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Investigating the Factors Affecting the Effectiveness of Virtual Education Using Artificial Intelligence in the Educational System of Islamic Azad Universities in West Azerbaijan Province

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ABSTRACT

This study aimed to identify, prioritize, and validate the factors affecting the effectiveness of virtual education using artificial intelligence in the educational system of Islamic Azad Universities in West Azerbaijan Province. This developmental–applied study employed a sequential exploratory mixed-methods design. In the qualitative phase, experts in virtual education, educational technology, artificial intelligence, and higher education management were selected through purposive and snowball sampling, with interviews continuing until theoretical saturation. Semi-structured interviews were analyzed through thematic analysis, resulting in seven dimensions and 26 components. The extracted indicators were subsequently evaluated through a two-round Delphi process. In the quantitative phase, data were collected from 140 faculty members selected from approximately 300 faculty members of Islamic Azad Universities in West Azerbaijan Province. Fuzzy Analytic Hierarchy Process was applied to prioritize the identified dimensions, and Partial Least Squares Structural Equation Modeling was used to validate the measurement model and examine the relationships between the first- and second-order constructs. Kendall's coefficient of concordance was statistically significant in the first Delphi round ($W = 0.147$, $\chi^2 = 110.866$, $p < .001$) and increased substantially in the second round ($W = 0.715$, $\chi^2 = 747.653$, $p < .001$), indicating strong final expert consensus. Confirmatory factor analysis showed that all first-order indicator loadings were statistically significant, with t values ranging from 10.032 to 49.261 ($p < .001$). All seven second-order dimensions also significantly contributed to the higher-order construct, with standardized loadings ranging from 0.784 to 0.840 and t values from 22.619 to 38.739 ($p < .001$). Thus, all hypothesized measurement relationships were statistically supported. The findings support a multidimensional model of AI-based virtual education effectiveness comprising educational, technological, psychological, social, managerial, human, and organizational dimensions. The validated model indicates that effective implementation requires coordinated attention to institutional management, technological readiness, human capabilities, social interaction, psychological preparedness, educational quality, and organizational support.

Keywords: Artificial Intelligence; Virtual Education; Higher Education; Educational Effectiveness; Delphi Method; Analytic Hierarchy Process; PLS-SEM; Islamic Azad University

Introduction

The rapid expansion of digital technologies has transformed the organization, delivery, and evaluation of higher education, with virtual education becoming an increasingly important component of university teaching and learning. What was initially developed primarily as an alternative mode of content delivery has progressively evolved into a complex educational ecosystem involving learning management systems, synchronous and asynchronous communication, digital assessment, multimedia content, data analytics, and intelligent support services. Within this transformation, artificial intelligence (AI) has emerged as one of the most influential technologies shaping the future of higher education because it can extend virtual learning beyond simple digitization toward adaptive, interactive, predictive, and personalized educational environments. AI-supported systems are increasingly capable of analyzing learner behavior, recommending resources, generating feedback, supporting assessment, facilitating communication, and assisting instructors with instructional and administrative tasks. Consequently, the effectiveness of virtual education can no longer be understood only in terms of access to online platforms or the availability of electronic content; it increasingly depends on how intelligently educational, technological, human, managerial, psychological, social, and organizational resources are integrated within the learning environment [1-3].

One of the most significant contributions of AI to virtual education is its potential to facilitate adaptive and personalized learning. Traditional virtual learning environments generally provide relatively standardized content, pacing, assignments, and feedback to heterogeneous groups of learners. AI-based systems, by contrast, can analyze students' learning patterns, previous performance, interactions, strengths, difficulties, and progression in order to provide differentiated learning pathways. Intelligent assistants and adaptive learning systems can recommend educational materials, adjust levels of task difficulty, provide individualized explanations, and deliver timely feedback according to learners' needs. Such capacities are particularly important in higher education, where students demonstrate considerable variation in prior knowledge, learning strategies, academic preparedness, and engagement. Research on AI-enabled intelligent assistants has shown the potential of these systems for personalized and adaptive learning, while more recent work has emphasized AI-based personalization as an increasingly important approach to improving higher education learning experiences [4, 5]. Accordingly, personalization represents not merely a technological feature but a potential mechanism through which virtual education can become more responsive to individual learning needs.

AI also has considerable implications for the quality of teaching and instructional design. University instructors in virtual environments face multiple demands, including preparing digital content, maintaining interaction, providing individual feedback, monitoring student progress, conducting assessment, and responding to diverse learning needs. AI applications can support instructors by automating routine functions, identifying patterns in learner performance, generating formative feedback, assisting in the production and revision of educational materials, and facilitating adaptive instruction. Studies focusing on the role of AI in supporting higher education teachers highlight its potential contribution to instructional processes and teacher support [6]. At the same time, successful integration depends substantially on educators' ability to combine technological knowledge with pedagogical and disciplinary competence. Evidence concerning teachers' AI competency and technological pedagogical content knowledge indicates that competence in using AI does not automatically translate into effective teaching unless it becomes pedagogically integrated into instructional practice [7]. Therefore, AI effectiveness in virtual education should be understood as a pedagogical issue as much as a technological one.

