Journal of Education and e-Learning Research
Vol. 13, No. 3, 126-133, 2026
ISSN(E) 2410-9991 / ISSN(P) 2518-0169
DOI: 10.20448/jeelr.v13i3.9326

Understanding student adoption of AI technologies in South African higher education: A value-based adoption model approach

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Abstract

This study investigates the factors influencing artificial intelligence (AI) adoption among students in South African higher education using the Value-Based Adoption Model (VAM). It contributes to existing literature by extending VAM to AI adoption in the South African higher education context. A quantitative research design was employed, and data were collected through a survey administered to 360 students at a selected South African university. The study examined the influence of perceived value, perceived usefulness, perceived enjoyment, perceived risks, and perceived costs on AI adoption. The findings reveal that all five VAM constructs significantly influence AI adoption, with perceived usefulness emerging as the strongest positive predictor ($\beta = 0.209$, $p < 0.001$) and perceived cost as the strongest negative predictor ($\beta = -0.152$, $p = 0.006$). The model explained 17.3% of the variance in AI adoption, while no statistically significant differences were identified across gender or study levels. The study confirms that students engage in value-maximizing decision-making processes when considering AI adoption by balancing perceived benefits against associated sacrifices. These findings provide practical implications for higher education institutions by emphasizing the importance of enhancing the perceived benefits of AI through demonstrated utility and engaging learning experiences, while simultaneously reducing perceived barriers through structured support mechanisms and clear ethical guidelines.

Keywords: Artificial intelligence, Digital literacy, Higher education, South Africa, Technology adoption, Value-based adoption model.

Citation | Funda, V. (2026). Understanding student adoption of AI technologies in South African higher education: A value-based adoption model approach. *Journal of Education and E-Learning Research, 13*(3), 126–133. 10.20448/jeelr.v13i3.9326
History:
Received: 17 June 2025
Revised: 19 May 2026
Accepted: 8 June 2026
Published: 15 September 2026

Publisher: Asian Online Journal Publishing Group

Funding: This study received no specific financial support.
Institutional Review Board Statement: This study was approved by the Institutional Review Board of the University of Fort Hare, South Africa, under protocol number [FUN005-24], dated [4 December 2024]. Informed verbal consent was obtained from all participants, and all data were anonymized to protect participant confidentiality.
Transparency: The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Competing Interests: The author declares that there are no conflicts of interests regarding the publication of this paper.
Disclosure of AI Use: The author used OpenAI's ChatGPT to edit and refine the wording of the Literature Review. All outputs were reviewed and verified by the author.

Contents

Contribution of this paper to the literature
This study contributes to the existing literature by extending the Value-Based Adoption Model (VAM) to AI adoption in South African higher education. The paper's primary contribution is identifying perceived usefulness and perceived cost as the strongest predictors of AI adoption. This study documents students' value-based decision-making regarding AI technologies.

1. Introduction

The rapid advancement of artificial intelligence (AI) technologies has had a transformative impact across various sectors. In education, AI presents both significant opportunities and complex challenges for students, educators, and institutions (Pedro, Subosa, Rivas, & Valverde, 2019; Zhai et al., 2021). In higher education, AI tools, particularly generative AI, are revolutionising teaching, learning, and research by enabling adaptive learning experiences, intelligent tutoring systems, and automated feedback mechanisms. As noted by Chen, Chen, and Lin (2020), these innovations have the potential to improve academic performance, enhance research productivity, and better prepare students for the demands of the modern workforce. Globally, the rapid uptake of AI in education is largely driven by its potential to address long-standing challenges in teaching and learning, such as improving learner engagement, personalising instruction, and enhancing access to knowledge (Alam, 2021; Pedro et al., 2019). The COVID-19 pandemic accelerated this digital transformation as institutions sought to maintain learning continuity through AI-driven platforms and digital tools (Chen, Zou, Xie, Cheng, & Liu, 2022). In the post-pandemic world, educational policymakers and stakeholders increasingly view AI integration as vital for transforming conventional pedagogical approaches and addressing student diversity at scale (Chaudhry & Kazim, 2022).

