

EXPLORING STUDENTS' PERCEPTION OF ARTIFICIAL INTELLIGENCE ADOPTION IN RURAL HIGHER EDUCATION IN PAKISTAN

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DOI: <https://doi.org/10.5281/zenodo.17906311>

Keywords

AI in higher education, AI Adoption in higher education, AI-enhanced learning, Students' perception of AI in education, AI Adoption in developing countries.

Article History

Received: 11 October 2025

Accepted: 21 November 2025

Published: 12 December 2025

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Abstract

The integration of AI in education, specifically in higher learning institutions, is especially prevalent in low-resource countries and rural settings is a less explored area. This study aims to explore the perceived adoption of AI tools in rural higher learning institutions in Pakistan. The study was conducted at a rural university, the University of Modern Sciences Tando Mohammad Khan, Pakistan. The study applied a survey based quantitative methodology and data were gathered on aspects of context awareness, hedonic motivation, self-directed learning, algorithmic transparency, trust, intelligent adaptive content, perceived intelligence, social influence, facilitating conditions, and behavioral intentions from students to investigate their perceived adoption of AI in higher education. Findings indicate that students show willingness toward AI-assisted learning, especially for personalized learning support, explicit recommendation, and learner-managed learning opportunities. However, challenges to effective AI integration persist in terms of infrastructural limitations, insufficient technical support, and restricted access to resources. The findings suggest infrastructural improvements, capacity building, and learner-focused system design.

INTRODUCTION

The technological advancements developed during the last century greatly impacted society [1]. In the field of education, the digitalization of resources and the recent application of AI technologies are changing both pedagogy and learning. Nevertheless, the

distribution of change across different educational systems and geographical areas is not uniform [2]. Even with substantial investments in equipment and connectivity, the gains are uneven in educational effectiveness, especially in low-resourced countries

where systemic and contextual barriers delay the assimilation of educational technologies. [3].

In Pakistan, the promise and complexity shaping the higher education sector is the rapid adoption of technology. Students engaging with digital tools for collaborative and experiential learning need to grasp the emerging pedagogical models [4]. Despite the growth of enrolments and the establishment of institutional networks since the late twentieth century, the fundamental structure of teaching, assessment, and governance continues to need extensive reform [5]. Educational approaches in different regions of the world are increasingly converging towards multifaceted, situated, and problem-oriented learning [6]. Similarly, the growing importance of AI in higher education will require more maturity in the strategic integration of AI in the institutional and pedagogical structures [7].

The growing use of smartphones and the popularity of messaging apps have greatly accelerated the integration of AI chatbot technology in consumer and business uses. Many industries, such as finance, retail, and supply chain logistics, have already deployed the technology widely, but the education sector, particularly in developing and rural settings, such as universities in Pakistan, represents a new point in the systemic improvement of AI chat technology adoption. The AI chatbot technology offers a seamless and effective integration of a range of communicative functions, teaching delivery, management of educational operations, and instructional discourse between learners and educators. When deployed as a targeted engagement tool, such systems enable educational institutions to work around a number of persistent structural tensions and enable personalized learning at scale.

Recent studies have concentrated on the uses of AI chatbots in teaching practices and their possible uses for academic performance enhancement and assisting students outside the classroom [8]. While this is going on, the integration of AI in Education is revolutionizing and streamlining the development and enhancement of sophisticated instruments that foster and improve deep Learning, actions, administration, operational frameworks, Governance, and overall Human Resource Development [9]. Despite this, there remains a significant backlog in the incorporation of AI in teaching and learning, and the

educational sector, including Ethical Issues, Data Privacy, Teacher Training, and the lack of comprehensive frameworks on Educational Objectives and Training [10]. The Effective and Ethical Use of AI Educational Tools is contrary to these needs [11].

This study intends to explore the dynamics of the barriers to the adoption of AI-enhanced learning systems in rural universities of developing countries, focusing on Pakistan as a case study.

Research Objectives

This investigation is guided by several objectives outlined to best meet study aims:

1. To investigate challenges and enabling aspects of students' perceptions of AI use within higher learning institutions focused on rural development.
2. To explore students' perceptions and their intent to adopt AI-enhanced learning systems at rural universities.

