

Human-Centric Explainable AI as a Catalyst for Responsible AI Adoption in Higher Education

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ABSTRACT

As Artificial Intelligence (AI) becomes increasingly integrated into academic workflows, the limited explainability of advanced AI models poses significant ethical and operational challenges, particularly in the Global South. This study proposes and validates an Extended Human-Centric Explainable AI (H-XAI) Adoption Framework within the context of Zimbabwean Higher Education. Utilizing a quantitative approach (N = 372 university students), regression analysis was employed to examine the relationships amongst five critical H-XAI constructs which are perceived interpretability, algorithm transparency, ethical alignment, AI literacy and human oversight together with traditional adoption drivers that include perceived usefulness, perceived ease of use, attitude and behavioral intention. Results demonstrate that the model explains 62% of the variance in Behavioral Intention ($R^2 = .62$). Findings reveal that ethical alignment ($\beta = .48$, $p < 0.001$) and human oversight ($\beta = .44$, $p < 0.001$) are the strongest predictors of responsible AI adoption, while perceived interpretability ($\beta = 0.42$, $p < 0.001$) significantly shapes Attitude. The implications for institutional governance and curriculum design are discussed, providing a roadmap for sustainable AI integration in resource-constrained educational environments.



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I. INTRODUCTION

The rapid evolution of artificial intelligence has positioned it as a cornerstone of digital transformation in higher education globally. In Zimbabwe, the drive toward "Education 5.0", which emphasizes on teaching, research, community service, innovation and industrialization has accelerated interest in generative AI for curriculum development, assessment automation and administrative efficiency [1]. However, the shift from experimental use to systemic, responsible adoption is hindered by significant challenges, including infrastructure gaps, low digital readiness and a lack of clear governance frameworks [2]. Responsible AI adoption in education transcends traditional metrics of utility and ease of use. In this study, AI adoption refers to students' intention to use AI-powered educational technologies, while responsible AI adoption refers to the intention to use such technologies in ways that are transparent, ethically aligned, accountable and subject to appropriate human oversight. Thus, responsible AI adoption extends

beyond mere technology usage to encompass ethical and governance considerations.

It requires a fundamental alignment with ethical principles, data privacy and stakeholder trust [3]. Central to this transition is explainable AI (XAI), a field dedicated to making the "black-box" nature of AI models transparent and understandable to human users [3]. Human-centric XAI frameworks prioritize the needs of educational stakeholders who are students, educators and administrators ensuring that AI-driven decisions are not only accurate but also interpretable and contestable [4]. Despite the theoretical promise of XAI, empirical evidence of its impact on trust and adoption in non-Western contexts, such as Zimbabwe, remains sparse. Existing literature often highlights the potential of AI to improve teaching and learning but also warns of ethical risks like bias, reduced academic integrity and the digital divide [5]. This study addresses this gap by proposing and validating a human-centric explainable AI adoption framework specifically tailored for the Zimbabwean higher education landscape. By examining how explainability

and ethical alignment drive adoption, this research aims to provide actionable insights for creating a responsible AI future in African universities.

The integration of AI into Zimbabwean higher education is at a crossroads, characterized by a series of critical gaps that this study seeks to address. Most traditional technology adoption models, such as the Technology Acceptance Model (TAM), focus primarily on perceived usefulness and ease of use. These models often fail to capture the complex ethical and transparency requirements of AI systems in sensitive educational settings. There is a lack of integrated frameworks that bridge the gap between technical XAI capabilities and the broader constructs of responsible AI adoption [6]. Furthermore, while XAI frameworks exist, empirical evaluations of their effectiveness in building trust among students produce mixed results. For instance, some studies suggest that explanations alone do not always increase trust if the outcome, for example a grade does not align with user expectations [7]. There is a pressing need for more quantitative evidence on how specific XAI attributes influence adoption decisions in diverse educational contexts. The Zimbabwean higher education sector faces unique systemic constraints, including limited ICT infrastructure and nascent AI policy environments [7]. Most AI adoption research originates from developed economies, leaving the specific needs and socio-cultural values of African institutions under-represented. Context-specific governance and adoption pathways are essential to ensure inclusive and ethical AI deployment [8]. These converging gaps motivate the present study, which seeks to develop and validate a human-centric explainable AI adoption framework (H-XAI-AF) incorporating human-centric XAI constructs. To guide this investigation, we pose two research questions:

- 1) What human-centric explainability factors influence responsible AI adoption in higher education?
- 2) How does a human-centric explainable AI framework explain students' adoption of AI systems in Zimbabwean universities?

