students in Zimbabwean universities. The model integrates five contemporary AI constructs which are perceived explainability, trust in AI, perceived human-centeredness, perceived sustainability and perceived fairness into the traditional UTAUT1 framework. Data were collected through a structured Likert-scale questionnaire from a sample of 352 students across major Zimbabwean HEIs. Regression analysis was employed to examine the relationships among constructs. The extended model explains 68.4% of the variance in behavioural intention ($R^2 = 0.684$). Results indicate that while performance expectancy and trust in AI are the strongest predictors, perceived explainability and human-centeredness significantly enhance adoption intentions. Surprisingly, perceived sustainability emerged as a nascent but significant driver, reflecting a growing awareness of "Green AI." The findings provide critical theoretical contributions by bridging the gap between instrumental adoption drivers and human-centric design. Practically, the study offers a roadmap for university administrators and AI developers in developing countries to foster transparent, fair and sustainable AI ecosystems.

I. Introduction

The global landscape of higher education is undergoing a seismic shift driven by the rapid proliferation of Artificial Intelligence (AI) technologies [1]. From generative AI tools like ChatGPT to sophisticated learning analytics and adaptive tutoring systems, AI promises to personalize learning, enhance administrative efficiency and foster pedagogical innovation [2]. However, this "AI revolution" in the classroom is not without friction. As AI systems become more complex, their "black-box" nature characterized by a lack of transparency in decision-making has raised significant ethical and practical concerns among students and educators alike [3].

Traditional technology adoption models, most notably the Unified Theory of Acceptance and Use of Technology (UTAUT1), have long focused on instrumental drivers such as perceived usefulness (performance expectancy) and ease of use (effort expectancy). While robust, these frameworks are increasingly seen as insufficient for the AI era [4]. AI adoption is uniquely influenced by psychological and ethical dimensions that traditional IT systems do not invoke as strongly: the need for explainability to understand system logic, trust in autonomous agents, the requirement for human-centered design to ensure pedagogical alignment, and the growing mandate for sustainability (Green AI) and fairness in algorithmic outcomes [5].

In developing countries like Zimbabwe, the challenges of AI adoption are compounded by structural and socioeconomic factors. Despite the government's "Education 5.0" initiative, which emphasizes innovation and industrialization, higher education institutions face infrastructure constraints, limited AI awareness and resource scarcity [6]. Furthermore, most AI models are developed in Western or Asian contexts, leading to concerns about cultural bias and lack of contextual fairness when deployed in African institutions. Therefore, investigating AI adoption through a lens that incorporates fairness, sustainability and human-centeredness is not just a theoretical exercise but a practical necessity for inclusive development. There is a notable theoretical gap in UTAUT-based research, the model lacks AI-specific constructs like explainability and sustainability and empirically, few studies have validated these ethical dimensions simultaneously within a single framework.

While prior studies have extended UTAUT to examine AI adoption, most extensions focus on a limited set of constructs such as trust, perceived risk, or privacy, often examined in isolation. In contrast, this study advances the literature by proposing a holistic and integrative framework that simultaneously incorporates five critical dimensions of contemporary AI systems: explainability, human-centeredness, sustainability, fairness, and trust. This multi-dimensional integration represents a significant theoretical advancement, as it captures the complex socio-technical and ethical landscape of AI adoption that traditional models do not fully address.

Furthermore, the proposed SHE-AI-UTAUT model shifts the focus from purely instrumental determinants of adoption toward a human-centered and ethically grounded perspective, reflecting the evolving nature of AI technologies in education. Unlike previous UTAUT-based studies that primarily emphasize performance and usability, this framework explicitly embeds transparency, accountability, inclusivity, and environmental responsibility as core adoption drivers.

In addition, the study contributes contextually by empirically validating this extended framework within the underrepresented context of Zimbabwean higher education, thereby addressing a critical geographical gap in AI adoption research. This contextual grounding enhances the generalizability of UTAUT extensions to developing regions and provides new insights into how ethical and sustainability considerations influence AI adoption in resource-constrained environments. Contextually, there is a dearth of high-impact AI adoption research focused on Zimbabwe. To address these gaps, this study asks two research questions:

1. What factors influence the adoption of sustainable and human-centered explainable AI in higher education?
2. How does an extended UTAUT model explain AI adoption among students in Zimbabwean universities?