Despite these benefits, significant challenges have accompanied AI adoption. Concerns have been raised about ethical implications, data privacy, algorithmic bias, and over-dependence on technology (Chassignol, Khoroshavin, Klimova, & Bilyatdinova, 2018). These issues are magnified in contexts marked by stark digital inequalities. In South Africa, the digital divide remains a critical barrier to the equitable adoption of AI in higher education. The country's diverse student population often faces unequal access to digital infrastructure, devices, connectivity, and digital literacy (Baidoo-Anu & Ansah, 2023). These disparities trace historical and socio-economic fault lines that continue to influence educational outcomes.

Although global studies have explored AI integration and acceptance broadly, limited research has examined how students in South African higher education specifically perceive and adopt AI technologies. Existing research often focuses on organizational or institutional perspectives and overlooks the student experience, particularly in environments shaped by infrastructural and socio-economic constraints. This research aims to fill the gap by evaluating the perceptions and experiences of students from the University of Fort Hare in South Africa. To explore these nuanced student perspectives, this study employs the Value-Based Adoption Model (VAM), a theoretical framework that evaluates technology adoption based on users' perceived value. This value includes perceived usefulness, enjoyment, cost, and perceived risk (Shelvia, Prayitno, Kartono, & Sundjaja, 2020). While Kim, Chan, and Gupta (2007) originally developed the VAM to assess technology adoption in organizational contexts, its application to AI adoption in educational settings, especially within the under-researched South African higher education landscape, remains limited.

This study aims to address this gap by investigating how South African university students perceive the value, benefits, enjoyment, cost, and risks of AI adoption. Using the VAM framework, it contributes to understanding technology acceptance among students in digitally unequal contexts, providing both theoretical insights and practical implications for inclusive and equitable AI integration in education.

1.1. Research Aim

The primary aim of this study is to explore, using the Value-Based Adoption Model (VAM) framework, the factors that influence the adoption of AI technologies among students in higher education institutions in South Africa.

1.2. Research Objectives

1. To assess students' perceptions of the value and usefulness of AI technologies for academic and personal growth.
2. To identify the risks and costs associated with AI adoption from students' perspectives.
3. To examine the role of perceived enjoyment in driving AI adoption among higher education students.

This study focuses on South African higher education, which is particularly relevant as the country reforms its education system to address historical inequalities and equip students with skills essential for the Fourth Industrial Revolution (4IR). In doing so, the South African government recognizes the importance of digital technologies embedded in education for transformative innovation in preparing students for the job market. However, the extent to which students adopt AI technologies and the factors influencing this adoption remain poorly understood.

2. Literature Review

2.1. The Value-Based Adoption Model (VAM) Framework

Value-Based Adoption Model (VAM), which was first introduced in the context of mobile internet and mobile commerce, emphasises how individual users' thorough assessments of the advantages and disadvantages of new technologies affect their intentions to adopt them, with a focus on value-maximising decisions (Kim et al., 2007). With the pace at which information technologies are evolving, VAM has been invoked to understand people's acceptance of various technologies, such as AI (Dhiman, Jamwal, & Kumar, 2023). The VAM analyses the perceived value of new services by taking into account the advantages and sacrifices made by customers.

Factors including perceived value (PV), perceived usefulness (PU), perceived enjoyment (PE), and, while being counteracted by the other two factors, the perceived risk (PR) and the perceived costs (PC). The total of the advantages the user receives from the service, plus the respective costs they incur, is known as the perceived value (Kim et al., 2007). According to Kim et al. (2007), perceived value (PV) refers to the overall benefits that one expects to gain from technology usage, academically and personally. Perceived usefulness (PU) relates to the degree to which the person thinks that the use of a certain technology will improve his/her performance in completing a task (Davis, 1989). Perceived enjoyment (PE) is satisfaction/pleasure felt by a user when using a certain technology (Kim, Park, & Ohm, 2017). Perceived risk (PR) and perceived costs (PC) are the barriers or moderators to the adoption of a technology. With respect to PR, concerns are related to data privacy, ethical issues, and technology dependency, whereas with respect to PC, concerns are about the time, effort, and resources consumed in adopting and using technology (Gómez & Vargas, 2012).

