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Perceptions of Online University Students Toward Artificial Intelligence Integration in Medical Education and Decision-Making: A Multi-Faculty Survey Study in Afghanistan

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Abstract: The integration of artificial intelligence (AI) into education has emerged as a transformative force reshaping pedagogical approaches, decision-making processes, and learning outcomes across disciplines. In Afghanistan, where the higher education system is navigating unprecedented digital transformation amid resource constraints and post-conflict reconstruction, understanding student perceptions of AI adoption is critically important. This cross-sectional survey study investigated the attitudes, awareness, perceived usefulness, and behavioral intentions of online university students across six faculties at the Vision Online University of Afghanistan toward AI integration in medical and general higher education. A structured, validated questionnaire was administered to 384 purposively sampled students from the Faculties of Medicine, Engineering, Law, Education, Natural Sciences, and Business Administration. Data were collected between March and June 2024 and analyzed using descriptive statistics, one-way ANOVA, and structural equation modeling. Results indicated that overall awareness of AI was moderately high ($M = 3.72$, $SD = 0.84$ on a 5-point Likert scale), with Medical Faculty students reporting significantly higher perceived usefulness ($M = 4.01$) compared to Law ($M = 3.45$) and Business ($M = 3.90$) faculties ($F(5,378) = 4.83$, $p < .001$). Students broadly favored AI-assisted clinical decision support and adaptive learning tools. Key barriers included limited digital infrastructure, inadequate AI literacy training, and language-related concerns specific to Dari and Pashto speakers. The findings provide empirical grounding for a faculty-differentiated AI integration strategy in Afghan higher education.

Keywords: Afghanistan; Artificial intelligence; Decision-making; Medical education; Online learning; Student perceptions; Survey study

Introduction

Artificial intelligence (AI) is increasingly recognized as a disruptive force in higher education, with the potential to personalize learning, automate administrative functions, augment clinical training, and enhance evidence-based decision-making across disciplines (Chen et al., 2020; Topol, 2019). The global acceleration of AI adoption in education has been particularly pronounced since 2020, driven by the COVID-19 pandemic's catalytic effect on digital transformation in universities worldwide (Doraiswamy et al., 2021). Yet the extent to which AI's promise translates to equitable educational improvement in low- and middle-income countries (LMICs) such as Afghanistan remains empirically underexplored (Wahl et al., 2018).

Afghanistan's higher education landscape is characterized by simultaneously expanding student enrollments and acute institutional resource constraints. As of 2023, the country hosted over 300,000 tertiary students across public and private institutions, with

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online universities such as Vision Online University playing an increasingly vital role in extending educational access to geographically and economically marginalized populations (Afghan Ministry of Higher Education, 2023). However, the integration of technology-enhanced pedagogical approaches, including AI-powered tools, remains nascent and highly variable across faculties and institutions.

Medical education in Afghanistan faces particular pressures. With a physician-to-population ratio of approximately 2.3 per 10,000 individuals among the lowest globally the country's medical schools bear an urgent mandate to produce competent clinicians capable of navigating complex, data-rich clinical environments with limited specialist supervision (World Health Organization [WHO], 2022). AI-integrated clinical decision support systems, adaptive learning platforms, and diagnostic assistance tools have the theoretical potential to substantially improve training quality and clinical reasoning among Afghan medical graduates (Sutton et al., 2020; Rajpurkar et al., 2022).

Critical to the successful adoption of any educational technology is an understanding of the perceptions, attitudes, and readiness of the primary intended beneficiaries: the students. The Technology Acceptance Model (TAM), originally proposed by Davis (1989) and subsequently extended in numerous educational technology studies, posits that perceived usefulness and perceived ease of use are the primary determinants of behavioral intention to use a technology (Venkatesh & Bala, 2008). Subsequent extensions incorporating subjective norms, computer anxiety, and institutional support have demonstrated strong predictive validity in LMIC educational contexts (Saleem et al., 2022).

Despite the theoretical importance of student perceptions in AI adoption, no published study has systematically examined these perceptions across multiple faculties of an Afghan online university. Most existing research on AI in Afghan education is either anecdotal, policy-oriented, or extrapolated from neighboring country studies (Rahimi & Haidari, 2022; Latif et al., 2023). This gap constitutes a significant evidence deficit at a critical juncture in Afghan higher education reform.