The integration of generative AI has further expanded the range of educational practices that can occur in virtual higher education. Generative systems can support brainstorming, academic writing, language learning, explanation, tutoring, feedback, content generation, and question development. Systematic examination of generative AI in academic writing suggests that these technologies are becoming increasingly embedded in university learning activities, while also generating important questions concerning originality, academic integrity, student dependence, assessment design, and responsible use [8]. Faculty experiences with the integration of generative AI into higher education curricula similarly demonstrate that instructors must negotiate both opportunities and pedagogical challenges when incorporating such tools into formal teaching

[9]. Practical discussions of ChatGPT in university education further indicate that institutions and educators are increasingly required to redesign teaching and assessment practices rather than simply prohibit or uncritically adopt AI tools [10]. Thus, generative AI creates substantial opportunities for virtual education, but its effectiveness depends on carefully designed educational practices and clearly articulated expectations regarding its appropriate use.

The educational benefits of AI also depend heavily on AI literacy among both students and faculty members. Effective interaction with intelligent systems requires more than basic digital skills; users must understand the capabilities and limitations of AI, evaluate generated outputs critically, formulate appropriate prompts, recognize potential inaccuracies and biases, and use AI in ethically responsible ways. AI literacy, prompt engineering, and critical thinking have therefore become increasingly relevant competencies in contemporary education [11]. At the student level, AI literacy may also interact with motivational and self-regulatory processes. Research has demonstrated meaningful relationships among need satisfaction, self-regulated learning strategies, and AI literacy in higher education, suggesting that learners' capacity to benefit from AI-supported environments is partially dependent on their ability to regulate their own learning [12]. Moreover, AI literacy has been linked with higher-order thinking through mechanisms such as behavioral engagement and peer interaction, emphasizing that meaningful AI use should strengthen rather than replace active cognitive participation [13].

From a broader educational perspective, AI can also support the development of competencies that extend beyond subject-specific knowledge. Higher education is increasingly expected to prepare graduates not only with disciplinary expertise but also with communication, collaboration, adaptability, creativity, decision-making, and other transferable competencies. A bibliometric review of AI in higher education has identified its potential contribution to soft-skill development [14], while other research has emphasized the use of AI to strengthen job-ready graduate capabilities [15]. AI-based coaching systems also illustrate the potential of intelligent technologies to support goal attainment and individualized developmental processes, providing a model for how conversational AI may contribute to learner guidance and transition-related support [16]. These developments indicate that AI-supported virtual education should be evaluated not only in terms of technological efficiency or course completion but also in relation to broader student development and educational outcomes.

Another important dimension of AI-supported virtual learning concerns student engagement and interaction. Virtual education may create flexibility and accessibility, yet it can also reduce spontaneous interpersonal contact and increase feelings of isolation when courses are poorly designed. AI-supported interactive systems have the potential to promote engagement by providing rapid responses, continuous support, adaptive learning prompts, and conversational interaction. The use of ChatGPT and similar technologies has been associated with new opportunities for creating more interactive learning experiences and strengthening student engagement [17]. Cross-national evidence concerning students' intention to use ChatGPT also demonstrates that adoption is shaped by user perceptions and may differ across educational and cultural environments [18]. Consequently, effective AI-supported virtual education must address not only the technical functionality of intelligent tools but also students' willingness to use them, their trust in these systems, and the quality of the social and educational interactions that surround their use.

Psychological conditions are equally relevant to virtual education effectiveness. Learning through technology can increase autonomy and flexibility, but it may also introduce cognitive overload, technological anxiety, motivational difficulties, or reduced belonging for some students. Academic performance in higher education is closely connected to psychological well-being, with depression and anxiety representing important concerns for university students [19]. Within AI-supported environments, intelligent tools may potentially reduce some forms of academic burden by offering rapid assistance and personalized guidance; however, poorly implemented technologies may also create uncertainty, dependency, anxiety, or concerns about competence. Therefore, learning motivation, active student participation, attitudes toward intelligent learning, technology-related anxiety, and perceived support should be treated as central components when evaluating the effectiveness of AI-enhanced virtual education rather than as secondary outcomes.

The effectiveness of AI integration also depends on the technological infrastructure within which it is implemented. Reliable internet access, stable learning platforms, user-friendly interfaces, sufficient computing capacity, interoperability between educational systems, and access to appropriate AI applications are prerequisites for meaningful implementation. Studies examining AI in higher education consistently emphasize its potential to reshape academic processes, teaching, and learning, but also indicate that institutional capabilities determine whether this potential can be translated into practice [20, 21]. Broader educational research likewise suggests that AI is likely to influence the future direction of education across different levels, reinforcing the need to examine the technological and institutional conditions required for responsible adoption [22]. In virtual universities or geographically dispersed university systems, infrastructure inequalities may be particularly consequential because limitations in connectivity or access to suitable devices can translate directly into unequal learning opportunities.