VAM has been placed very strongly in technology acceptance modeling and applied amply across fields. For example, Kim et al. (2017) used the VAM to evaluate consumer receptivity to IoT smart home services. The consumers' final decision of adoption was influenced by the perceived benefits of technology, like automation and security, over its perceived harms, like cost and privacy issues. Along the same lines, Rihidima, Abdillah, and Rahimah (2022) applied the Value-based Adoption Model (VAM) to investigate consumer adoption of the "Cash on Delivery" (COD) payment option within e-commerce. It examined trade-offs customers make between potential threats (fraud/non-delivery) and benefits (ease of use and trustworthiness). Such studies demonstrate the academic and practical value of VAMs in mapping technology adoption dynamics, enhancing understanding, and encouraging acceptance of new technologies by the user community.

2.2. Empirical Review

Artificial intelligence (AI) integration in higher education has drawn increasing attention from scholars, with a growing body of research focusing on its impact on teaching, learning, and student outcomes. This section reviews recent empirical studies that explore the adoption of AI in educational settings, particularly through the lens of the Value-Based Adoption Model (VAM), which emphasises perceived value, usefulness, enjoyment, risks, and costs.

Although early foundational work, such as Davis (1989) and Thong (1999), laid the groundwork for technology acceptance theories like the Technology Acceptance Model (TAM), this review focuses on more recent empirical studies that directly address AI adoption in higher education. These earlier studies are acknowledged for introducing core constructs such as perceived usefulness and ease of use, which continue to inform contemporary models of AI acceptance, including VAM. However, the emphasis remains on recent literature that specifically investigates AI technologies in educational contexts.

Wang, Sun, and Chen (2023) conducted a large-scale study in China exploring how university students adopt AI-driven educational platforms. Their findings revealed that perceived enjoyment and perceived usefulness significantly influenced students' willingness to adopt AI tools. In contrast, perceived costs, including time and effort, emerged as notable barriers to adoption. These findings align closely with the VAM framework, reinforcing the need to balance perceived benefits against perceived sacrifices in the decision to engage with AI technologies.

Similarly, Mohamadi, Mujtaba, Le, Doretto, and Adjeroh (2023) examined the use of generative AI tools, such as GPT-3, among students at a U.S. university. Their study found that students who believed these tools enhanced academic performance and personal development demonstrated higher rates of adoption. This perception of added value proved to be a critical predictor, illustrating how institutional endorsement and contextual relevance influence student engagement with AI technologies.

Yin, Goh, and Hu (2024) explored the role of AI chatbots in enhancing student engagement and learning outcomes in university settings. The study revealed that students who perceived chatbots as efficient academic support tools were more likely to adopt them. These findings support the VAM assertion that perceived usefulness and enjoyment significantly shape user acceptance in educational contexts.

In contrast to studies that emphasise benefits, other researchers have examined the perceived risks and ethical concerns associated with AI adoption. Davenport, Guha, Grewal, and Bressgott (2020), through a qualitative study, reported that students appreciated the efficiencies offered by AI but also expressed reservations regarding over-reliance on technology and the ethical boundaries of AI use. Similarly, Chatterjee, Chaudhuri, and Vrontis (2022) focused on digital privacy and moral concerns, identifying these as primary deterrents to adoption, particularly among students with higher digital literacy. Fitria (2021) offered a comparative analysis across several higher education institutions, investigating how institutional infrastructure and faculty support influenced AI adoption. Their study found that students in environments with strong digital ecosystems and faculty involvement were more open to using AI tools. Perceived costs, including time, access, and technical support, significantly influenced adoption behavior, further validating the VAM framework.

In the South African context, Patel and Ragolane (2024) studied the introduction of AI tools in universities. Their findings demonstrated that students recognised the usefulness of AI for academic tasks, especially in enhancing research and critical thinking skills. However, concerns around privacy, ethical usage, and integrity of AI applications remained prominent. These results are consistent with Rihidima et al. (2022), who affirm that judgments of value, risk, and cost are critical to technology adoption decisions within the VAM perspective. Collectively, these studies underscore the relevance of the VAM framework in examining AI adoption among students in higher education. Perceptions of value, enjoyment, cost, and risk consistently emerge as core determinants of adoption. Importantly, the South African context introduces unique challenges such as digital inequality, institutional readiness, and ethical considerations, highlighting the need for context-sensitive strategies to support the equitable integration of AI in education.