The present study addresses this gap by conducting a structured, multi-faculty survey of online university students at Vision Online University of Afghanistan. The study aims to: (1) assess AI awareness and exposure levels among students across six faculties; (2) measure perceived usefulness, ease of use, and behavioral intentions toward AI in education; (3) identify faculty-level differences in AI perceptions; (4) examine the structural relationships among TAM constructs and AI adoption intentions; and (5) identify key barriers and facilitators to AI integration as perceived by students.

Theoretical Framework

This study is grounded in the extended Technology Acceptance Model (TAM2/TAM3), which provides a well-validated theoretical lens for understanding individual adoption of educational technologies (Venkatesh & Bala, 2008). In the context of AI integration in higher education, four core constructs are posited as central: (1) AI Awareness (AIAW), representing students' prior knowledge and exposure to AI tools; (2) Perceived Usefulness (PU), reflecting students' belief that AI will enhance their academic performance and decision-making capabilities; (3) Perceived Ease of Use (PEOU), capturing beliefs about the cognitive effort required to use AI tools; and (4) Behavioral Intention to Use (BIU), operationalized as students' self-reported likelihood of engaging with AI-powered educational tools.

Supplementary constructs integrated in this study's model include Subjective Norm (SN), reflecting perceived social pressure to adopt AI; Institutional Support (IS), capturing perceived availability of university infrastructure and guidance; and Anxiety toward AI (AITAX), measuring technophobia as a potential inhibitor. This integrated model aligns with the Unified Theory of Acceptance and Use of Technology (UTAUT2) as adapted for LMIC educational settings by Saleem et al. (2022) and provides a rigorous basis for structural equation modeling.

Method

Study Design and Setting

A cross-sectional quantitative survey design was employed. The study was conducted at Vision Online University of Afghanistan, a private accredited institution offering undergraduate and postgraduate programs entirely through online platforms. The university enrolls students from all 34 Afghan provinces and maintains six active faculties: Medicine, Engineering, Law, Education, Natural Sciences, and Business Administration. Data collection occurred between March 1 and June 30, 2024.

Participants and Sampling

The target population comprised all currently enrolled undergraduate students at Vision Online University (N = 2,140 at the time of study). Using the Krejcie and Morgan (1970) formula for sample size determination with a 95% confidence interval and 5% margin of error, a minimum sample of 327 participants was required. Accounting for an anticipated 15% non-response rate, the target recruitment was set at 384 students. Stratified purposive sampling was employed to ensure proportional representation across faculties, with strata defined by faculty affiliation and academic year. Students were eligible if they were: (1) currently enrolled full-time; (2) aged 18 years or older; and (3) had access to a smartphone or computer for survey completion.

Survey Instrument

The survey instrument was adapted from three validated questionnaires: the AI Attitude Scale for Higher Education (AIASHE; Sindermann et al., 2021), the TAM-based Digital Technology Acceptance Scale (DTAS; Saleem et al., 2022), and the AI Literacy Scale for Students (AILIS; Long & Magerko, 2020). The final instrument comprised 42 items across seven constructs, each measured on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Additional sections collected demographic data, faculty affiliation, prior AI exposure, and open-ended responses on barriers and facilitators.

The questionnaire was developed in English and professionally translated into Dari and Pashto, with back-translation conducted by two bilingual academic linguists to ensure semantic equivalence. Face validity was established through expert panel review (n = 8 academics); content validity index (CVI) was 0.91. A pilot test administered to 30 students not included in the main sample yielded a Cronbach's alpha of 0.88 across all constructs (range: 0.79–0.93).

Data Collection Procedure

The online survey was hosted on Google Forms and distributed via the university's learning management system (LMS), faculty WhatsApp groups, and direct email. Two reminder notifications were sent at two-week intervals. Participation was entirely voluntary and anonymous. The study protocol was approved by the Institutional Review Board of Kabul University of Medical Sciences (Ref: KUMS-IRB-2024-017). Informed digital consent was obtained prior to survey commencement.

Data Analysis

Quantitative data were analyzed using SPSS version 27.0 and AMOS version 25.0. Descriptive statistics (means, standard deviations, frequencies) were computed for all scale items and demographic variables. Internal consistency was confirmed using Cronbach's alpha. Faculty-level differences in key constructs were examined using one-way ANOVA with Tukey's post-hoc test, setting the significance threshold at $p < .05$. Structural equation modeling (SEM) was employed to test the hypothesized TAM-based model, with model fit evaluated using CFI (≥0.95), TLI (≥0.95), RMSEA (≤0.06), and SRMR (≤0.08) criteria (Hu & Bentler, 1999). Open-ended responses were analyzed using inductive thematic analysis.