II. RELATED WORKS

Explainable AI in education (XAI-ED) has emerged as a specialized field focusing on providing transparent rationales for AI-generated outcomes, such as automated grading or student attrition prediction [8]. Frameworks like the XAI-ED model emphasize identifying stakeholder needs and selecting appropriate explanation modes, whether global or local [9]. For example, local explanations using tools like SHAP or LIME are particularly valuable for academic advising, as they provide actionable insights into why a specific student might be at risk of dropping out [9]. The evolution of technology adoption models has shifted from purely functional perspectives to human-centered and ethically-aware paradigms. Modern frameworks now incorporate constructs such as algorithmic fairness, accountability and transparency [10]. In the context of AI, trust is no longer viewed as a static attribute but as a dynamic relationship shaped by the system's

ability to communicate its competence and minimize perceived ethical risks [10]. This study extends the Technology Acceptance Model (TAM) by integrating five core human-centric XAI constructs derived from recent literature which are perceived interpretability, algorithm transparency, ethical alignment, AI literacy and human oversight. Perceived interpretability is defined as the degree to which a user believes they can understand the logic behind an AI decision [11]. Perceived interpretability focuses on users' understanding of specific AI-generated outputs and decisions, whereas algorithm transparency concerns the broader visibility of how the system operates, including data sources, algorithms and limitations. Similarly, ethical alignment concerns whether AI behaviour adheres to ethical principles, whereas human oversight concerns the mechanisms through which humans retain supervisory authority over AI outputs.

Algorithm transparency is defined as the clarity of the AI system's processes, data usage and limitations [12]. Ethical alignment refers to the extent to which AI systems operate in accordance with institutional and societal ethical principles, including fairness, transparency, accountability, privacy protection, bias mitigation and academic integrity[13]. AI literacy is the level of stakeholder understanding and perceived competence in interacting with AI systems [14]. Human oversight refers to mechanisms that enable human review, intervention, correction and final authority over AI-generated recommendations or decisions[15].

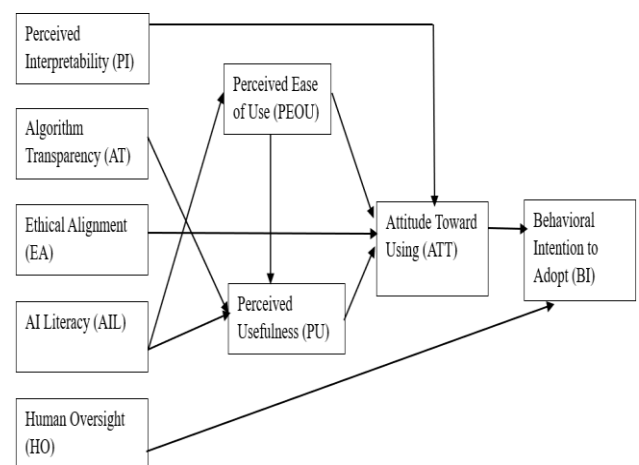


Figure 1. Extended Human-Centric Explainable AI Adoption Framework (H-XAI AF)

The novelty of the H-XAI Adoption Framework lies in integrating explainability-oriented constructs and responsible AI principles within the well-established TAM structure. While existing AI adoption studies examine technology acceptance and some XAI studies focus on interpretability, few frameworks simultaneously model interpretability, transparency, ethical alignment, AI literacy and human oversight as determinants of responsible AI adoption within higher education. Figure 1 presents the conceptual model.

III. METHODS

A. Theoretical Framework

This study utilizes the Technology Acceptance Model as the theoretical foundation to provide actionable insights for creating a responsible AI future in African universities. The Technology Acceptance Model (TAM), developed by [16], posits that two beliefs, perceived usefulness (PU) and perceived ease of use (PEU) are primary determinants of technology acceptance. PU is defined as the degree to which a person believes that using a particular system would enhance his or her job performance, while PEU is the degree to which a person believes that using a particular system would be free of effort. TAM has been extensively validated across technologies and contexts, demonstrating robust predictive power for behavioral intention and actual use.