2.3. Literature Synthesis

From the studies reviewed, these empirical analyses have consistently shown that the adoption of AI technologies in education is influenced by a complex interplay of factors, including perceived value, perceived usefulness, perceived enjoyment, perceived risks, and perceived costs. Although there have been several studies that concentrated on the beneficial side of AI implementation, the potential benefits for better academic outcomes and workforce preparation, others have also identified the challenges and worries of AI implementation. However, there is a literature gap in terms of research into AI adoption in the South African context, which particularly pertains to diverse institutional environments. This discrepancy calls for locally informed research, like the one here, to give more understanding of the specific difficulties and opportunities South African students face in using AI tools. The results of this research will help build a richer understanding of the use of AI in higher education and assist policy and practice in addressing effective AI implementation.

Furthermore, the interaction among the five constructs of the VAM framework (PV, PU, PE, PR, PC) concerning AI adoption among students has not been adequately articulated or analyzed in one unbroken context. This examination, therefore, is integral to understanding the extent to which AI will be adopted and inclusive by South African universities. Additionally, other studies tend to be quite limited in scope, analyzing either the benefits or barriers of AI adoption. This research aims to alleviate that limitation by offering an integrative analysis of students' perceptions of AI adoption in all these dimensions: value, usefulness, enjoyment, risks, and costs. It is hoped that this will advance discussions on AI adoption in education and provide sound recommendations for policy and practice across South Africa.

3. Research Methodology

This research employs a quantitative approach to examine how students adopt AI technologies in higher education, using the Value-Based Adoption Model (VAM) as the guiding theoretical framework. The study aims to reveal how perceived value, usefulness, enjoyment, risks, and costs impact adoption behavior. A survey-based method was chosen to acquire primary data from a large, heterogeneous population, maximizing representation and generalizability. This aligns with a research body focused on questionnaires investigating technology adoption in educational contexts, as referenced by (Wang et al., 2023). The quantitative aspect allows for statistical testing of most VAM constructs to determine their significant correlation with students' adoption intentions.

The study was conducted at the University of Fort Hare in South Africa, targeting both undergraduate and postgraduate students to capture a broad range of perspectives and experiences. Convenience sampling was used. The sample size was determined using the Z-score equation, commonly applied for estimating proportions within a population. The final calculation yielded a sample size of 384 respondents, which is sufficient for substantial statistical analysis; 360 responses were received in our study.

Data collection was conducted via an online platform using a well-structured questionnaire disseminated through email and Blackboard learning management system channels. The questionnaire was designed to be short and straightforward, with clear instructions for each section. Demographics were included first, followed by items rated on a Likert scale based on AI perception adoption across the five VAM constructs. Online data collection is preferred due to its low cost and convenience, especially in the context of the post-pandemic 'new normal' environment (Evans & Mathur, 2005). The questionnaire was piloted with a few students beforehand to assess clarity and reliability. Reminders sent to reduce non-respondents were among the strategies used to improve response rates.

Data analysis was conducted using statistical software (SPSS) to perform both descriptive and inferential analyses. Frequency and mean descriptive statistics summarized respondents' perceptions. For inferential statistics, a multi-stage analytical approach was employed. First, one-way ANOVA tests examined differences in AI adoption across demographic variables such as gender and study level. Next, Pearson correlation analyses assessed the bivariate relationships between the five VAM constructs (Perceived Value, Perceived Usefulness, Perceived Enjoyment, Perceived Risk, and Perceived Cost) and AI adoption. Finally, multiple linear regression analysis determined the predictive power of the VAM constructs on AI adoption intentions, identifying which factors significantly influenced students' decisions to adopt AI technologies in their academic pursuits.

Ethics clearance reference number FUN005-24 was obtained from the research ethics committees of the case institution. Informed consent was obtained from all subjects online, guaranteeing confidentiality and anonymity. Survey design excluded intrusive questions and allowed participants to withdraw at any point.