Perceived Usefulness, Ease of Use, and Behavioral Intention

Table 2 presents mean scores for all TAM constructs across faculties. Overall perceived usefulness was high (M = 3.78, SD = 0.79), indicating that students broadly recognized AI's potential to improve their academic and professional performance. Medical students reported the highest perceived usefulness (M = 4.01), particularly for items related to AI-assisted diagnosis, clinical case analysis, and evidence-based decision support. Business Administration students also scored high on perceived usefulness (M = 3.90), driven by enthusiasm for AI in data analytics and market forecasting.

Perceived ease of use was moderate overall (M = 3.52, SD = 0.91), suggesting that while students valued AI, many harbored concerns about the technical complexity of AI tools. Engineering students reported the highest ease of use (M = 3.88), while Law students reported the lowest (M = 3.30), a finding consistent with their lower digital exposure. Behavioral intention to use AI in education was generally positive (M = 3.68, SD = 0.87), with significant faculty-level variation ($F(5,334) = 4.83$, $p < .001$).

Table 2. Mean TAM Construct Scores by Faculty (N = 340; 5-Point Likert Scale)

Faculty	AI Awareness M (SD)	Perceived Usefulness M (SD)	Ease of Use M (SD)	Behavioral Intention M (SD)	Institutional Support M (SD)
Medicine	3.88 (0.78)	4.01 (0.74)	3.61 (0.88)	3.85 (0.81)	3.42 (0.90)
Engineering	4.08 (0.71)	3.82 (0.80)	3.88 (0.76)	3.79 (0.83)	3.35 (0.95)
Law	3.41 (0.92)	3.45 (0.96)	3.30 (0.99)	3.38 (0.94)	3.10 (1.02)
Education	3.56 (0.88)	3.62 (0.89)	3.49 (0.91)	3.60 (0.87)	3.28 (0.94)
Natural Sciences	3.70 (0.82)	3.74 (0.86)	3.67 (0.85)	3.71 (0.80)	3.38 (0.91)
Business Admin	3.68 (0.85)	3.90 (0.77)	3.55 (0.90)	3.76 (0.84)	3.20 (0.97)
Overall	3.72 (0.84)	3.78 (0.83)	3.59 (0.89)	3.68 (0.87)	3.30 (0.94)

ANOVA Results: Faculty-Level Differences

One-way ANOVA revealed statistically significant faculty-level differences across all five TAM constructs (Table 3). The largest effect size was observed for perceived usefulness ($F(5,334) = 5.21$, $p < .001$, $\eta 2 = 0.072$), followed by behavioral intention ($F(5,334) = 4.83$,

$p < .001$, $\eta^2 = 0.067$). Tukey's post-hoc analysis identified the following significant pairwise differences: Medical vs. Law ($p = .001$), Medical vs. Education ($p = .038$), Engineering vs. Law ($p = .004$), Business vs. Law ($p = .021$). No significant difference was found between Medicine and Engineering or between Natural Sciences and Business Administration, suggesting relative homogeneity in AI enthusiasm among science- and technology-oriented faculties.

Table 3. One-Way ANOVA Results for TAM Constructs Across Faculties

Construct	SS	df	MS	F	p	η^2
AI Awareness	12.84	5	2.57	3.92	.002*	0.055
Perceived Usefulness	17.36	5	3.47	5.21	<.001***	0.072
Ease of Use	14.21	5	2.84	3.58	.004**	0.051
Behavioral Intention	16.10	5	3.22	4.83	<.001***	0.067
Institutional Support	10.94	5	2.19	2.98	.012*	0.043

Note. *$p < .05$, **$p < .01$, ***$p < .001$. η^2 = eta-squared (effect size). SS = sum of squares; MS = mean square.*

Structural Equation Modeling Results

The hypothesized TAM-based structural model demonstrated acceptable fit: CFI = 0.962, TLI = 0.951, RMSEA = 0.054 (90% CI [0.041, 0.067]), SRMR = 0.063. All factor loadings were statistically significant ($p < .001$) and ranged from 0.61 to 0.88, confirming convergent validity. Average variance extracted (AVE) exceeded the 0.50 threshold for all constructs, and composite reliability (CR) ranged from 0.81 to 0.93, confirming construct reliability.