Research Questions

1. What barriers and facilitating factors influence students' attitudes toward AI adoption in rural higher educational institutions in developing countries?
2. What is the influence of the students' attitudes on the intention to adopt AI-integrated learning systems in these institutions?

Scope of the Study

The present study is focused on AI-integrated learning systems in rural higher educational institutions of Pakistan, particularly for university students in the fields of Medicine, Computer Science/Information Technology, Pharmacy, Allied Health Sciences, and Medical Laboratory Technology. The study analyzes students' perception and behavioral intention, the drivers behind the adoption of AI learning technologies. In contrast to the majority of previous research, this study includes AI-specific constructs of algorithmic trust, algorithmic transparency, perceived intelligence, and intelligent adaptive content, in addition to the conventional constructs of hedonic motivation, self-directed learning, and contextual awareness, which focus on learning adaptivity to the user's situation.

This study focuses on students who have the opportunity to examine digital learning materials

while investigating the engagement and interaction perceptions with AI tools in educationally limited and rural settings. This scholarship will assist in addressing the existing literature gaps on the use of AI in higher education and help in the development of adaptive, transparent, and student-centered AI learning systems.

LITERATURE REVIEW

Practical Experiences in AI Adoption

The performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value are key indicators to understand students' behavioral intention and actual technology use in various educational settings [12]. In rural higher education contexts, the lack of AI-enabled learning systems is primarily due to infrastructural challenges, including unreliable internet, hardware insufficiencies, and inconsistent electricity [13]. These challenges are most often exacerbated by a lack of institutional funding and administrative capacity to implement and maintain AI systems [14]. Digital literacy and limited technical training, and low confidence, coupled with little to no support, can prevent people from properly engaging with and working with AI-powered systems [15]. In systems with little to no resources and external initiatives aimed at developing systems, AI technology becomes increasingly difficult to adopt [16]. Even more obstacles arise with cultural skepticism, ethical issues about the use of technology, and the potential for privacy violations, including algorithmic bias, unequal access, and the digital divide [17]. Educators lacking structured professional development will more often than not use AI non-strategically and minimally [18]. On the other hand, engagement and adoption of technology are greatly improved with targeted actions, such as student training, collaborative initiatives, and highly accessible AI tools [19], [20]. Most of the literature agrees that for AI to have any real impact, the approach must be systemic and include infrastructure, policies, and resource support [21]. This explains the strong focus on the students' behavioral intention and engagement with AI technology in the literature, as most developing countries focus on under-resourced, rural educational environments.

Research Gap

There is a growing interest in the role of AI in educational practices in the world. However, comparatively little research has explored the reasons for the acceptance and use of AI-enhanced learning systems, especially in countries such as Pakistan. The Unified Theory of Acceptance and Use of Technology 2 has offered a more comprehensive approach to understanding the acceptance and use of technology. However, studies applying this theory to AI-enhanced pervasive learning contexts are almost non-existent. There is little theoretical and definitional clarity around AI-related constructs such as algorithmic trust and transparency, perceived intelligence, intelligent adaptive content, and prior AI experience, all of which are critical to understanding user engagement and interaction with AI tools. There is little research that integrates hedonic motivation, self-directed learning, and context awareness to examine students' behavioral intention in an AI educational context. The absence of studies in these areas indicates an urgent need for context-appropriate research on the interrelated and AI technology adoption in educational practices.

MATERIALS AND METHODS

Research Design

This study employed the quantitative approach to investigate how students perceive, use, and intend to use AI-enhanced learning systems, focusing on rural higher education. Data were collected as part of a cross-sectional quantitative study. This methodology serves to assess attitudes, adoption factors, and user experience with the AI learning systems, as well as the patterns of behavior to be adapted for statistical learning [22,23,24,25].

Questionnaire Pre-test and Response Rate

- i) Expert review: - Before data collection, the study had the questionnaire reviewed by 5 field experts to ensure its clarity and relevance.
- ii) Reliability analysis: - A pilot study at the University of Modern Sciences, Tando Mohammad Khan, was conducted to ensure the questionnaire's reliability before actual data collection for the study.

Data Collection

We then distributed the online questionnaire to 200 students and received 82 valid responses, a response rate of 41%. The collected responses were considered sufficient for subsequent statistical analysis to investigate higher educational students' perception of AI adoption in education.