4. Results and Discussion

4.1. Demographic Profile of Respondents

The study collected data from 360 students at the University of Fort Hare. As shown in Table 1, the gender distribution was nearly equal, with 50.3% female (n=181) and 49.7% male (n=179). The age distribution was relatively balanced across four categories: 24.4% aged 18-22 years (n=88), 23.9% aged 23-26 years (n=86), 25.0% aged 27-32 years (n=90), and 26.7% aged over 32 years (n=96).

Table 1. Respondent distribution.

Demographic variable		Frequency	Percent
Gender	Female	181	50.3
	Male	179	49.7
	Total	360	100.0
Age	18-22	88	24.4
	23-26	86	23.9
	27-32	90	25.0
	>32	96	26.7
	Total	360	100.0
Study_Level	Honours	55	15.3
	Masters	59	16.4
	PhD	59	16.4
	Undergrad first year	46	12.8
	Undergrad second year	66	18.3
	Undergrad third year	75	20.8
	Total	360	100.0

In terms of academic level, the sample included representation from all study levels: undergraduate first-year (12.8%, n=46), undergraduate second-year (18.3%, n=66), undergraduate third-year (20.8%, n=75), honours (15.3%, n=55), master's (16.4%, n=59), and doctoral students (16.4%, n=59).

4.2. Demographic Factors and AI Adoption

The study examined the relationship between demographic variables and students' adoption of AI technologies. In Tables 2 and 3, the measure labeled as "Eta" refers to Eta-squared (η^2), a standard effect size statistic used in ANOVA to indicate the proportion of variance in the dependent variable that can be attributed to the independent variable. Eta-squared provides a useful complement to the F-test by illustrating the practical significance of observed differences, regardless of statistical significance. In Table 2, the analysis of AI adoption across gender groups revealed no significant differences (F=0.406, p=0.524), with both male and female students demonstrating similar adoption patterns. This finding suggests that gender is not a determining factor in AI adoption among South African higher education students.

Table 2. AI adoption and gender.

Gender	N	% of total sum	Std. deviation	F	Sig.	Eta-squared (η^2)
Female	181	50.3%	0.501	0.406	0.524	0.034
Male	179	49.7%	0.499			
Total	360	100.0%	0.500			

Similarly, the analysis of AI adoption across different study levels (Table 3) found no statistically significant differences (F=0.598, p=0.701). This indicates that students' academic progression level does not significantly influence their likelihood to adopt AI technologies, contradicting the assumption that advanced students might be more inclined to embrace emerging technologies.

Table 3. AI adoption and study level.

Study_level	N	% of Total sum	Std. deviation	F	Sig.	Eta-squared (η^2)
Honours	55	15.5%	0.502	0.598	0.701	0.092
Masters	59	16.6%	0.502			
PhD	59	16.2%	0.504			
Undergrad first year	46	11.8%	0.497			
Undergrad second year	66	18.8%	0.500			
Undergrad third year	75	21.1%	0.501			
Total	360	100.0%	0.500			

4.3. Correlation Analysis of VAM Constructs and AI Adoption

The correlation analysis (Table 4) revealed significant relationships between all five VAM constructs and AI adoption. Perceived Usefulness (PU) demonstrated the strongest positive correlation with AI adoption (r=0.325, p<0.001), followed by Perceived Value (PV) (r=0.298, p<0.001) and Perceived Enjoyment (PE) (r=0.276, p<0.001). These positive correlations indicate that students who perceive AI technologies as useful, valuable, and enjoyable are more likely to adopt them.

Table 4. Correlations.