II. Related Works

Explainable AI (XAI) refers to the suite of techniques that make AI outputs understandable to human users. In education, XAI is crucial for "academic integrity" and "learner agency," allowing students to understand why an AI-driven feedback system gave a specific grade or recommendation [4]. Human-Centered AI (HCAI) emphasizes design that amplifies and empowers human capabilities rather than replacing them. It focuses on the immersive and engaging nature of AI educational agents [5]. Sustainable AI (or Green AI) considers the environmental footprint of training large models and the institutional longevity of AI systems, aligning adoption with Sustainable Development Goals (SDGs).

The original UTAUT model [7] posits that performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) are the primary determinants of Behavioral Intention (BI). While PE and EE consistently predict student adoption of digital tools, recent 2024-2025 research suggests that for AI, social influence (SI) is often moderated by ethical perceptions and facilitating conditions (FC) is heavily reliant on institutional digital readiness [11].To capture the nuances of AI, this study integrates trust in AI (TAI), perceived explainability (PEX), perceived human-centeredness (PHC), perceived sustainability (PSU), perceived fairness (PFA) into UTAUT 1 model. Trust in AI is defined as the user's confidence in the reliability and integrity of the AI system [3]. Perceived explainability (PEX) is the degree to which a student believes the AI’s logic is transparent. Perceived human-centeredness (PHC) is the extent to which AI aligns with human educational values [5]. Perceived sustainability (PSU) is defined as the perceived environmental and social responsibility of the AI tool [4]. Perceived fairness (PFA) is the belief that the AI system is free from algorithmic bias [6].

Contemporary research on Explainable AI (XAI) highlights that students are more likely to adopt AI systems when they can understand and interpret the reasoning behind algorithmic outputs, particularly in assessment and feedback systems [8]. Similarly, emerging work on trustworthy AI frameworks underscores that transparency, reliability, and ethical alignment are critical for fostering user confidence in AI technologies, especially in sensitive domains such as education [9].

Furthermore, recent sustainable AI research has introduced the concept of Green AI, which advocates for energy-efficient model development and responsible computational practices. Studies published between 2024 and 2026 demonstrate that sustainability perceptions are beginning to influence user attitudes, particularly among younger, environmentally conscious student populations [10]. Additionally, integrated frameworks combining explainability, fairness, and sustainability suggest that AI adoption is no longer driven solely by performance and usability, but increasingly by broader ethical and societal considerations. These developments reinforce the need for extended theoretical models, such as the SHE-AI-UTAUT framework, that explicitly incorporate these contemporary dimensions into the study of AI adoption in higher education. Figure 1 below presents the conceptual model.

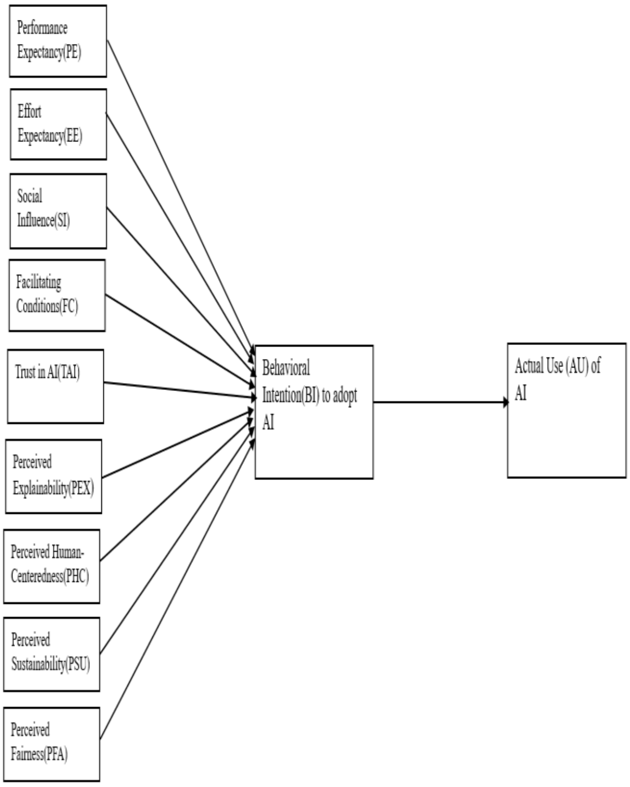

Figure 1: Sustainable, Human-Centered, Explainable AI UTAUT Model (SHE-AI-UTAUT Model)