In educational contexts, TAM has been applied to learning management systems, mobile learning, e-learning platforms, and, more recently, AI tools such as ChatGPT and intelligent tutoring systems. Studies consistently find that PU and PEU predict students' intention to use educational technologies, with PU typically showing stronger effects than PEU. However, as AI systems introduce new ethical and relational concerns, scholars have called for extensions that incorporate interpretability, transparency, ethical alignment, AI literacy and human oversight. Our framework builds on TAM by retaining its core constructs while integrating human-centric explainable AI constructs. This approach allows us to assess the incremental explanatory power of these constructs over baseline TAM and to test their effects to behavioral intention. Figure 2 presents the Technology Acceptance Model as the theoretical framework for this study.

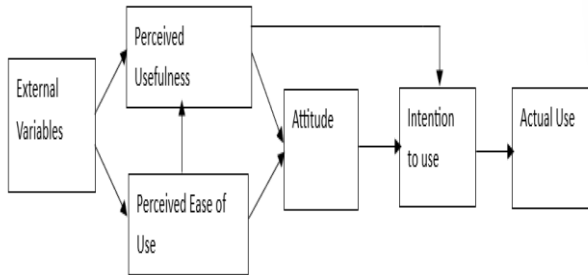


Figure 2. Theoretical Foundation – Technology Acceptance Model: Source [16]

B. Research Model and Hypotheses

The extended H-XAI adoption framework (H-XAI AF) embeds traditional TAM constructs while integrating five human-centric principles as antecedents. Building on TAM and human-centric XAI constructs, we propose the following hypotheses:

H1: Perceived Interpretability (PI) positively influences Attitude Toward Using (ATT).

H2: Algorithm Transparency (AT) positively influences Perceived Usefulness (PU).

H3: Ethical Alignment (EA) positively influences Attitude Toward Using (ATT).

H4: AI Literacy (AIL) positively influences Perceived Ease of Use (PEOU).

H5: AI Literacy (AIL) positively influences Perceived Usefulness (PU).

H6: Human Oversight (HO) positively influences Behavioural Intention to Adopt (BI).

H7: Perceived Ease of Use (PEOU) positively influences Perceived Usefulness (PU).

H8: Perceived Usefulness (PU) positively influences Attitude Toward Using (ATT)

H9: Perceived Ease of Use (PEOU) positively influences Attitude Toward Using (ATT)

H10: Attitude Toward Using (ATT) positively influences Behavioural Intention to Adopt (BI).

Figure 3 presents the Extended Human Centric-XAI TAM Framework (H-XAI AF).

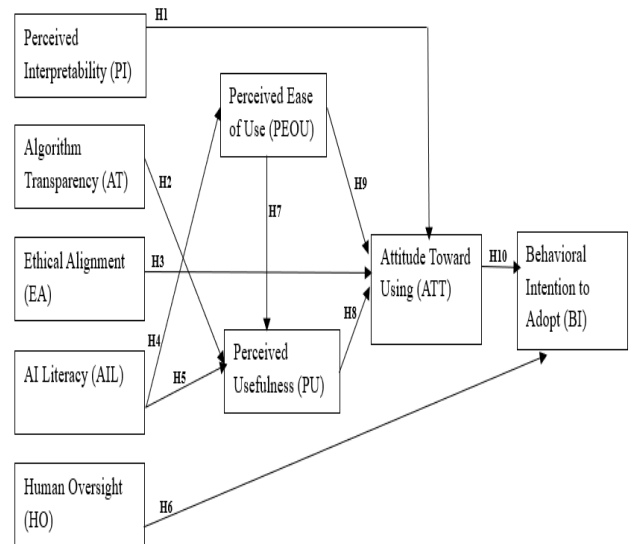


Figure 3. Human Centric-XAI TAM Framework (H-XAI AF).

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 and two private universities. 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

372 valid responses with a response rate of 83%. Of the 372 respondents, the sample included undergraduate and postgraduate students from Information Systems, Computer Science, Education, Business and Social Sciences disciplines. The majority reported prior experience with generative AI tools such as ChatGPT, Gemini and Copilot for academic purposes.