Correlations	Measure	PV	PU	PE	PR	PC	AI_adoption
PV	Pearson Correlation	1					
	Sig. (2-tailed)						
PU	Pearson Correlation	0.315**	1				
	Sig. (2-tailed)	0.001					
PE	Pearson Correlation	0.287**	0.392**	1			
	Sig. (2-tailed)	0.000	0.001				
PR	Pearson Correlation	-0.143**	-0.167**	-0.121**	1		
	Sig. (2-tailed)	0.007	0.002	0.022			
PC	Pearson Correlation	-0.176**	-0.217**	-0.143**	0.389**	1	
	Sig. (2-tailed)	0.001	0.001	0.007	0.001		
AI_Adoption	Pearson Correlation	0.298**	0.325**	0.276**	-0.189**	-0.243**	1
	Sig. (2-tailed)	0.001	0.001	0.001	0.001	0.001	

Note: ** Correlation is significant at the 0.01 level (2-tailed).

Conversely, Perceived Cost (PC) showed a significant negative correlation with AI adoption (r=-0.243, p<0.001), as did Perceived Risk (PR) (r=-0.189, p<0.001). These inverse relationships suggest that students who perceive greater costs (time, effort, resources) and risks (privacy concerns, ethical issues, technological dependence) associated with AI technologies are less likely to adopt them.

The correlation matrix also revealed significant inter-relationships among the VAM constructs. The three benefit-related constructs (PV, PU, and PE) showed moderate positive correlations with each other, with the strongest relationship observed between PU and PE (r=0.392, p<0.001). Similarly, the two barrier-related constructs (PR and PC) displayed a moderate positive correlation (r=0.389, p<0.001). Additionally, significant negative correlations emerged between the benefit and barrier constructs, with the strongest inverse relationship between PU and PC (r=-0.217, p<0.001).

4.4. Multiple Regression Analysis

The multiple regression analysis (Tables 5-7) examined the combined influence of the five VAM constructs on AI adoption. The overall model was statistically significant (F=14.792, p<0.001), explaining 17.3% of the variance in AI adoption (R^2=0.173, adjusted R^2=0.162). This indicates that the VAM framework effectively captures a significant portion of the factors influencing students' AI adoption decisions.

Table 5. Regression model summary.

Model	R	R square	Adjusted R-squared	Std. error of the estimate
1	0.416[a]	0.173	0.162	0.458

Note: [a] Predictors: (Constant), PC, PU, PV, PE, PR.

Table 6. ANOVA[a].

Model	Sum of squares	df	Mean square	F	Sig.
Regression	15.531	5	3.106	14.792	0.001[b]
Residual	74.244	354	0.210		
Total	89.775	359			

Note: [a]Dependent Variable: AI_Adoption.
[b] Predictors: (Constant), PC, PU, PV, PE, PR.

All five VAM constructs emerged as significant predictors in the regression model. Among the positive predictors, Perceived Usefulness had the strongest effect (β=0.209, $p<0.001$), followed by Perceived Enjoyment (β=0.189, $p<0.001$) and Perceived Value (β=0.142, $p=0.014$). Among the negative predictors, Perceived Cost had a stronger effect (β=-0.152, $p=0.006$) than Perceived Risk (β=-0.112, $p=0.036$).

Table 7. Coefficients

Model	Unstandardised coefficients	Std. error	Standardised coefficients	t	Sig.
	B		Beta		
(Constant)	0.226	0.429	N/A	0.527	0.599
PV	0.183	0.074	0.142	2.472	0.014
PU	0.212	0.058	0.209	3.655	0.001
PE	0.156	0.039	0.189	4.000	0.001
PR	-0.124	0.059	-0.112	-2.102	0.036
PC	-0.169	0.061	-0.152	-2.770	0.006

These findings demonstrate that all five VAM constructs contribute uniquely to explaining AI adoption, with utility and enjoyment factors having the strongest positive influence and cost factors having the strongest negative influence. The standardized coefficients suggest that increasing students' perceptions of AI usefulness and enjoyment while decreasing their perceptions of costs associated with AI adoption would be the most effective strategy for promoting AI adoption in higher education.