III. METHODS

A. Theoretical Foundation

The study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT1) proposed by [7]. UTAUT integrates elements from eight prior models to explain user intentions to adopt a new technology. Recent studies demonstrate that the Unified Theory of Acceptance and Use of Technology (UTAUT 1) remains a dominant framework for examining AI adoption in higher education, including emerging domains such as explainable and responsible AI. Originally developed by [7], UTAUT explains technology acceptance through performance expectancy, effort expectancy, social influence and facilitating conditions, which continue to significantly predict behavioral intention in educational contexts. In higher education, multiple empirical studies have applied UTAUT to artificial intelligence adoption, showing that factors such as perceived usefulness and institutional support strongly drive students' and academics' willingness to adopt AI tools. More recent extensions of UTAUT have begun integrating trust, ethical awareness and transparency-related constructs, reflecting the growing need for explainable and human-centered AI systems in academia. [12] found that while traditional UTAUT predictors remain significant, ethical concerns such as trust and privacy shape acceptance of generative AI in higher education environments.

In parallel, emerging research increasingly incorporates sustainability and human-centered perspectives into UTAUT-based AI adoption models, aligning closely with the concept of Sustainable and Human-Centered Explainable AI. Studies such as [13] explicitly extend UTAUT by including sustainability perceptions, demonstrating that long-term educational outcomes and responsible AI use significantly influence students' behavioral intentions. Similarly, systematic reviews of AI adoption in higher education highlight that ethical considerations that include fairness, explainability and user-centered design are becoming critical determinants for technology acceptance, beyond purely technical performance factors. These findings suggest a clear research gap and opportunity for integrating explainability, human-centeredness and sustainability within UTAUT 1, supporting the development of extended frameworks such as the SHE-AI-UTAUT model to holistically explain AI adoption in higher education. Figure 2 below presents the Unified Theory of Acceptance and Use of Technology (UTAUT 1).

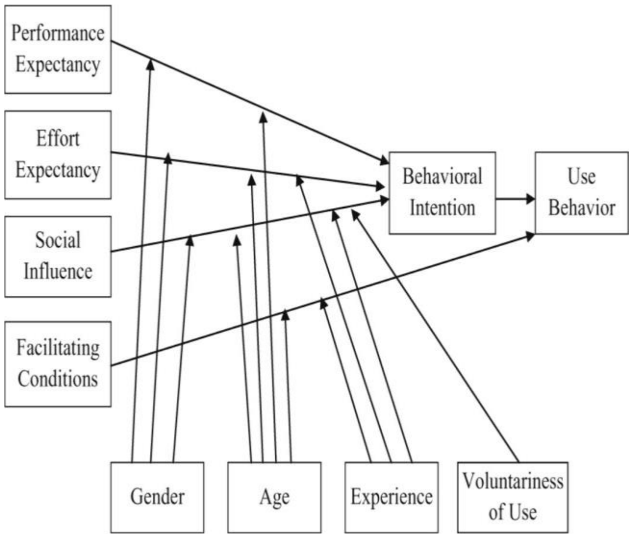

Figure 2: Theoretical Foundation UTAUT1 Model: [7]

B. Research Model and Hypotheses

The proposed Sustainable, Human-Centered, Explainable AI UTAUT Model (SHE-AI-UTAUT Model) is illustrated in Figure 3. It integrates five contemporary AI constructs into the core UTAUT1 framework to address the unique sustainable and human-centric requirements of AI adoption in higher education. Building on UTAUT1, sustainable and human-centered explainable AI constructs, we propose the following hypotheses:

H1: Performance Expectancy (PE) positively influences Behavioural Intention (BI).

H2: Effort Expectancy (EE) positively influences Behavioural Intention (BI).

H3: Social Influence (SI) positively influences Behavioural Intention (BI).

H4: Facilitating Conditions (FC) positively influences Behavioural Intention (BI).

H5: Trust in AI (TAI) positively influences Behavioural Intention (BI).

H6: Perceived Explainability (PEX) positively influences Behavioural Intention (BI).

H7: Perceived Human-Centeredness (PHC) positively influences Behavioural Intention (BI).

H8: Perceived Sustainability (PSU) positively influences Behavioural Intention (BI).

H9: Perceived Fairness (PFA) positively influences Behavioural Intention (BI).

H10: Behavioural Intention (BI) to adopt AI has a positive influence on Actual Use (AU) of AI.