This sample size exceeds the minimum requirement for regression analysis and provides adequate statistical power to detect medium effect sizes. Several procedural remedies were implemented to reduce common method bias. Respondents were assured of anonymity, participation was voluntary, item wording was carefully reviewed to reduce ambiguity, and demographic questions were separated from construct measurement items.

Data were collected over a four-week period from April to May 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 nine constructs in the research model. Participation was voluntary, anonymous and not linked to course grades. The measurement instrument consisted of 45 items distributed across nine constructs, with five items assigned to each construct. Items were adapted from validated AI adoption, explainable AI and technology acceptance literature [17] and [18]. The adaptation process involved expert review by three Information Systems academics and pilot testing with 40 students. Minor modifications were made to improve contextual relevance to Zimbabwean higher education while preserving the underlying construct meaning. All items were measured on a seven-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree).

D. Research Design Workflow

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

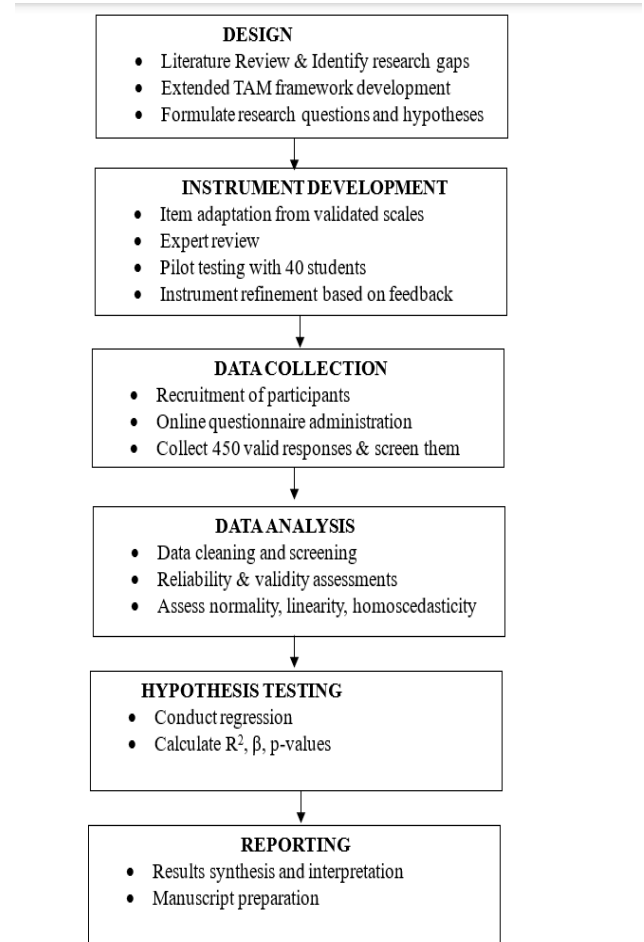


Figure 4. Research Design Workflow

E. 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 $\alpha \geq 0.70$, 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. Specifically, Behavioural intention ($\alpha = 0.92$) and perceived usefulness ($\alpha = 0.91$) demonstrated the highest reliability. The results are shown in table 1.

TABLE 1
RELIABILITY AND VALIDITY ASSESSMENT RESULTS

Construct	Items	Cronbach's alpha (α)	CR	AVE
Perceived Interpretability (PI)	5	0.87	0.86	0.60
Algorithm Transparency (AT)	5	0.84	0.87	0.61
Ethical Alignment (EA)	5	0.89	0.93	0.67
AI Literacy (AIL)	5	0.82	0.85	0.58

Human Oversight (HO)	5	0.85	0.88	0.66
Perceived Usefulness (PU)	5	0.91	0.91	0.69
Perceived Ease of Use (PEOU)	5	0.85	0.82	0.56
Attitude (ATT)	5	0.88	0.93	0.68
Behavioural Intention (BI)	5	0.92	0.94	0.73

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-centric XAI constructs and the results are summarized in Figure 5, where the model presents the regression model with standardized beta coefficients for predictors of Behavioural Intention.