Alongside infrastructure, security and privacy represent fundamental conditions for sustainable AI adoption. AI-based education may require the collection and processing of large amounts of learner data, including academic performance, behavioral patterns, interactions, preferences, and sometimes sensitive personal information. The increased use of these systems raises questions concerning data ownership, transparency, algorithmic accountability, privacy protection, and ethical decision-making. Ethical education concerning AI has therefore become an important element of higher education curriculum development and professional training [23]. More broadly, responsible AI adoption requires universities to develop governance systems capable of defining appropriate uses, monitoring risks, adapting policies to emerging technologies, and protecting academic values. Research on AI governance in higher education emphasizes the importance of policy design, implementation, and institutional adaptability in responding to rapidly evolving technologies [24]. Consequently, the effectiveness of virtual education supported by AI cannot be separated from the ethical and governance environment in which these technologies are deployed.

Institutional policy is particularly important because universities are currently developing different responses to generative AI and other intelligent technologies. Analysis of higher education policies and guidelines has shown that institutions are actively attempting to define acceptable, restricted, and responsible uses of generative AI [25]. However, policy alone is insufficient unless it is supported by appropriate leadership and implementation mechanisms. Educational leaders must determine institutional priorities, allocate resources, develop staff capacity, encourage innovation, establish accountability systems, and coordinate academic and technological units. Research on AI in educational leadership has emphasized the expanding range of leadership functions associated with AI adoption and the need for clearer strategic frameworks [26]. Accordingly, managerial capacity may represent one of the central determinants of whether AI is integrated into virtual education as a coherent educational strategy or remains a fragmented collection of technological applications.

Responsible strategic leadership is especially important because AI implementation simultaneously affects academic and administrative processes. Higher education institutions require leaders who can align technological adoption with institutional missions, create appropriate governance arrangements, allocate financial and human resources, and manage organizational change. Research addressing responsible strategic leadership in AI implementation highlights the importance of leadership in coordinating academic and administrative applications of artificial intelligence [27, 28]. At the organizational level, a supportive culture is also necessary to encourage experimentation, interdisciplinary cooperation, continuous learning, and responsible innovation. Where faculty members perceive AI as externally imposed, poorly supported, or inconsistent with educational values, resistance may limit implementation regardless of the availability of technology. Thus, organizational culture and strategic leadership constitute mutually reinforcing elements of successful AI-based virtual education.

Faculty development is another essential organizational requirement. The rapid evolution of intelligent technologies means that instructors cannot rely solely on skills acquired during their initial professional preparation. Teacher education must increasingly include opportunities to understand AI, evaluate its pedagogical relevance, redesign learning activities, manage ethical challenges, and critically assess AI-generated materials. AI has been identified as potentially transformative for both pre-service and in-service teacher education, particularly when professional learning is designed to help educators integrate intelligent technologies into teaching practice [29]. Faculty readiness is therefore multidimensional, involving technical competence, pedagogical knowledge, ethical awareness, willingness to experiment, and confidence in adapting instructional roles. This is particularly important in virtual education, where instructors already operate through technology-mediated teaching environments and may face additional workload and complexity when new AI systems are introduced.

The transformative potential of AI also extends to curriculum development. AI-driven approaches can support the redesign of university curricula by facilitating adaptive content organization, personalized pathways, data-informed revision, and innovative disciplinary applications. Research on AI-driven curriculum design in higher education, including within aesthetic education, demonstrates how intelligent technologies can be incorporated into specialized curricular contexts rather than being treated solely as general-purpose tools [30]. This disciplinary adaptability is important because the educational value of AI is likely to differ across fields, instructional goals, and student populations. Effective institutional models must therefore be sufficiently flexible to accommodate disciplinary differences while maintaining shared standards concerning educational quality, ethical use, accessibility, and technological support.

At the same time, the growing use of AI in higher education has produced a need for inclusive and socially responsible implementation. AI-enhanced universities should not simply maximize efficiency or technological sophistication; they should also ensure that intelligent systems contribute to equitable learning opportunities, employability, inclusion, and meaningful student development. Recent scholarship has emphasized the importance of constructing inclusive, ethical, and employability-oriented higher education ecosystems around AI rather than allowing technological innovation to deepen existing educational inequalities [31]. Such concerns are particularly relevant in virtual education, where disparities in connectivity, digital literacy, access to devices, and institutional support may influence who is able to benefit from intelligent educational tools. Educational equity and equal access must consequently be considered core effectiveness criteria rather than peripheral social concerns.

Taken together, the literature indicates that effective AI-supported virtual education is inherently multidimensional. Technological infrastructure alone cannot ensure educational effectiveness if instructional design is weak, faculty members are unprepared, students lack motivation or digital competence, institutional policies are unclear, or organizational leadership fails to coordinate implementation. Similarly, well-designed courses may not achieve their objectives when systems are unstable, privacy protections are insufficient, or students lack equal access to digital resources. Current scholarship therefore increasingly points toward an ecosystem perspective in which technological, educational, managerial, psychological, social, human, and organizational conditions interact dynamically. The emerging international literature provides important evidence regarding individual aspects of this ecosystem, including adaptive learning, AI literacy, faculty competency, student engagement, institutional governance, leadership, curriculum development, and ethical adoption; however, these dimensions are frequently examined separately rather than integrated into a context-specific model of virtual education effectiveness.