Figure 3 below presents the Sustainable, Human-Centered, Explainable AI- UTAUT Conceptual Model (SHE-AI-UTAUT Model)

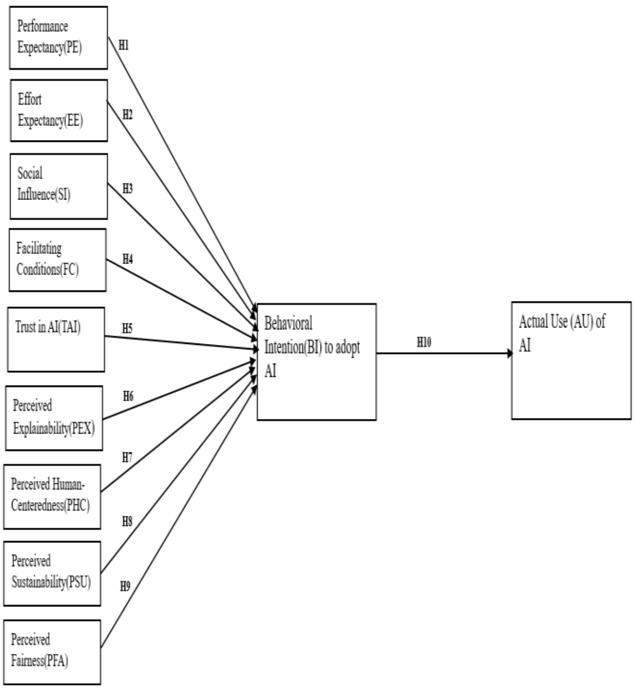

Figure 3: Sustainable, Human-Centered, Explainable AI-UTAUT Model (SHE-AI-UTAUT Model)

C. Research Design and Data Collection

This study employed a cross-sectional survey design to collect quantitative data on students' perceptions and acceptance of AI learning tools. The design was appropriate for testing hypothesized relationships among constructs and assessing the explanatory power of the proposed framework. The target population comprised undergraduate and postgraduate students enrolled in Zimbabwean universities. We used stratified random sampling to ensure representation across institution types, academic disciplines and study levels.

Three universities were selected: one large public university, one medium-sized public university and one private university. Within each institution, students were randomly selected from course rosters across faculties. A total of 400 students were invited to participate. After excluding incomplete responses, the final sample comprised 352 valid responses with a response rate of 88%. This sample size exceeds the minimum requirement for regression analysis and provides adequate statistical power to detect medium effect sizes.

Data were collected over a four-week period in February to March 2026. Students were invited via email and learning management system announcements to complete an online questionnaire. The questionnaire included an informed consent statement, demographic questions and items measuring the ten constructs in the research model. Participation was voluntary, anonymous and not linked to course grades. The questionnaire comprised 35 items adapted from validated scales in prior technology acceptance and sustainable, human-centered, explainable AI research. All items used five-point Likert scales (1 = strongly disagree, 5 = strongly agree). Measurement items were adapted from [14]. The questionnaire was pilot tested with 30 students to assess clarity and face validity, and minor wording adjustments were made based on feedback.

D. Research Design Workflow

Figure 4 below presents the complete research workflow from design to hypothesis testing.

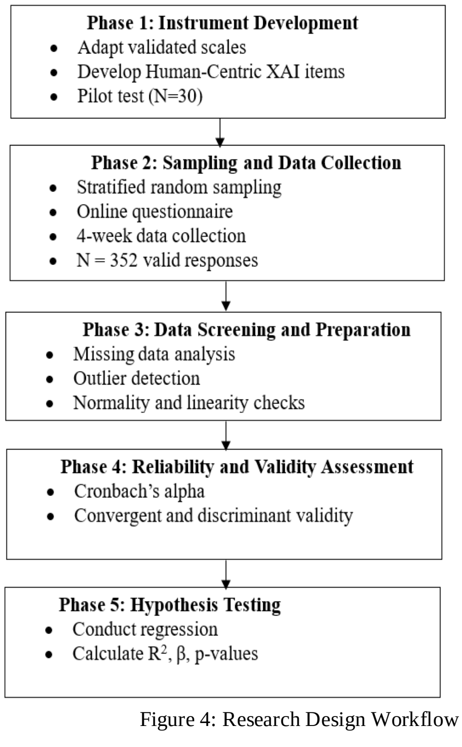

Figure 4: Research Design Workflow

E. Construct Development and Measurement

The measurement items for all constructs were adapted from previously validated scales in technology acceptance, explainable AI, human-centered AI and ethical AI literature. All constructs were operationalized using multi-item Likert scales (1 = strongly disagree, 5 = strongly agree). Perceived Explainability (PEX) was measured using four items adapted from prior studies on explainable AI and transparency, reflecting the extent to which students understand and can interpret AI outputs.