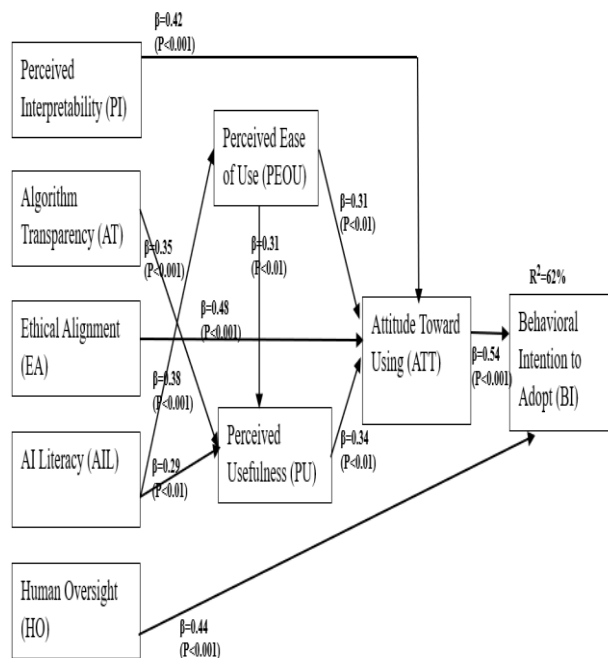


Figure 5. Structural model results

The model achieved high predictive accuracy, explaining 62% of the variance in Behavioral Intention ($R^2 = 0.62$). This indicates that the combination of human-centric XAI constructs and TAM variables provides a comprehensive explanation of student adoption intentions. Standardized multiple linear regression analyses were conducted to test the hypothesized relationships. Regression assumptions relating to linearity, normality and multicollinearity were examined prior to analysis. All reported β coefficients represent standardized regression coefficients, thereby enabling meaningful comparisons of predictor strength across constructs.

A comparative analysis of path coefficients reveals that attitude ($\beta = .54$) is the strongest direct predictor of intention.

However, the external constructs of ethical alignment ($\beta = 0.48$) and human oversight ($\beta = 0.44$) emerged as the most potent distal predictors, showing significantly higher influence than the traditional perceived usefulness ($\beta = 0.34$) in the final model. Among the antecedents of attitude, perceived interpretability ($\beta = 0.42$) outperformed usefulness, highlighting the primacy of "understanding" over "utility" in the adoption of complex AI systems. Table 2 presents a summary of hypothesis testing.

TABLE 2.
SUMMARY OF HYPOTHESIS TESTING

Hypothesis	Path Relationship	β (Standardized Coefficient)	p-value	Supported / Not Supported
H1	PI ATT	0.42	$p < 0.001$	Supported
H2	AT PU	0.35	$p < 0.001$	Supported
H3	EA ATT	0.48	$p < 0.001$	Supported
H4	AIL PEOU	0.38	$p < 0.001$	Supported
H5	AIL PU	0.29	$p < 0.01$	Supported
H6	HO BI	0.44	$p < 0.001$	Supported
H7	PEOU PU	0.31	$p < 0.01$	Supported
H8	PU ATT	0.34	$p < 0.01$	Supported
H9	PEOU ATT	0.31	$p < 0.01$	Supported
H10	ATT BI	0.54	$p < 0.001$	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 empirical validation of the extended human-centric explainable AI adoption framework (H-XAI AF) provides critical insights into the anatomy of responsible AI acceptance. The analysis of each variable reveals a sophisticated interplay between cognitive understanding, ethical assurance and functional utility. The results for ethical alignment (EA) ($\beta = 0.48$, $p < 0.001$) and human oversight (HO) ($\beta = 0.44$, $p < 0.001$) are particularly significant. Their high beta values suggest that for Zimbabwean higher education students, adoption is not merely a pragmatic decision based on ease of use. Instead, it is a value-laden choice.

The strong support for **H3** and **H6** indicates that "Responsible AI" is perceived as a system that respects localized values, such as communal fairness (Ubuntu) and maintains human control. This implies that even a technically superior AI tool will face adoption resistance if it is perceived as an "autonomous black box" that lacks ethical guardrails or human intervention points. Perceived interpretability (PI) ($\beta = 0.42$, $p < 0.001$) emerged as a critical driver of attitude (ATT) (**H1**). In the context of AI, interpretability serves as a cognitive bridge. When students feel they can decipher the "how" and "why" of an AI's output, their "algorithmic anxiety" decreases, leading to a more positive disposition. The fact that PI's influence on attitude is stronger than that of perceived usefulness (PU) ($\beta = 0.34$) suggests that transparency is the prerequisite for utility. In other words, a tool must be understandable before its usefulness can be fully embraced.