Population and Sample

The participants were students from different disciplines at the University of Modern Sciences, Tando Muhammad Khan, including the medical program (MBBS), Computer Science / Information Technology, Pharmacy, Allied Health Sciences, and Medical Laboratory Technology. For this purpose, 200 students were contacted and, through internal advertising, 82 questionnaires were returned fully and correctly completed. The sampling technique used was purposive sampling, which is most suitable for exploratory research. Participation was completely voluntary, and total adherence to ethical standards of confidentiality, as well as informed consent, was guaranteed and maintained.

Survey Instrument

The primary means of data collection was a structured online questionnaire, which was based on previous literature. The questionnaire was based on the ten facets of AI adoption: Context Awareness, Hedonic Motivation, Self-Directed Learning, Algorithmic Transparency, Algorithmic Trust, Intelligent Adaptive Content, Perceived Intelligence, Social Influence, Facilitating Conditions, and Behavioral Intention. Reportedly, three items of a seven-point Likert scale (1 = 'Strongly Disagree', 7 = 'Strongly Agree') were used for each of the facets of the AI adoption [26].

Data Collection Procedure

The online survey was conducted on Google Forms, which allowed the collection of student responses at their convenience. Participants were informed about the objective of the study, the voluntary nature of their participation, and the precautions that had been taken to preserve their anonymity. Participants documented informed consent electronically before commencing the survey. In order to obtain a sufficient number of completed surveys, non-participating students were sent reminders to complete the forms. A total of 82 valid responses were obtained to conduct the study.

Data Processing and Statistical Analysis

This research survey results in Microsoft Excel and a prepared statistical analysis in Google Colab. For data analysis in Google Colab. Python and its associated libraries: data processing and analysis were done using Pandas and NumPy, data visualization with Matplotlib and Seaborn, and statistical analysis was done with SciPy/Stats models [27,28]. Descriptive statistics were generated to summarize key variables and demographic data, and calculated means, standard deviations, frequencies, and percentages. Cronbach's alpha was estimated for each construct in order to assess the internal consistency. To assess the assumptions for the use of parametric statistical methods, the values of skewness and kurtosis were calculated and confirmed normality.

RESULTS

Reliability Analysis

The internal consistency of each construct was measured by Cronbach's alpha. All constructs had a value above the minimum threshold considered acceptable, with $\alpha = 0.7$, at least acceptable.

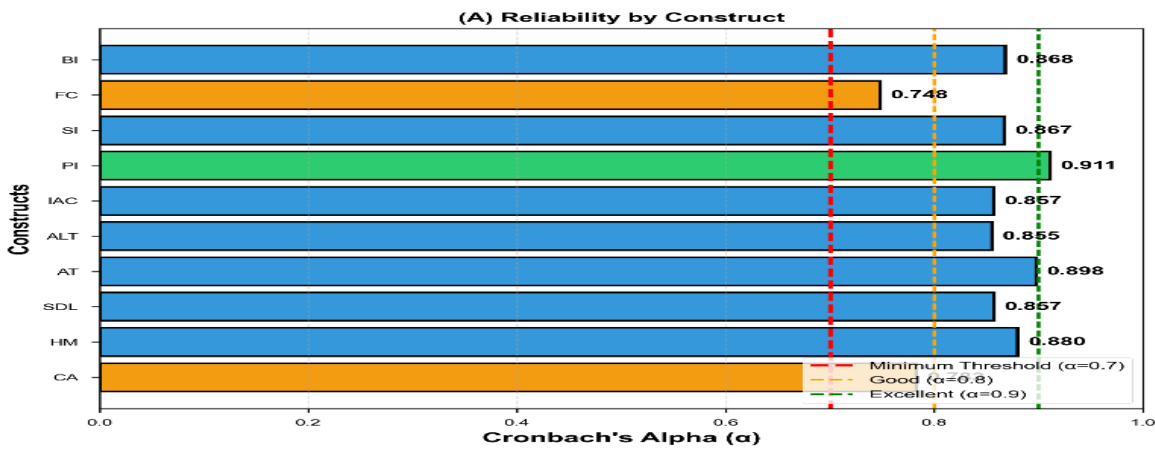


Figure 1. Reliability by Construct

Most of the constructs showed good internal consistency, $\alpha \geq 0.8$, or excellent, $\alpha \geq 0.9$, whereas

only two, Context Awareness and Facilitating Condition, were classified as acceptable.