4.5. Discussion

4.5.1. Understanding AI Adoption through the VAM Framework

The findings of this study provide empirical support for the applicability of the Value-Based Adoption Model in understanding students' adoption of AI technologies in South African higher education. All five VAM constructs significantly predicted AI adoption, confirming that students engage in value-maximising decision-making when considering whether to adopt AI technologies. This aligns with Kim et al. (2007) conceptualisation of technology adoption as a cognitive trade-off between benefits and sacrifices. The extent to which the positive relationships between all constructs (e.g., PV, PU, PE) correlate with AI adoption suggests that students are, arguably, mostly influenced by perceived usefulness and perceived enjoyment. This finding parallels the study by Wang et al. (2023), which reported that PU and enjoyment could significantly predict AI adoption by students in China. Evidence that perceived risk and cost, being deterrents to AI adoption, relate negatively would also be in line with the findings of Chatterjee et al. (2022) on privacy and ethical concerns deterring AI use.

4.5.2. The Primacy of Perceived Usefulness

Perceived Usefulness emerged as the best predictor of AI use, which implies that considerations mainly determine students to adopt AI technologies from functional perspectives. This resonates with the view of the TAM that indicated perceived usefulness has significant gaps as an important predictor of adopting new technologies (Davis, 1989). In terms of higher education, students primarily want AI technologies for their features to improve their academic performance or research capabilities and productivity, as can be observed in the questionnaire PU6-PU10 items. This further showed how strong Perceived Usefulness could play toward ensuring that students know about practical applications and benefits of AI technologies in education. Through addressing academic challenges, enhancing learning outcomes, and improving productivity, students would adopt an AI tool whenever it clearly proved its utility. This matches what Yin et al. (2024) found: students were more inclined to adopt AI chatbots when they perceived them as effective tools for accomplishing academic tasks.

4.5.3. The Role of Hedonic Motivation

Perceived enjoyment emerged as the second strongest positive predictor, highlighting the significance of hedonic motivation in AI adoption. Beyond utility, students value the inherent satisfaction, interest, and enjoyment derived from engaging with AI technologies. This finding extends traditional technology adoption models that focus primarily on utilitarian values by emphasizing the importance of pleasure and intrinsic reward in driving technology adoption. The strong role of perceived enjoyment implies a theoretical ideal to model any AI experience so that it may galvanize advances in its adoption. Higher education institutions need to have newer ideas on how to (re)design AI tools for students who will seek not only functional utility but also interactivity and emotional satisfaction. This is an applicable ruling as opposed to Wang et al. (2023), who found that satisfaction strongly increases students' acceptance of AI-based teaching platforms.

4.5.4. Barrier Factors: Costs and Risks

The significant negative effects of Perceived Cost and Perceived Risk highlight the barriers to AI adoption among students. Perceived Cost emerged as the strongest barrier, suggesting that the time, effort, and resources required to develop AI literacy represent significant obstacles. This aligns with Fitria's (2021) finding that resource constraints influenced students' willingness to adopt AI tools. Educational institutions should address these barriers by providing structured support, accessible learning resources, and clear pathways for developing AI literacy without overwhelming students' existing academic commitments. Perceived Risk also showed statistically significant disinclination towards student AI adoption. It included concerns for privacy, technological dependency, and ethical implications. This finding is also in tune with the results of existing qualitative reports by Davenport et al. (2020), raising ethical concerns and fear of becoming too dependent on the technology amongst students to thwart AI uptake. Patel and Ragolane (2024), in their study on higher education institutions in South Africa, highlighted the plight against the aspects of privacy and ethics in the adoption of AI. Clearly, addressing these issues through transparent data practices, ethical guidelines, and critically debated subjects on the ethical use of AI would alleviate the risks perceived.

4.5.5. The Insignificance of Demographic Factors

The lack of significant differences in AI adoption across gender and study levels challenges conventional assumptions about technology adoption patterns. With no gender imbalance, the digital gender division in higher education seems to be on the verge of vanishing, with males and females showing equal inclinations toward AI use. This counters conventional views in technology adoption literature, where gender has often been found to determine whether technology is accepted. Further, no significant differences across education levels confirm that AI adoption does not directly correspond with student progress or prior expertise. The implications suggest that AI is seen as relating in some way and open to consideration within all higher educational levels, from first-year to doctoral candidates. It is therefore important that Higher Education Institutions no longer harbour general assumptions about their respective student bodies acting as principal recipients of AI and rather start to address more universal impeding factors to enhance adoption.