Perceived Human-Centeredness (PHC) was measured using four items derived from human-centered AI literature, capturing the degree to which AI systems align with user needs, values, and learning processes. Perceived Sustainability (PSU) was measured using three items adapted from sustainable technology and Green AI studies, reflecting students' perceptions of the environmental and societal impact of AI systems.

Perceived Fairness (PFA) was measured using four items adapted from algorithmic fairness and ethical AI research, capturing the extent to which AI systems are perceived as unbiased and equitable. All measurement items were contextually adapted to the higher education environment in Zimbabwe to ensure relevance and clarity. A pilot study with 30 students was conducted to refine item wording and ensure face validity. Minor modifications were made to improve comprehension and contextual alignment.

Construct reliability and validity were rigorously assessed. Internal consistency reliability was confirmed through Cronbach's alpha and composite reliability (CR), with all values exceeding the recommended threshold of 0.70. Convergent validity was established using Average Variance Extracted (AVE), where all constructs exceeded the threshold of 0.50. These results confirm that the measurement model is both reliable and valid for empirical analysis.

F. Reliability and Validity

To ensure the robustness of the measurement instrument, reliability and validity tests were conducted. Cronbach's alpha (α) and Composite Reliability (CR) were computed for each construct to assess internal consistency reliability. All constructs exceeded the conventional threshold of $\alpha > 0.80$, indicating acceptable reliability. Convergent validity was assessed through Average Variance Extracted (AVE), which should exceed 0.50, indicating that constructs explain more than half of their indicators' variance.

The results are shown in table 1 below:

Table 1: Reliability and Validity Assessment Results

Construct	Items	Cronbach's alpha (α)	CR	AVE
Perfomance Expectancy (PE)	5	0.86	0.89	0.62
Effort Expectancy (EE)	5	0.83	0.88	0.59
Social Influence (SI)	5	0.88	0.91	0.65
Facilitating Conditions (FC)	5	0.81	0.86	0.57
Trust in AI (TAI)	5	0.84	0.87	0.61
Perceived Explainability (PEX)	5	0.93	0.93	0.68
Perceived Human-Centeredness (PHC)	5	0.86	0.88	0.58
Perceived Sustainability (PSU)	5	0.87	0.90	0.63
Behavioural Intention (BI)	5	0.93	0.94	0.70
Actual Use (AU)	5	0.91	0.96	0.72

IV. RESULTS

This section presents the empirical results of hypothesis testing and model performance. Regression analysis was used to test hypotheses and assess the incremental explanatory power of human-centered XAI constructs and the results are summarized in Figure 5 below where the model presents the regression model with standardized beta coefficients for predictors of Behavioural Intention.

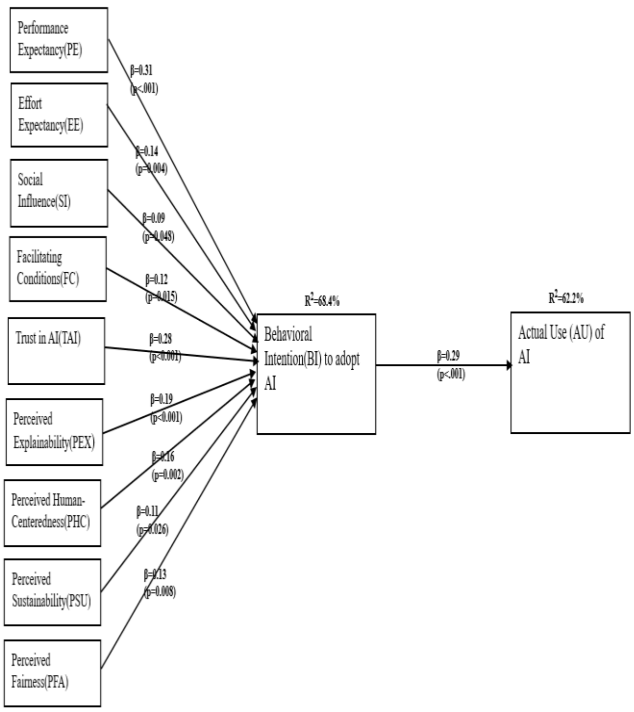

Figure 5: Structural model results

The regression results indicate that the proposed model demonstrates substantial explanatory power, accounting for 68.4% of the variance in students' behavioral intention (BI) to adopt artificial intelligence (AI) in Zimbabwean higher education ($R^2 = 0.684$). All hypothesized relationships (H1–H9) are statistically significant and supported, suggesting a robust and comprehensive model. Performance expectancy ($\beta = 0.31$, $p < 0.001$) and trust in AI ($\beta = 0.28$, $p < 0.001$) emerge as the strongest predictors of behavioral intention, highlighting the importance of perceived usefulness and confidence in AI systems.