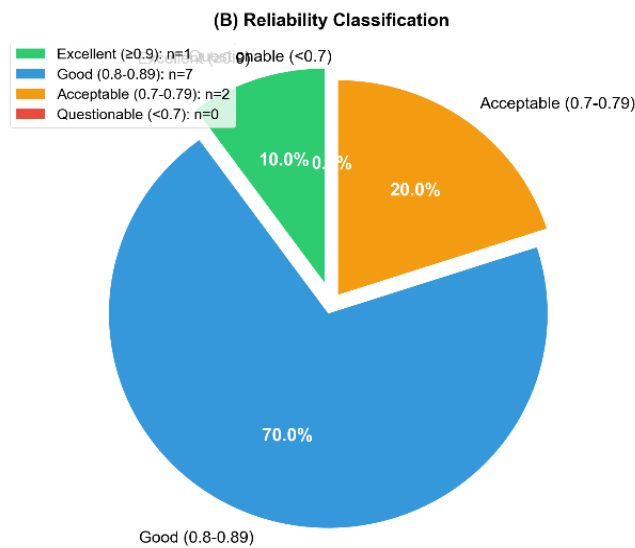


Figure 2. Cronbach's alpha and reliability of constructs

This reliability distribution confirms that the items demonstrated solid enough reliability to support further sophisticated analyses.

Demographics

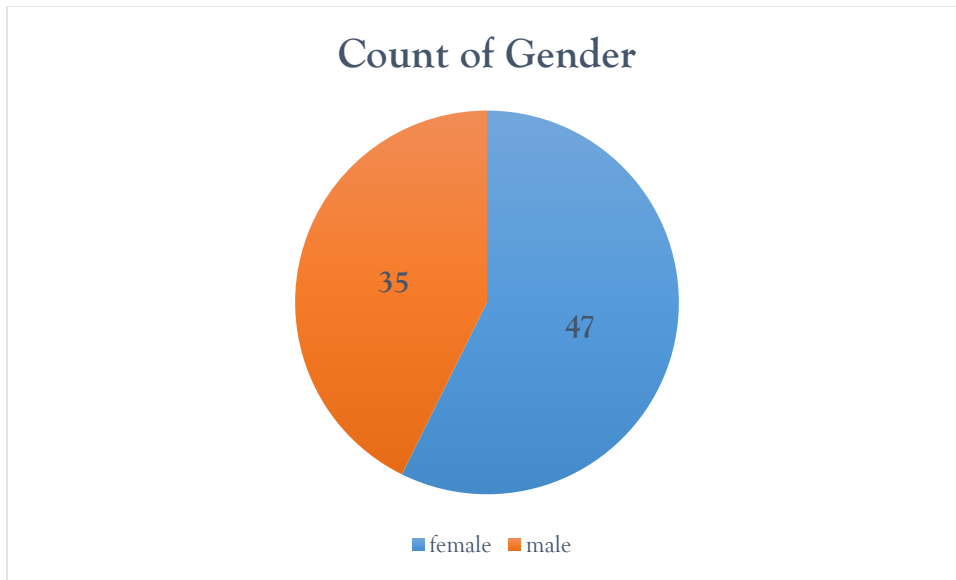


Figure 3. Gender Distribution

Of 82 responding students, over half were female (57.32%), and 42.68% were male.