This limitation is particularly important within the Iranian higher education context and the Islamic Azad University system, where universities differ in institutional capacities, technological infrastructure, faculty preparedness, student characteristics, resource availability, and local implementation conditions. In West Azerbaijan Province, the effectiveness of AI-supported virtual education therefore requires an empirical framework that reflects the actual conditions of universities in the province rather than relying exclusively on generic international models. Such a framework should identify the relevant dimensions and components, determine which factors experts consider most important, examine the degree of consensus regarding these indicators, and empirically test whether the identified dimensions form a reliable and valid higher-order model. Developing such an integrated model can provide a stronger basis for prioritizing investment, designing faculty development programs, improving digital infrastructure, establishing responsible AI governance, supporting students, and aligning technological innovation with educational objectives.

Accordingly, the aim of this study was to investigate and develop a validated model of the factors affecting the effectiveness of virtual education using artificial intelligence in the educational system of Islamic Azad Universities in West Azerbaijan Province.

Methodology

This study employed a mixed-methods research design and was developmental–applied in terms of its purpose. A mixed-methods approach was selected because investigating the effectiveness of artificial intelligence-supported virtual education requires both an in-depth understanding of experts' experiences and perspectives and an empirical examination of the relative importance and structural relationships among the identified factors. More specifically, the study followed a sequential exploratory mixed-methods design in which the qualitative phase preceded the quantitative phase. In the first phase, qualitative data were collected and analyzed using thematic analysis to identify the major dimensions, components, indicators, roles, challenges, and contextual conditions associated with the effectiveness of virtual education using artificial intelligence in the educational system of Islamic Azad Universities in West Azerbaijan Province. The findings of the qualitative phase subsequently provided the conceptual basis for developing the quantitative measurement instruments. In the second phase, the factors extracted from the qualitative analysis were evaluated, prioritized, and validated quantitatively using Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and Partial Least Squares Structural Equation Modeling (PLS-SEM). Therefore, integration between the two phases occurred through the use of qualitative findings in the construction of the quantitative instruments and through the incorporation of the quantitative results into the final conceptual model. The overall design was intended to move from exploration and conceptual development toward prioritization, empirical validation, and examination of the relationships among the dimensions of artificial intelligence-based virtual education effectiveness.

The statistical population differed between the qualitative and quantitative phases in accordance with the sequential mixed-methods design. In the qualitative phase, the study population consisted of experts affiliated with Islamic Azad Universities in West Azerbaijan Province as well as experienced organizational and educational consultants with relevant expertise in virtual education, digital learning, educational technologies, artificial intelligence, and higher education management. Participants were selected on the basis of their capacity to provide specialized, experience-based, and analytically rich information regarding the phenomenon under investigation. Eligibility was therefore determined by several substantive considerations, including possession of specialized knowledge of virtual education, digital learning, artificial intelligence, or emerging educational technologies; practical experience in university teaching, educational administration, virtual course development, or educational technology implementation; participation in educational decision-making, policy development, or management; a relevant academic or research background in virtual education or artificial intelligence in education; familiarity with the challenges and opportunities of technology-mediated higher education; and the ability to provide critical and analytical responses during in-depth interviews. These criteria were intended to ensure that the qualitative data reflected both theoretical expertise and practical experience within university educational environments.

Sampling in the qualitative phase was conducted using purposive and snowball sampling. Initially, information-rich participants who fulfilled the inclusion criteria and had substantial knowledge of the research topic were purposively identified and invited to participate. Subsequently, participants were asked to recommend other experts who possessed relevant knowledge or experience, thereby extending recruitment through snowball sampling. Data collection and participant recruitment continued until theoretical and thematic saturation was achieved. Saturation was defined as the point at which additional interviews no longer generated substantially new concepts, codes, categories, or themes relevant to the research questions. On the basis of the focused nature of the expert population and the relative homogeneity of participants in terms of professional expertise, approximately 15 to 20 experts were considered sufficient for the qualitative phase, although the final sample size was determined by saturation rather than by a predetermined numerical threshold. This sampling strategy allowed the researchers to obtain diverse yet specialized perspectives concerning the educational, technological, psychological, social, managerial, human, and organizational conditions influencing the effectiveness of artificial intelligence-supported virtual education.