Additionally, perceived explainability ($\beta = 0.19$, $p < 0.001$), perceived human-centeredness ($\beta = 0.16$, $p = 0.002$) and effort expectancy ($\beta = 0.14$, $p = 0.004$) exhibit moderate positive effects, emphasizing the role of transparency, user-centric design and ease of use. Other factors, including perceived fairness ($\beta = 0.13$, $p = 0.008$), facilitating conditions ($\beta = 0.12$, $p = 0.015$), perceived sustainability ($\beta = 0.11$, $p = 0.026$), and social influence ($\beta = 0.09$, $p = 0.048$), also contribute significantly, albeit with relatively smaller effect sizes. The findings underscore that both traditional technology acceptance factors and emerging ethical and design-related constructs jointly influence AI adoption intentions, providing strong empirical support for an extended theoretical model in this context.

To ensure the robustness of the regression results, additional diagnostic tests were conducted. Multicollinearity was assessed using Variance Inflation Factor (VIF) values for all independent variables. The VIF values ranged between 1.21 and 2.87, which are well below the commonly accepted threshold of 5.0, indicating that multicollinearity is not a concern in the model. The key assumptions of regression analysis were also examined. Linearity was confirmed through scatterplot inspections, while normality of residuals was assessed using histogram and normal probability plots, which indicated approximately normal distribution. Homoscedasticity was verified by examining residual plots, showing constant variance across predicted values.

Additionally, the Durbin–Watson statistic indicated no significant autocorrelation in the residuals, confirming the independence of errors. In terms of effect sizes, standardized beta coefficients (β) were used to evaluate the relative strength of each predictor. Performance expectancy ($\beta = 0.31$) and trust in AI ($\beta = 0.28$) demonstrated the largest effect sizes, indicating strong practical significance. Other predictors, including perceived explainability ($\beta = 0.19$) and human-centeredness ($\beta = 0.16$), exhibited moderate effect sizes, while sustainability, fairness, and social influence showed smaller yet meaningful effects. These results confirm that both traditional and AI-specific constructs contribute substantively to the model. Table 2 below shows the summary of hypothesis testing.

Table 2. Summary of Hypothesis Testing

Hypothesis	Path Relationship	β (Standardized Coefficient)	p-value	Supported /Not Supported
H1	PE → BI	0.31	p<0.001	Supported
H2	EE→ BI	0.14	p=0.004	Supported
H3	SI → BI	0.09	p=0.048	Supported
H4	FC → BI	0.12	p=0.015	Supported
H5	TAI → BI	0.28	p<0.001	Supported
H6	PEX → BI	0.19	p<0.001	Supported
H7	PHC → BI	0.16	p=0.002	Supported
H8	PSU → BI	0.11	p=0.026	Supported
H9	PFA→ BI	0.13	p=0.008	Supported
H10	BI → AU	0.29	p<0.001	Supported

V. DISCUSSION

The results, summarized in Table 2, indicate that all ten hypotheses (H1– H10) were statistically supported ($p < 0.01$), validating the framework's structural integrity. The study addresses RQ1 and RQ2 by testing ten hypotheses within the SHE-AI-UTAUT framework. The model explains 68.4% of the variance in behavioral intention (BI), indicating strong explanatory power and confirming the robustness of the extended framework.

Performance expectancy *(β=0.31, p<0.001)* emerges as the strongest predictor of behavioral intention, indicating that students are primarily driven by the perceived usefulness of AI technologies. This aligns closely with UTAUT theory, where performance expectancy consistently dominates other predictors [7]. Empirical studies in educational technology adoption similarly confirm that perceived benefits such as improved learning efficiency and academic performance strongly influence AI adoption [15, 16]. In relation to RQ1, these findings highlight that functional value remains central even in advanced AI contexts. Regarding RQ2, it confirms that the extended model retains the predictive strength of core UTAUT constructs.