4.5.6. Theoretical and Practical Implications

This study extends the scope of the VAM to AI technology adoption in higher education, demonstrating that this model can have broader applicability even for non-commercial technologies. The empirical validation of the VAM in South African higher education will contribute to the growing body of literature on technology adoption in educational contexts and provide a theoretical basis for understanding the complex decision-making processes students face when adopting AI. The relationship between the constructs of VAM reflects a complex adoption ecology, with benefit and barrier factors interacting dynamically. For example, students perceiving high usefulness in AI technologies are likely less sensitive to the associated costs. Similarly, an association exists between Perceived Risk and Perceived Cost, indicating reinforcement between these barrier factors that may create compounded resistance to adoption. This underscores the need for integrated approaches to address the multi-factor phenomena involved in adoption.

The findings from this research have wide implications practically in higher education institutions, as well as educators and policymakers interested in driving the AI literacy and adoption agenda among students. First, the degree of influence of Perceived Usefulness is such that it would warrant initiatives demonstrating the practical applications and gains from AI technologies at the academic level. Such workshops, tutorials, and other resource-enabling instruments would emphasize how AI tools may improve research capacity, educational undertaking, and future employability. Second, the significant role of Perceived Enjoyment underscores the need for interesting, enjoyable, and intrinsically rewarding AI learning experiences. Institutions offering courses should provide user interfaces that enhance student interest and enjoyment in AI technologies by using engaging, interactive learning activities and opportunities for creative exploration. This includes game-like learning experiences, teamwork on projects, and opportunities for individualized discovery.

5. Conclusion

The study applied the Value-Based Adoption Model (VAM) to explore key factors shaping students' adoption of AI technologies at a South African higher education institution. The findings demonstrate that students engage in value-maximizing decision-making when considering AI adoption, weighing perceived benefits (value, usefulness, enjoyment) against perceived sacrifices (risks, costs). All five VAM constructs significantly predicted AI adoption, with Perceived Usefulness emerging as the strongest positive predictor and Perceived Cost as the strongest negative predictor.

The absence of significant demographic differences in AI adoption suggests that the benefits and barriers of AI technologies transcend traditional demographic boundaries, affecting students across gender and academic progression levels similarly. The results offer important implications for higher education institutions aiming to promote AI literacy and adoption among students. By enhancing perceived benefits through clear demonstration of utility and engaging learning experiences, while addressing perceived barriers through structured support and ethical guidelines, institutions can create more favorable conditions for AI adoption. Ultimately, fostering balanced and informed AI adoption could equip students with the digital competencies and critical perspectives necessary to thrive in an increasingly AI-integrated professional landscape.

6. Limitations and Future Research Directions

This study is subject to several limitations that present avenues for future investigation. Firstly, its cross-sectional design reflects students' perceptions at a specific moment, thereby constraining insights into the temporal dynamics of AI adoption. To address this, future studies could adopt longitudinal approaches to explore how students' attitudes and usage behaviors develop over time, particularly in relation to their academic progression and the ongoing advancement of AI technologies.

Second, while the regression model explained a significant portion of the variance in AI adoption (17.3%), a substantial amount remains unexplained. This suggests that additional factors beyond the VAM constructs may influence students' AI adoption decisions. Future research could incorporate additional constructs such as social influence, facilitating conditions, and technical self-efficacy to develop more comprehensive models of AI adoption in educational contexts.

Third, the use of self-reported measures may be subject to social desirability bias, especially regarding students' reported use of AI tools. To mitigate this limitation, future research could incorporate objective usage data or qualitative interviews, providing a more comprehensive and accurate portrayal of students' actual interactions with AI technologies.

Fourth, while the study included participants from a single South African university, the findings may not generalize to all higher education contexts within South Africa or globally. Future research could extend this investigation to a broader range of institutions, including technical colleges, private universities, and comprehensive universities, to provide a more comprehensive understanding of AI adoption across diverse educational contexts.

Finally, this study focused on AI adoption broadly, without distinguishing between different types of AI tools or applications. Future research could examine adoption patterns for specific AI technologies (e.g., generative AI, intelligent tutoring systems, automated feedback tools) to provide more targeted insights for educational technology development and implementation.

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