In the quantitative phase, the statistical population consisted of all faculty members employed at Islamic Azad Universities in West Azerbaijan Province, estimated at approximately 300 individuals. The purpose of this phase was to evaluate the factors derived from the qualitative findings, determine the relative importance of the identified dimensions and indicators, and empirically examine the relationships proposed in the conceptual model. Sample size determination was therefore guided by the requirements of structural equation modeling and the number of latent constructs included in the proposed model. The conceptual model consisted of seven principal dimensions, namely educational, technological, psychological, social, managerial, human, and organizational factors. Considering a minimum of approximately 20 participants for each latent construct, a quantitative sample of 140 faculty members was considered appropriate for the structural analysis. Participants in the quantitative phase were selected through convenience sampling from the accessible faculty population of Islamic Azad Universities across West Azerbaijan Province. Participation was voluntary, and only questionnaires with sufficiently complete responses for statistical analysis were included. The quantitative phase was designed to provide empirical evidence regarding the measurement properties of the identified constructs and the magnitude and significance of the relationships among the main dimensions of the proposed artificial intelligence-based virtual education effectiveness model.

Data collection in the qualitative phase was conducted primarily through semi-structured interviews. This method was selected because it provided a consistent framework for addressing the principal research questions while maintaining sufficient flexibility to explore participants' specialized experiences, interpretations, and perspectives in greater depth. The interview guide was developed in accordance with the objectives of the study and focused on identifying the main dimensions and components of effective virtual education using artificial intelligence, the educational and technological functions of artificial intelligence, appropriate indicators for evaluating the effectiveness of artificial intelligence-supported virtual learning, barriers and challenges affecting implementation, the relationships among the identified dimensions, and the applicability of the proposed framework to the Iranian higher education system. The interview process began with arrangements for contacting eligible participants and explaining the general purpose and scope of the research. At the beginning of each interview, the researcher provided a brief explanation of the research objectives and clarified the meaning of the central concepts where necessary. Core questions were then presented, while probing and follow-up questions were used to elaborate on important issues raised by participants. The interview guide was treated flexibly and was refined during the data collection process in response to emerging concepts and insights from previous interviews.

The interviews lasted approximately 30 to 45 minutes and were conducted face-to-face whenever possible. Where in-person interviewing was impractical, interviews were conducted by telephone or other appropriate communication methods. Detailed notes were taken during the interviews, and interviews were audio-recorded when participants granted permission. Recorded interviews were subsequently transcribed, while notes from non-recorded interviews were organized immediately following each session to preserve the accuracy and contextual meaning of participants' responses. The transcripts were repeatedly reviewed before formal coding to facilitate immersion in the data and to identify initial analytical ideas. Data collection and preliminary analysis were conducted concurrently so that emerging findings from earlier interviews could inform subsequent questioning and permit deeper exploration of concepts that required clarification.

The trustworthiness of the qualitative phase was addressed through the principles of credibility, dependability, transferability, and confirmability. Credibility was strengthened by selecting knowledgeable participants, conducting sufficiently detailed interviews, comparing information obtained from different experts, repeatedly examining interview transcripts, and returning selected interpretations or the emerging model to participants and other specialists for review. Where contradictory or negative cases appeared in the data, they were examined rather than excluded so that competing explanations could be considered and the resulting themes could more accurately represent the range of expert perspectives. Dependability was supported through the use of a structured interview procedure and the systematic documentation of data collection, transcription, coding, categorization, and interpretation. The analytical process was maintained in a form that could be reviewed by other researchers or academic supervisors. Confirmability was enhanced through the examination of raw data, coding decisions, interpretations, and revisions to the conceptual framework, as well as through expert review of the emerging categories and model. Transferability was facilitated by providing a clear description of the participant characteristics, institutional context, sampling strategy, data collection process, and conceptual categories, enabling readers to determine the extent to which the findings may be applicable to comparable higher education settings. The developing theoretical model was also presented to selected participants and specialists after its initial formulation, and their comments regarding modification, deletion, clarification, and integration of components were incorporated where appropriate.

In the quantitative phase, data were obtained through researcher-developed questionnaires derived directly from the qualitative findings and the theoretical background of the study. Two complementary forms of quantitative measurement were employed. The first instrument was designed for Fuzzy AHP analysis and consisted of pairwise comparisons among the principal dimensions and their respective indicators. This instrument was developed to convert experts' subjective judgments regarding the relative importance of the identified factors into analyzable quantitative information. For each pairwise comparison, respondents evaluated the relative priority of one dimension or indicator over another. Linguistic judgments were represented through triangular fuzzy numbers, thereby allowing uncertainty, ambiguity, and imprecision inherent in expert judgments to be incorporated into the decision-making process rather than forcing respondents to provide unrealistically precise numerical assessments. The hierarchical structure underlying the Fuzzy AHP questionnaire placed the effectiveness of virtual education using artificial intelligence at the highest level, followed by the major dimensions identified through thematic analysis and, subsequently, the corresponding indicators and subcomponents within each dimension.