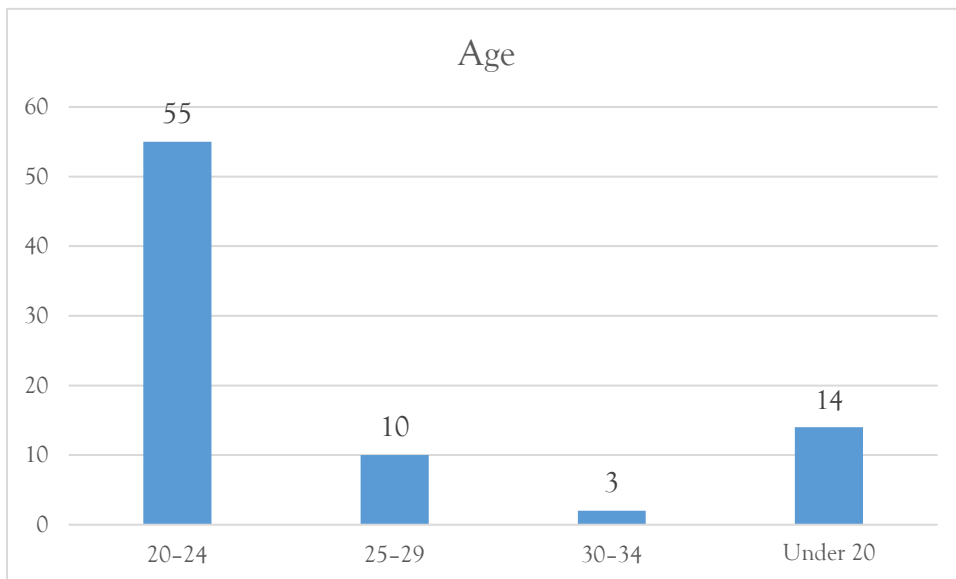


Figure 4. Age distribution

Most students were in the age group 20-24 years (67.07%), followed by those under 20 years (17.07%), 25-29 years (12.20%), and 30-34 years (3.66%).

Academic Programs

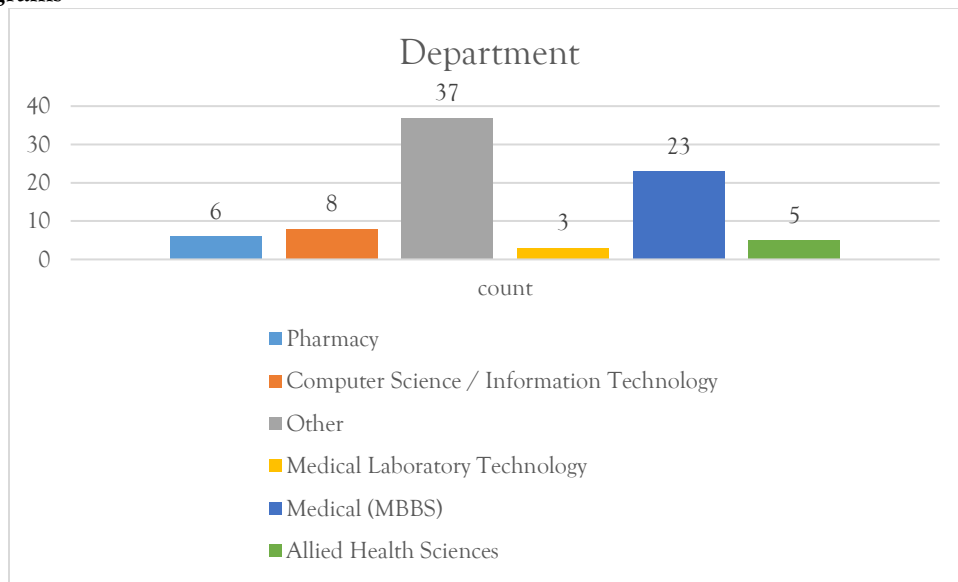


Figure 5. Academic Disciplines Distributions

In terms of specific programs, Medical (MBBS) students were 28.05%, 9.76% were in Computer Science/IT, 7.32% in Pharmacy, 6.10% in Allied

Health Sciences, 3.66% Medical Laboratory Technology, while the majority, 45.12% of the respondents were in the category of 'Others'.