Algorithm transparency (AT) ($\beta = 0.35$, $p < 0.001$) significantly impacts perceived usefulness (PU) (H2), suggesting that transparency is viewed as a functional quality. When students can verify the data and logic sources, they perceive the tool as more reliable and thus more useful for their academic tasks. Simultaneously, AI literacy (AIL) ($\beta = 0.38$) acts as a dual-action enabler, significantly influencing both ease of use (H4) and Usefulness (H5). This confirms that literacy is the foundational skill that reduces the perceived complexity of AI and allows students to discern its practical benefits.

The traditional TAM paths (H7-H10) remain significant, but their roles are transformed within the H-XAI AF. Attitude (ATT) ($\beta = 0.54$) remains the final arbiter of intention, but it is now shaped more by interpretability than by functional utility alone. Perceived usefulness (PU) ($\beta = 0.34$) and perceived ease of use (PEOU) ($\beta = 0.31$) act as necessary but insufficient conditions for adoption, serving as the functional scaffolding upon which the more dominant ethical and explainability factors are built.

The validation of all ten hypotheses confirms that the H-XAI AF provides a more granular and theoretically robust explanation of AI adoption than classical models. It moves the discourse from "Technology Acceptance" to "Responsible Adoption." Universities should prioritize the procurement of explainable AI systems and establish human oversight committees to ensure students feel in control of the automated learning process.

Policymakers must mandate ethical alignment audits for any AI tool deployed in high-stakes educational environments, for example admissions or automated grading. AI developers should focus on developing interactive explanations and user override features, as these directly feed into the strongest predictors of adoption found in this study. Curriculum designers must treat AI literacy not as a technical skill, but as a responsibility skill that empowers students to critically interact with and supervise AI tools.

The Zimbabwean context offers important insights into AI adoption. Infrastructure limitations, uneven internet accessibility, varying levels of digital literacy and the absence of comprehensive institutional AI policies may increase the importance of explainability and human oversight. In resource-constrained environments, students may rely more heavily on trust and transparency cues when evaluating AI systems than users in technologically mature settings.

VI. CONCLUSION

This study has successfully developed and empirically validated the extended human-centric explainable AI adoption framework (H-XAI AF), providing a comprehensive analysis of the factors driving the responsible adoption of AI in Zimbabwean higher education. By integrating five human-centric constructs which are perceived interpretability (PI), algorithm transparency (AT), ethical alignment (EA), AI literacy (AIL) and human oversight (HO) with the classical

Technology Acceptance Model, this research offers a superior explanatory paradigm for the AI era. Although the model explained 62% of the variance in behavioural intention, this explanatory power should not be interpreted as evidence of comprehensive framework validation. Further validation through confirmatory factor analysis, structural equation modelling and independent samples remains necessary.

The findings demonstrate that adoption intentions are primarily driven by a positive user Attitude, which is itself more strongly influenced by the Interpretability of the system than by its functional utility. Furthermore, ethical alignment (EA) and human oversight (HO) emerged as dominant, high-impact predictors, proving that for students in the Global South, the "responsibility" of an AI system is as critical as its technical performance. The model's high explanatory power ($R^2 = 0.62$) confirms that when AI is transparent, fair and under human control, adoption resistance is minimized.

Ultimately, this research concludes that the catalyst for AI adoption in higher education is not algorithmic complexity, but human centricity. To ensure the sustainable and ethical integration of AI, institutions must move beyond "black-box" efficiency toward "explainable-by-design" frameworks. This study provides the empirical roadmap for such a transition, asserting that trust is built at the intersection of understanding, agency and ethical alignment. The findings should be interpreted within the context of Zimbabwean university students. While the results provide useful insights for similar educational environments, broader generalization requires replication among lecturers, administrators and institutions across different cultural and socio-economic contexts. Behavioural intention was used as the outcome variable and may not fully reflect actual responsible AI usage behaviour. Longitudinal studies are needed to examine whether intention translates into responsible adoption practices.

Future research should explore the longitudinal impact of these constructs as AI literacy levels evolve across diverse cultural contexts. Future studies should also include statistical evaluations of common method bias and incorporate control variables such as age, gender, academic discipline, AI usage frequency and AI literacy level.

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