The second quantitative instrument was a structured questionnaire developed for PLS-SEM. Its items were generated from the codes, categories, and themes extracted during the qualitative phase and were refined in accordance with the conceptual definitions of the seven principal dimensions. The questionnaire consisted of closed-ended statements representing observable indicators of the latent constructs, and responses were recorded on a Likert-type scale ranging from strong disagreement to strong agreement. The instrument was designed to generate data suitable for simultaneous assessment of the measurement model, which specifies the relationships between observed indicators and their corresponding latent constructs, and the structural model, which specifies the hypothesized relationships among the latent dimensions. In this manner, the instrument enabled the researchers to determine whether the qualitative components could be empirically represented as coherent constructs and whether the proposed relationships among educational, technological, psychological, social, managerial, human, and organizational factors were supported by the quantitative data.

Validity of the quantitative instrument was assessed at several levels. Face validity was initially examined through consultation with 10 experts familiar with the research field. The experts reviewed the items with regard to comprehensibility, wording, difficulty, relevance to the intended construct, appropriateness for the target population, and potential ambiguity. Their recommendations were used to make minor revisions to the wording and organization of the questionnaire. Construct validity was subsequently examined within the PLS measurement model. Convergent validity was evaluated by examining indicator loadings and the average variance extracted (AVE), with an AVE value of at least 0.50 considered indicative of adequate convergence because it demonstrates that a latent construct explains at least half of the variance in its observed indicators. Discriminant validity was evaluated to ensure that each construct was empirically distinguishable from the other constructs in the model. This assessment included examination of the Fornell–Larcker criterion, according to which the square root of the AVE for a construct should exceed its correlations with other latent constructs, as well as inspection of cross-loadings to determine whether each observed indicator loaded more strongly on its theoretically assigned construct than on competing constructs.

Reliability of the quantitative questionnaire was assessed using internal consistency indices. Cronbach's alpha was calculated to evaluate the consistency among the items representing each dimension, with higher coefficients indicating greater internal consistency. Because Cronbach's alpha assumes approximately equal contributions of the observed indicators, composite reliability was also examined. Composite reliability incorporates the actual factor loadings of the indicators and is therefore particularly appropriate for PLS-SEM. Evaluation of both Cronbach's alpha and composite reliability provided complementary evidence regarding the stability and consistency of the constructs used in the proposed model. The reliability analyses were performed using the quantitative questionnaire data, while the final validity and reliability coefficients formed part of the empirical evaluation of the measurement model.

The qualitative data were analyzed using thematic analysis. The analysis was conducted systematically from initial familiarization with the interview data through the development of the final thematic structure. First, all available interview material was transcribed and organized, and the transcripts were read repeatedly to achieve familiarity with the participants' accounts and to document preliminary analytical observations. The researchers then identified meaningful segments of data relevant to the objectives of the study and assigned initial codes to these segments. Coding was performed across the entire dataset rather than being restricted to predetermined theoretical categories, thereby allowing both anticipated and emerging aspects of artificial intelligence-supported virtual education to be identified. Following initial coding, conceptually related codes were compared, grouped, and reorganized into potential subthemes and broader themes. The developing themes were then reviewed against both the coded extracts and the complete dataset to determine whether they demonstrated sufficient internal coherence and clear conceptual differentiation. Themes that overlapped substantially were combined, whereas overly broad themes were subdivided and weak or unsupported categories were revised or removed. In the subsequent stage, the meaning and scope of each theme were clearly defined and appropriate labels were assigned. The final thematic structure was interpreted in relation to the research questions and used as the conceptual foundation for the quantitative phase. Both manual coding and computer-assisted qualitative data analysis were employed. MAXQDA 11 was used to facilitate the organization of transcripts, assignment and retrieval of codes, comparison of categories, management of researchers' analytical notes, and systematic review of coded segments. The software was used as an organizational and analytical support tool, while the interpretation and conceptual development of themes remained the responsibility of the researchers.

Following development of the qualitative framework, Fuzzy AHP was applied to determine the relative weights and priorities of the dimensions and indicators identified through thematic analysis. The analytical procedure began by constructing a hierarchical model in which the overall goal, namely the effectiveness of virtual education using artificial intelligence, was positioned at the highest level. The principal dimensions constituted the next level of the hierarchy, and their associated components and indicators were positioned at subordinate levels. Expert judgments concerning the relative importance of the factors were then obtained through fuzzy pairwise comparisons. Rather than representing preferences as single exact values, linguistic judgments were converted into triangular fuzzy numbers to account for the uncertainty and imprecision associated with human evaluation. Individual fuzzy pairwise comparison matrices were subsequently aggregated to create a collective representation of expert judgments. Fuzzy weights were calculated for the dimensions and indicators, after which the fuzzy results were defuzzified to obtain crisp numerical values. These values were normalized and used to rank the factors according to their relative contribution to the effectiveness of artificial intelligence-supported virtual education. Accordingly, factors with greater normalized weights were interpreted as having higher priority within the proposed framework.