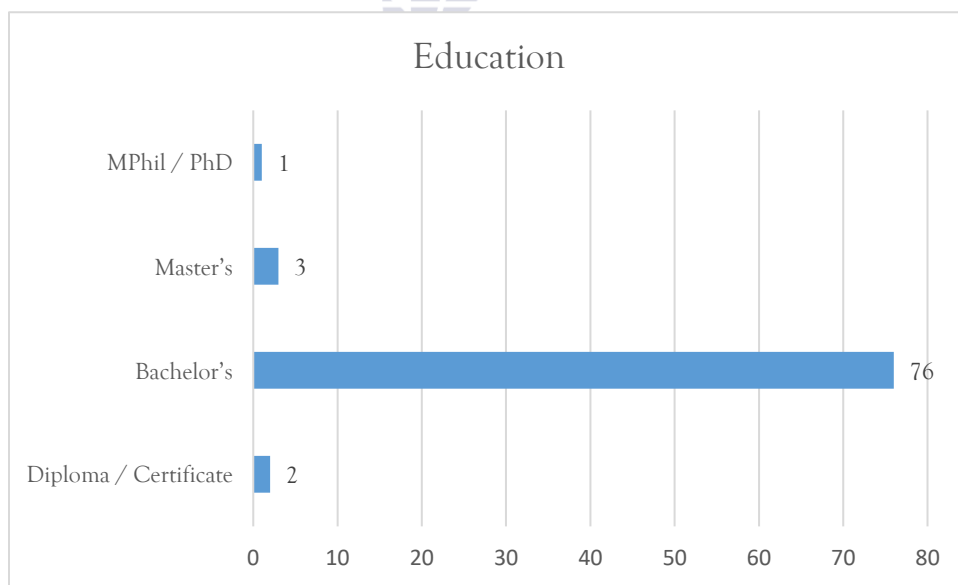


Figure 6. Educational Level Distributions

The respondents' distribution in different academic programs reveals that the largest educational group was students of Bachelor's programs (92.68%).

Experiences with AI Tools

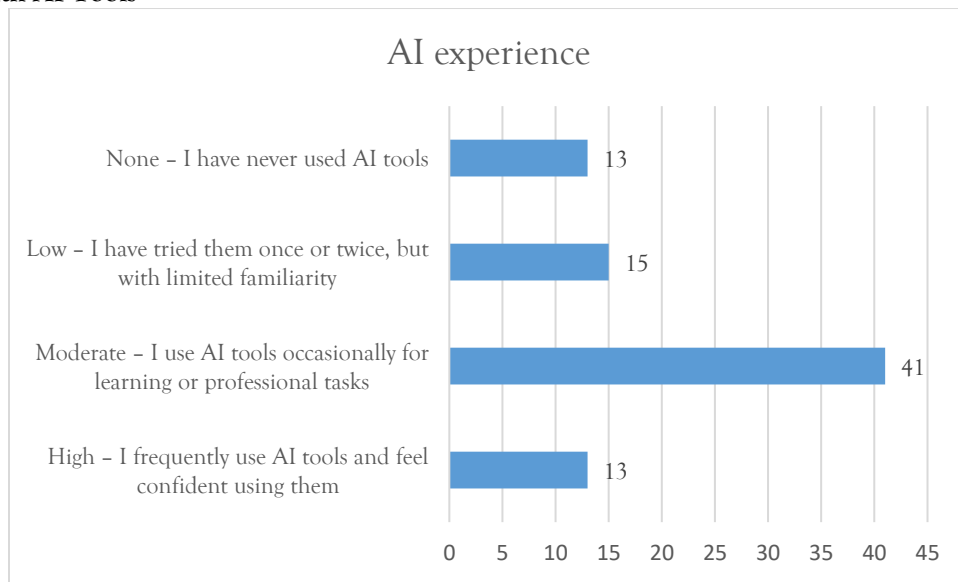


Figure 7. AI Experience Statistics

The analysis of students' years of experience with the AI-powered learning tools revealed that 50% of the respondents were moderately experienced, while 18.29% were less experienced, and 15.85% each were more experienced or non-experienced in the

use of such educational tools. The different levels of experience are likely to impact their engagement and behavioral intentions in the use of AI tools in education.



Descriptive Statistics

Table 1. Descriptive statistics for the measured constructs.

Construct	Items	N	Mean	SD
CA	3	82	5.171	1.589
HM	3	82	5.602	1.436
SDL	3	82	5.309	1.634
AT	3	82	5.402	1.504
ALT	3	82	5.244	1.519
IAC	3	82	5.305	1.454
PI	3	82	5.496	1.439
SI	3	82	5.142	1.558
FC	3	82	5.138	1.709
BI	3	82	5.394	1.458

In each of the constructs, the overall mean was greater than 5.0 on a scale of 7, reflecting positive assessment of perceptions related to AI-enhanced learning. All constructs yielded standard deviation

from 1.436 to 1.709, which also fell within a moderate/acceptable range.