Effort expectancy (*β=0.14, p=0.004*) exhibits a moderate positive effect, indicating that ease of use significantly shapes AI adoption. This is consistent with prior findings that lower cognitive and technical complexity increases user acceptance [7, 17]. Although weaker than performance expectancy, the significance of EE suggests that usability remains crucial in AI systems, particularly in contexts where students may lack advanced technical skills. This directly contributes to RQ1, emphasizing usability as a key adoption determinant.

Social influence (*β=0.09, p= 0.048*) has a positive but relatively weak effect, indicating that peer, lecturer, and institutional pressures play a limited but significant role. This finding is consistent with literature showing that SI often has weaker effects in voluntary settings [7] but remains relevant in collectivist or academic environments [18].This suggests that AI adoption among students is more individually driven than socially enforced, contributing nuanced insight to RQ1 and refining RQ2 by showing that traditional social drivers are less dominant compared to cognitive and ethical factors.

Facilitating conditions *(β=0.12, p=0.015)* show a small but significant effect, reflecting the importance of institutional infrastructure and technical support. Prior studies highlight the importance of access to resources, training, and infrastructure in technology adoption [19,20]. This finding reinforces RQ1, demonstrating that institutional readiness plays a supportive role. For RQ2, it confirms that traditional organizational enablers remain relevant even in AI adoption contexts.

Trust in AI *(β=0.28, p<0.001)* is the second strongest predictor, underscoring its central role in student adoption. This aligns with emerging literature emphasizing trust as a critical determinant in AI acceptance due to concerns around reliability, bias, and autonomy [21, 22]. This finding strongly addresses RQ1, demonstrating that trust is a key factor in adopting intelligent systems. In terms of RQ2, it validates the integration of AI-specific constructs into UTAUT, significantly enhancing explanatory power.

Perceived explainability *(β=0.19, p<0.001)* has a moderate and highly significant effect, indicating that students value transparency and understanding of AI outputs. This is consistent with explainable AI (XAI) literature, which emphasizes interpretability as critical for user acceptance [23]. This finding directly contributes to the study by identifying explainability as a core adoption driver as well as demonstrating the importance of integrating transparency-related constructs into UTAUT. Human-centeredness *(β=0.16, p=0.002)* significantly influences adoption, suggesting that students prefer AI systems aligned with human values and user needs. This aligns with human-centered AI frameworks emphasizing fairness, usability, and ethical design [25,26].

Perceived sustainability *(β=0.11, p=0.026)* has a small but significant effect, indicating that environmental and societal considerations influence AI adoption. This aligns with research showing that sustainability concerns increasingly shape technology acceptance, particularly among younger users [27]. This finding reflects a broader global shift toward sustainable and responsible technology use, particularly among younger and more environmentally conscious populations. One possible explanation for this result is the growing awareness of the environmental costs associated with AI technologies, including the high computational energy required for training and deploying large-scale models. The concept of Green AI emphasizes the need for energy-efficient algorithms, reduced carbon footprints, and responsible resource utilization in AI development.

Recent studies highlight that integrating sustainability considerations into AI systems can positively influence user perceptions and acceptance, particularly in educational settings where social responsibility and long-term impact are highly valued. In the context of higher education, students are increasingly exposed to sustainability discourses aligned with the United Nations Sustainable Development Goals (SDGs), which may shape their expectations of emerging technologies. As a result, AI tools perceived as environmentally responsible and socially beneficial are more likely to be accepted. This suggests that sustainability is evolving from a peripheral concern to a meaningful adoption criterion, even if its effect size remains smaller compared to traditional factors such as performance expectancy and trust.

The significance of perceived sustainability is particularly relevant in developing countries such as Zimbabwe, where resource constraints and infrastructure limitations heighten awareness of efficiency and long-term viability. In such contexts, students may be more sensitive to whether AI technologies are sustainable, accessible, and aligned with broader developmental goals. This finding contributes to emerging literature by demonstrating that sustainability is not merely an ethical add-on but a functional and perceptual driver of AI adoption. It reinforces the importance of integrating Green AI principles into the design and deployment of educational technologies, ensuring that AI systems are not only effective and trustworthy but also environmentally and socially responsible.