PLS-SEM was subsequently used to validate the conceptual model and investigate the relationships among the latent constructs. PLS-SEM was selected because the study was oriented toward model development and prediction and involved the simultaneous estimation of relationships between latent variables and their observable indicators. The analysis proceeded through evaluation of the measurement model followed by assessment of the structural model. In the measurement model, the adequacy of the relationships between questionnaire items and their corresponding latent constructs was examined through indicator loadings, internal consistency reliability, composite reliability, average variance extracted, convergent validity, and discriminant validity. Indicators and constructs were evaluated to determine whether they demonstrated acceptable psychometric properties before interpretation of the structural relationships. The Fornell–Larcker criterion and cross-loading patterns were examined as part of the assessment of discriminant validity so that the conceptual distinctiveness of the principal dimensions could be established.

After establishing the adequacy of the measurement model, the structural model was examined to determine the magnitude and direction of the relationships among the principal dimensions. Path coefficients were estimated for the hypothesized relationships, and their statistical significance was evaluated to determine which dimensions exerted meaningful effects within the model. The explanatory capacity of the model was assessed by examining the proportion of variance in endogenous constructs explained by their predictors. The structural analysis therefore provided evidence concerning the relative influence of the educational, technological, psychological, social, managerial, human, and organizational dimensions and clarified the internal structure of the proposed framework. The results of the Fuzzy AHP analysis were interpreted together with the PLS-SEM findings so that factor prioritization and structural validation complemented one another. Fuzzy AHP identified which dimensions and indicators were considered most important on the basis of expert judgments, whereas PLS-SEM determined whether the proposed measurement structure and relationships among the constructs were empirically supported by data from university faculty members. The integration of the qualitative thematic findings, fuzzy prioritization results, and structural modeling evidence formed the basis for developing and validating the final model of factors affecting the effectiveness of virtual education using artificial intelligence in the educational system of Islamic Azad Universities in West Azerbaijan Province.

Findings and Results

In the first Delphi round, 26 components derived from the qualitative interviews and coding process were presented to the expert panel. Descriptive statistics were calculated to determine the perceived importance of each component and to conduct an initial screening of the indicators. As presented in Table 1, all 26 components were initially accepted by the experts.

Table 1

Descriptive Statistics of Expert Responses in the First Delphi Round

Dimension	Component	Mean	SD	Initial Result
Educational	Effective instructional design	3.6000	1.32873	Accepted
Educational	Instructor–student interaction	3.9667	1.09807	Accepted
Educational	Intelligent and continuous feedback	4.2414	0.91242	Accepted
Educational	Quality and currency of content	4.3333	0.47946	Accepted

Educational	Intelligent assessment	3.9333	0.98027	Accepted
Educational	Personalized learning	3.0000	1.36458	Accepted
Educational	Intelligent support	4.5333	1.04166	Accepted
Technological	Infrastructure and internet access	4.1333	0.86037	Accepted
Technological	Stable and user-friendly systems	4.1333	0.86037	Accepted
Technological	Artificial intelligence tools	4.4000	0.72397	Accepted
Technological	Security and privacy	4.3667	0.80872	Accepted
Psychological	Learning motivation	4.5333	0.50742	Accepted
Psychological	Active student participation	3.7667	1.16511	Accepted
Psychological	Reduction of technology anxiety	3.3667	1.49674	Accepted
Social	Group interaction	3.6207	1.49795	Accepted
Social	Sense of belonging	3.6333	1.15917	Accepted
Social	Educational equity and equal access	3.8000	1.18613	Accepted
Managerial	Data-driven decision-making	4.1000	1.15520	Accepted
Managerial	Optimal resource allocation	4.2667	0.78492	Accepted
Managerial	Faculty support and professional development	4.3000	0.79438	Accepted
Human	Faculty readiness and acceptance	4.3333	0.66089	Accepted
Human	Students' digital skills	3.8000	1.21485	Accepted
Human	Attitude toward intelligent learning	3.9000	1.32222	Accepted
Organizational	Macro-level policies and strategies	3.8000	1.09545	Accepted
Organizational	Organizational culture supportive of innovation	3.3000	1.39333	Accepted
Organizational	Investment in digital infrastructure	4.2333	1.00630	Accepted

Within the educational dimension, intelligent support obtained the highest mean score (M = 4.5333), followed by quality and currency of content (M = 4.3333) and intelligent and continuous feedback (M = 4.2414). These findings indicated that experts attached considerable importance to intelligent support systems, continuous feedback, and dynamically updated educational content. Personalized learning received the lowest mean score within this dimension (M = 3.0000) and was accompanied by relatively high dispersion (SD = 1.36458), suggesting less uniformity in experts' judgments regarding its immediate feasibility within the existing university context.

All technological components obtained mean scores above 4.00. Artificial intelligence tools received the highest score in this dimension (M = 4.4000), closely followed by security and privacy (M = 4.3667). Infrastructure and internet access and stable and user-friendly systems both obtained a mean of 4.1333. Thus, technological readiness was consistently evaluated as an important component of effective AI-supported virtual education.

Within the psychological dimension, learning motivation received one of the highest ratings across the entire first Delphi round (M = 4.5333, SD = 0.50742). Active student participation also received a favorable assessment (M = 3.7667), whereas reduction of technology anxiety obtained a lower mean (M = 3.3667) and relatively high dispersion (SD = 1.49674). The latter finding indicated greater heterogeneity in experts' perceptions of the psychological challenges associated with intelligent educational technologies.