Normality Statistics

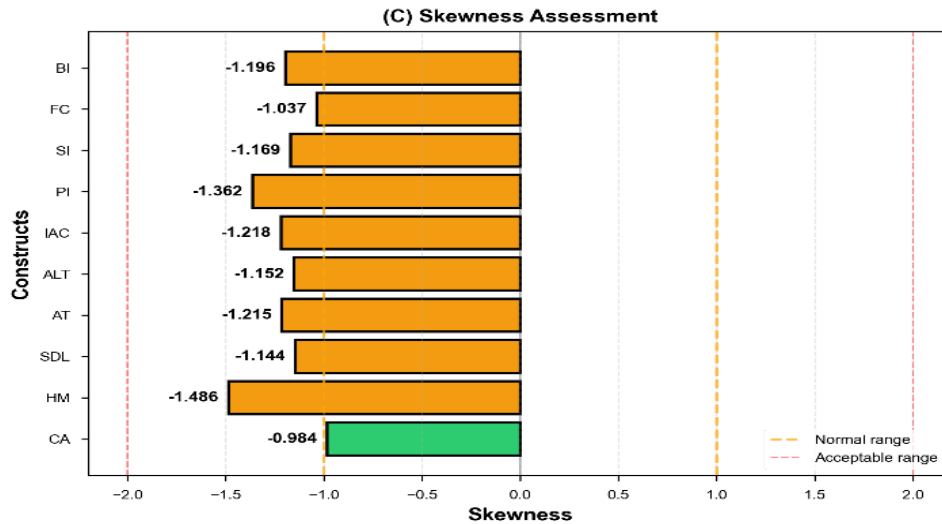


Figure 8. Skewness Assessment for the measured constructs.

The skewness shows that all constructs of the study fall within the acceptable skewness range (-2 to +2). All constructs show negative skewness (-0.984 to -

1.486). This suggests that participants choose higher values on Likert-scale items. They have positively perceived the AI-based learning.

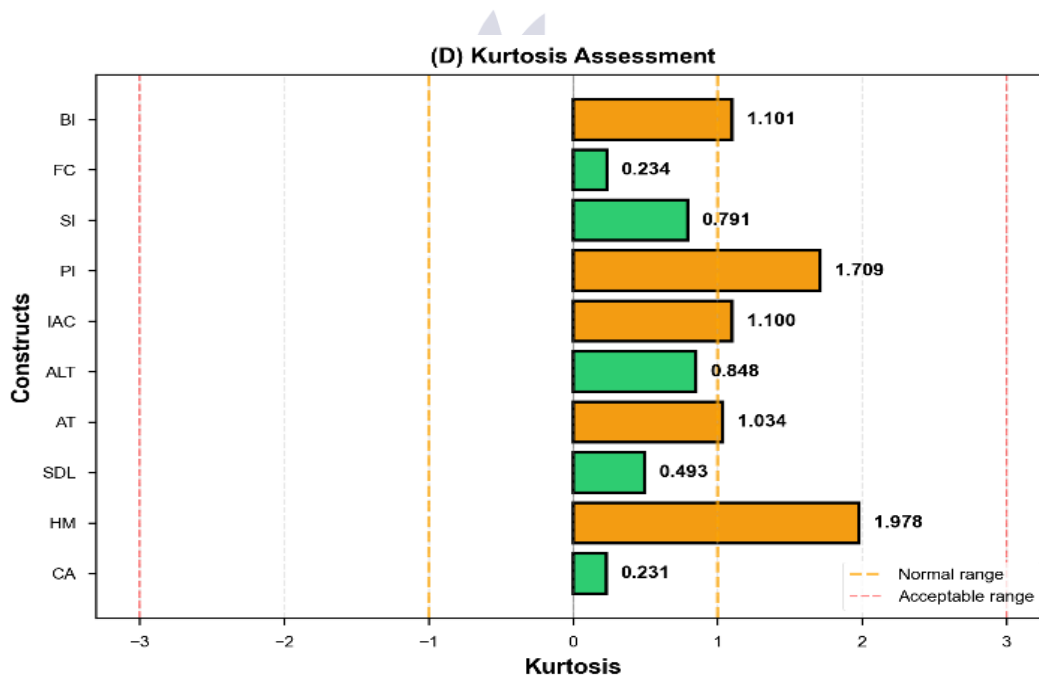


Figure 9. Kurtosis assessment for the measured constructs

The statistics show that the kurtosis values for all constructs are within the acceptable range of -3 to +3, indicating the suitability of constructs for descriptive analysis. Further, the result suggests that there is

consistency among students' responses regarding constructs.