AI Awareness was the strongest predictor of Perceived Usefulness ($\beta = 0.52$, $p < .001$) and Perceived Ease of Use ($\beta = 0.44$, $p < .001$). Perceived Usefulness was the strongest direct predictor of Behavioral Intention ($\beta = 0.61$, $p < .001$), followed by Perceived Ease of Use ($\beta = 0.34$, $p < .001$) and Institutional Support ($\beta = 0.28$, $p < .001$). AI Anxiety was a significant negative predictor of both Ease of Use ($\beta = -0.39$, $p < .001$) and Behavioral Intention ($\beta = -0.22$, $p = .003$). Subjective Norm showed a modest positive effect on Behavioral Intention ($\beta = 0.19$, $p = .014$). The model explained 58% of the variance in Behavioral Intention to Use AI in education *(N = 340).*

Table 4. Structural Model Path Coefficients (Standardized)

Path	β	SE	z	p	95% CI
AI Awareness → Perceived Usefulness	0.52	0.07	7.43	<.001	[0.38, 0.66]
AI Awareness → Perceived Ease of Use	0.44	0.08	5.50	<.001	[0.28, 0.60]
Perceived Usefulness → Behavioral Intention	0.61	0.06	10.17	<.001	[0.49, 0.73]
Ease of Use → Behavioral Intention	0.34	0.07	4.86	<.001	[0.20, 0.48]
Institutional Support → Behavioral Intention	0.28	0.07	4.00	<.001	[0.14, 0.42]
AI Anxiety → Ease of Use	−0.39	0.07	−5.57	<.001	[−0.53, −0.25]
AI Anxiety → Behavioral Intention	−0.22	0.07	−3.14	.002	[−0.36, −0.08]
Subjective Norm → Behavioral Intention	0.19	0.08	2.38	.017	[0.03, 0.35]

Faculty-Level Perceptual Profiles

Medicine and Natural Sciences students formed a high-engagement cluster characterized by strong perceived usefulness and clinical relevance of AI. Engineering and Business Administration students constituted a high-awareness, moderate-concern cluster, acknowledging AI's practical utility while expressing moderate concerns about job displacement. Law and Education students formed a low-readiness cluster with lowest scores across all dimensions, particularly on ease of use and institutional support, suggesting that targeted faculty-level interventions are warranted.

Barriers and Facilitators (Qualitative Themes)

Inductive thematic analysis of open-ended responses (n = 298 respondents providing text) yielded five primary barrier themes and four facilitator themes. The most frequently cited barrier was inadequate digital infrastructure (cited by 68.5% of respondents), followed by limited AI literacy training in curricula (61.2%), language barriers with English-dominant AI tools (55.8%), distrust of AI outputs in clinical contexts (39.4%), and cost of internet access (34.1%). Facilitator themes included perceived career relevance of AI skills (72.3%), institutional encouragement from faculty (48.6%), peer influence and social modeling (41.5%), and availability of free AI tools such as ChatGPT (38.9%).

Table 5. Thematic Analysis: Barriers and Facilitators to AI Adoption (N = 298 Open-Response Participants)

Theme	Category	Frequency n (%)	Representative Quotation (Translated)
Inadequate digital infrastructure	Barrier	204 (68.5)	'My internet cuts out during lectures. How can I use AI tools?'
Limited AI literacy in curriculum	Barrier	182 (61.2)	'We were never taught what AI is or how to use it for studying.'
English-only AI interfaces	Barrier	166 (55.8)	'Most AI tools do not support Dari or Pashto at all.'
Distrust of AI in clinical use	Barrier	117 (39.4)	'I would not trust an AI to help diagnose a patient. It could be wrong.'
Cost of internet	Barrier	102 (34.1)	'Data packages are very expensive here. AI needs constant internet.'
Perceived career relevance	Facilitator	216 (72.3)	'Knowing AI will help me get a better job and serve my patients better.'
Faculty encouragement	Facilitator	145 (48.6)	'When our professor showed us how AI helps in diagnosis, I was convinced.'
Peer influence	Facilitator	124 (41.5)	'My classmates use ChatGPT and I started using it too after seeing their results.'
Free tool availability	Facilitator	116 (38.9)	'ChatGPT is free. If AI tools were always free, I would use them every day.'

Discussion

This study represents the first multi-faculty empirical investigation of AI perceptions among online university students in Afghanistan, and its findings carry both theoretical and practical significance. The overall moderate-to-high levels of AI awareness (M = 3.72) and perceived usefulness (M = 3.78) observed across faculties suggest that Afghan online students are neither uninformed about nor hostile to AI technologies. This is a more optimistic baseline than some prior studies of LMICs suggested, potentially reflecting the rapid penetration of AI-powered consumer tools such as ChatGPT in the Afghan student community since 2023 (Latif et al., 2023).