Perceived fairness *(β=0.134, p=0.008)* significantly affects adoption, reflecting concerns about bias and ethical decision-making in AI systems. This aligns with studies emphasizing algorithmic fairness as a key driver of trust and adoption [28,22]. The results demonstrate that while traditional UTAUT constructs remain significant, AI-specific factors substantially enhance explanatory power. This provides strong evidence that the SHE-AI-UTAUT model offers a more comprehensive framework for understanding AI adoption in higher education, directly answering both research questions.

VI. Conclusion

This study provides strong empirical support for the robustness and theoretical advancement of the SHE-AI-UTAUT model in explaining the adoption of artificial intelligence (AI) within higher education. With an explanatory power of $R^2 = 0.684$, the model demonstrates substantial predictive capability, confirming that a combination of traditional technology acceptance factors and emerging AI-specific constructs is essential for understanding students' behavioral intentions.

The findings reveal that performance expectancy and trust in AI are the most influential determinants of behavioral intention, emphasizing that both functional utility and confidence in AI systems are central to adoption decisions. At the same time, effort expectancy, facilitating conditions and social influence, although significant, exert comparatively weaker effects, suggesting that while traditional UTAUT constructs remain relevant, their influence is increasingly complemented and, in some cases, overshadowed by more contemporary considerations.

Notably, perceived explainability, human-centeredness, fairness and sustainability emerge as critical drivers, underscoring a paradigm shift toward ethical, transparent, and user-centric AI systems. In direct response to RQ1, the study demonstrates that AI adoption in higher education is shaped not only by usability and performance-related factors but also by trust, transparency, ethical design and sustainability considerations. This indicates that students are not merely passive users of technology but are critically engaged with the broader societal and ethical implications of AI. Regarding RQ2, the results confirm that extending the UTAUT framework with AI-specific constructs significantly enhances its explanatory power, thereby validating the theoretical contribution of the SHE-AI-UTAUT model.

This study advances technology acceptance literature by providing a holistic, future-oriented framework that integrates technical, social and ethical dimensions of AI adoption. The results suggest that higher education institutions and AI developers must move beyond conventional usability-focused approaches and prioritize trust-building, explainability, fairness and human-centered design to foster meaningful and sustainable AI integration. Consequently, the SHE-AI-UTAUT model offers a valuable foundation for both future research and policy formulation aimed at promoting responsible AI adoption in educational contexts.

From a practical perspective, the findings offer several concrete recommendations. For university administrators, there is a need to invest in digital infrastructure and institutional support mechanisms that enhance facilitating conditions, including reliable internet access, AI training programs, and user support services. Universities should also develop AI governance frameworks that promote transparency, fairness, and ethical use, ensuring that AI systems used in teaching and learning are explainable and aligned with academic integrity principles. Additionally, integrating AI literacy into curricula will help students better understand, evaluate and trust AI technologies.

For AI system developers, the results highlight the importance of designing systems that prioritize explainability, user control, and human-centered interaction. Developers should incorporate interpretable interfaces that clearly communicate how AI-generated outcomes are produced, thereby strengthening user trust. Furthermore, embedding fairness-aware algorithms and regularly auditing systems for bias is critical, particularly in diverse educational contexts such as Zimbabwe. Developers are also encouraged to adopt sustainable AI practices, including optimizing models for energy efficiency and minimizing computational resource consumption, to align with emerging environmental expectations. The successful adoption of AI in higher education requires a collaborative approach in which institutional strategies and technological design jointly address both functional and ethical dimensions of AI use.

Despite its contributions, this study has some limitations related to sampling and generalizability. The data were collected from students in Zimbabwean higher education institutions, which operate within a unique socio-economic, technological, and cultural context. Factors such as infrastructure constraints, varying levels of digital literacy, and localized educational policies may influence students' perceptions of AI differently compared to those in more developed or differently structured educational systems. Consequently, the findings should be interpreted with caution when generalizing beyond this context. While the proposed SHE-AI-UTAUT model demonstrates strong explanatory power within Zimbabwe, its applicability to other regions may vary depending on institutional readiness, cultural attitudes toward AI, and levels of technological advancement.

However, the study offers analytical generalizability to other developing countries with similar socio-economic and educational conditions, particularly within sub-Saharan Africa and comparable Global South contexts. The integration of explainability, trust, fairness, human-centeredness, and sustainability reflects broader global concerns surrounding AI adoption, suggesting that the theoretical framework may be adaptable across diverse educational environments.

Future research is therefore recommended to conduct cross-country comparative studies and multi-context validations of the SHE-AI-UTAUT model to enhance its external validity and generalizability across different educational and cultural settings.

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