DISCUSSION

The findings of this study provide important insights into students' perceptions and behavioral intentions relating to AI-enhanced learning within a rural higher education context. The demographic data showed that the females formed the major representation of the respondents (56.79%), aged between 20-24 years (67.90%), and studying for their Bachelor's degrees (94.87%). This distribution is consistent with previous studies that have reported young adult students to be more open toward technology-mediated learning environments [29,29].

Descriptive statistics showed that perceptions of AI-based learning were generally positive, with mean scores higher than 5 for all constructs on a 7-point scale. Skewness and kurtosis values were small enough to approximate normality of data, thus allowing the use of parametric analyses. This is in line with prior literature, which identifies normality as a key issue when statistical modeling is used on survey data [30]. The structures of the comparisons and the heatmaps confirm that Hedonic Motivation was the highest with regards to mean and reliability due to enjoyment and engagement being core motivations of acceptance of AI learning tools, and, Facilitating Conditions being of more distributed variance and lesser reliability due to limitations of infrastructure, access, or lack of institutional support that may contribute to the lack of acceptance of learning AI tools [5]. Hence, the results once more pose the question, where center stage intrinsic motivation and support were established as pivotal to the seamless integration of AI-based educational technologies. The data gathered, however, suggest that students enrolled in rural-serving universities have a broad AI-enhanced learning acceptance: although the improvement of certain parameters does appear necessary, particularly those related to the provision of adequate resources, to fully support unimpeded access to technologies.

CONCLUSION

In the context of the rural higher education paradigm, this research analyzed the perception and behavioral intention of students towards AI-enhanced learning. The perception of students toward AI tools for learning was positive.

This engagement was significantly high in the construct of Hedonic Motivation. Regarding

assistance to students with the use of AI in learning activities, students are generally positive and willing to accept the assistance. However, the lack of infrastructural and technological assistance and the lack of accessibility to the problems are challenges to the acceptance and integration of AI assistance in learning activities. The results support the calls from educational institutions to focus on the integration of AI in teaching in a way context, and to improve the gaps in the pedagogical use of learning AI assistance. AI-driven learning will improve the educational experience, especially for students located in rural areas. AI technologies focused on student engagement, tailoring learning to students, and enhancing students' academic outcomes will improve the academic experience when higher education institutions improve motivational and infrastructural conditions.

Limitations

The cross-sectional design means that the students' perceptions are captured at a single point in time, which makes it difficult to draw any inferences with respect to causality in this sense or to track changes in attitudes, behavioral intentions in a sequential manner over time.

Self-reporting measures were another limitation in use due to their high risk of response bias, including but not limited to social desirability bias and overreporting of AI skills.

Theoretical Implications

This research study advances the understanding of AI-enabled learning in rural higher education contexts by establishing empirical evidence related to Hedonic Motivation, Context Awareness, and Facilitating Conditions as the key variables influencing students' behavioral intention. This research enriches other works, particularly on technology adoption, within a new educational setting.

Practical Implications

The results demonstrated the importance of considering student readiness and the need for engagement and relevance when designing AI-assisted learning systems. This principle can inform the improvement of targeted training, enhancement of AI infrastructure, social learning space integration, AI

technology adoption, and learners' Educational Benefits. Incorporating AI tools designed for adaptive and self-directed learning has the potential to support self-directed learning as long as the AI-produced content is coherent and reliable. Hedonic and social factors should be considered to increase the experience and acceptance of AI tools.

Future Research Directions

Future research would benefit from longitudinal frameworks, given that the positive behavioral and attitudinal changes of students over the period of engagement with the program would be better understood, and some of the limitations of cross-sectional studies would be alleviated. Additionally, research that employs qualitative methodologies would enhance our understanding of the cognitive and emotional dimensions associated with the degrees of proficiency with which AI is employed. The adaptable nature of AI and the transparency of the algorithms used could influence students' learning and performance, which warrants further research.

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