The significantly higher AI engagement scores among Medical students align with theoretical expectations grounded in TAM: students in clinical training programs are more likely to encounter concrete, domain-relevant use cases for AI such as diagnostic imaging assistance, drug dosing calculators, and clinical decision algorithms that make the perceived usefulness of AI more tangible and motivating (Sutton et al., 2020). This finding replicates patterns reported in medical AI attitude studies from Pakistan (Iqbal et al., 2021) and Bangladesh (Hossain et al., 2023), suggesting some cross-cultural robustness.

The low AI engagement scores among Law students warrant particular attention. This finding is consistent with the relative absence of AI-integrated pedagogy in Afghan legal education, where faculty may perceive AI tools as supplementary at best and threats to legal reasoning at worst. However, international evidence increasingly demonstrates the utility of AI in legal research, case analysis, and document drafting applications that could substantially benefit Afghan law students navigating complex multilingual legal systems (Davenport & Kalakota, 2019). Targeted faculty development and demonstration of relevant AI use cases may be particularly effective in shifting perceptions among this cohort.

The SEM results offer important theoretical contributions. The dominant role of Perceived

Usefulness (β = 0.61) as a predictor of Behavioral Intention replicates TAM's core proposition and is consistent with a meta-analysis of 82 TAM studies in educational contexts by Scherer et al. (2019). Notably, AI Anxiety emerged as a significant suppressor of both ease of use and behavioral intention, a finding that aligns with technophobia literature showing that anxiety is a more powerful inhibitor of technology use in populations with limited prior digital exposure (Coiera et al., 2016). Institutional Support's independent contribution to behavioral intention (β = 0.28) underscores the critical role universities must play in creating enabling environments for AI adoption, beyond merely deploying tools.

The qualitative barrier themes reveal a structural challenge: even students who are attentive to AI's value cannot consistently access or benefit from AI tools due to infrastructure gaps. Afghanistan's 18.4% internet penetration rate and the high cost of mobile data create a paradox in which students may be cognitively ready for AI adoption but practically unable to act on that readiness (ITU, 2023). This gap between intention and behavior a known limitation of TAM in LMIC contexts points to the importance of offline-capable AI tools, SMS-based platforms, and institutional device lending programs as complementary infrastructure investments. The language barrier finding is particularly consequential. With 55.8% of respondents citing English-only AI interfaces as a barrier, and with NLP model performance on Dari and Pashto significantly below that for English (Bird et al., 2023), there is an urgent need for Afghan-language AI development. This parallels the language justice argument advanced in the global AI ethics literature and suggests that international AI developers and funding organizations should prioritize multilingual LMIC deployment as a core equity imperative (Schiff et al., 2020).

Conclusion

This cross-sectional survey study provides the first robust empirical portrait of AI perceptions across multiple faculties of an Afghan online university. The findings establish that Afghan online students hold broadly positive attitudes toward AI in education, with perceived usefulness as the strongest driver of adoption intention. Significant faculty-level variation with Medical and Engineering students most receptive, and Law and Education students least prepared argues for differentiated, faculty-contextualized AI integration strategies rather than one-size-fits-all approaches.

The structural model confirms the applicability of the extended TAM framework in this LMIC context and highlights AI Awareness and Institutional Support as two modifiable antecedents through which universities can most effectively increase AI adoption. Critically, AI Anxiety's negative predictive role underscores the importance of AI literacy education not merely as technical training but as affective reassurance helping students engage confidently and critically with AI outputs.

For policymakers and university administrators, these findings justify prioritizing three immediate actions: first, the integration of AI literacy modules into all faculty curricula; second, the development or procurement of Dari- and Pashto-language AI tools suitable for academic and clinical use; and third, infrastructure investment in reliable internet connectivity and institutional device access. For the medical education sector specifically, the high perceived utility among medical students, combined with Afghanistan's acute physician shortage, makes AI-assisted clinical training a particularly high-return investment for national health human resource development.

This study is subject to limitations including self-selection bias inherent in online survey designs, reliance on self-reported measures of AI use, and restriction to a single university. Future studies should employ longitudinal designs to track AI perception changes over time, expand sampling to multiple universities and regions, and incorporate observational methods to capture actual AI use behavior alongside self-reported attitudes.

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Conflicts of Interest
The authors declare no conflict of interest.

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