In the social dimension, educational equity and equal access obtained the highest mean (M = 3.8000), followed by sense of belonging (M = 3.6333) and group interaction (M = 3.6207). The findings therefore indicated that equitable access to virtual learning opportunities and technological resources was regarded as an important social consideration.

All managerial indicators received mean scores above 4.00. Faculty support and professional development achieved the highest managerial mean (M = 4.3000), followed by optimal resource allocation (M = 4.2667) and data-driven decision-making (M = 4.1000). The results indicated a consistently high level of perceived importance for managerial capacity in supporting AI-based virtual education.

Within the human dimension, faculty readiness and acceptance received the highest mean score (M = 4.3333), followed by attitudes toward intelligent learning (M = 3.9000) and students' digital skills (M = 3.8000). The relatively greater variation in assessments of student digital skills suggested that respondents differed to some extent in their perceptions of students' preparedness to participate effectively in AI-supported learning environments.

Within the organizational dimension, investment in digital infrastructure obtained the highest mean (M = 4.2333), whereas organizational culture supportive of innovation obtained the lowest mean (M = 3.3000) and relatively high dispersion (SD = 1.39333). Macro-level policies and strategies obtained a mean of 3.8000. Overall, the first-round findings showed that most indicators were rated above the midpoint of the response scale and therefore warranted retention for further Delphi evaluation.

Kendall's coefficient of concordance was used to assess the extent of agreement among the experts across the two Delphi rounds. Table 2 presents the comparative results.

Table 2

Kendall's Coefficient of Concordance Across the Delphi Rounds

Delphi Round	Number of Indicators	Kendall's W	Chi-Square	p
First round	26	0.147	110.866	< .001
Second round	26	0.715	747.653	< .001

In the first Delphi round, Kendall's coefficient was W = 0.147, indicating a relatively low level of agreement among experts. Nevertheless, the corresponding chi-square statistic was statistically significant, $\chi^2 = 110.866$, $p < .001$, demonstrating that the observed concordance was greater than would be expected by chance. The relatively modest coefficient was consistent with the exploratory function of an initial Delphi round, during which divergent perspectives are expected to emerge and indicators are subject to conceptual refinement.

The first-round results therefore supported continuation of the Delphi process. The variation in judgments also suggested that several indicators required clarification and reconsideration before final consensus could be established. The combination of a statistically significant but relatively small Kendall coefficient indicated that experts shared a partially common evaluative framework while still differing in the relative importance they assigned to individual indicators.

In the second Delphi round, the 26 indicators retained from the first round were presented again to the expert panel. Experts reconsidered the indicators after receiving the aggregated results of the preceding round. Table 3 presents the second-round descriptive findings.

Table 3

Descriptive Statistics of Expert Responses in the Second Delphi Round

Dimension	Component	Mean	SD	Mean Difference	Final Result
Educational	Effective instructional design	3.6161	0.50543	0.0161	Agreement
Educational	Instructor–student interaction	3.9683	0.47539	0.0016	Agreement
Educational	Intelligent and continuous feedback	4.2150	0.45198	−0.0264	Agreement
Educational	Quality and currency of content	4.3075	0.47960	−0.0258	Agreement
Educational	Intelligent assessment	4.0075	0.43470	0.0742	Agreement
Educational	Personalized learning	3.1075	0.53541	0.1075	Agreement
Educational	Intelligent support	4.5950	0.43870	0.0617	Agreement
Technological	Infrastructure and internet access	4.1775	0.46533	0.0442	Agreement
Technological	Stable and user-friendly systems	4.1450	0.45771	0.0117	Agreement
Technological	Artificial intelligence tools	4.3825	0.43551	−0.0175	Agreement
Technological	Security and privacy	4.3775	0.44327	0.0108	Agreement

Psychological	Learning motivation	4.5500	0.46155	0.0167	Agreement
Psychological	Active student participation	3.7850	0.40766	0.0183	Agreement
Psychological	Reduction of technology anxiety	3.3475	0.55318	−0.0192	Agreement
Social	Group interaction	4.1900	0.43517	0.5693	Agreement
Social	Sense of belonging	3.5650	0.43961	−0.0683	Agreement
Social	Educational equity and equal access	3.8975	0.52314	0.0975	Agreement
Managerial	Data-driven decision-making	4.1300	0.50867	0.0300	Agreement
Managerial	Optimal resource allocation	4.1950	0.50459	−0.0717	Agreement
Managerial	Faculty support and professional development	4.2625	0.54021	−0.0375	Agreement
Human	Faculty readiness and acceptance	4.3375	0.53788	0.0042	Agreement
Human	Students' digital skills	3.8975	0.56016	0.0975	Agreement
Human	Attitude toward intelligent learning	3.9525	0.47414	0.0525	Agreement
Organizational	Macro-level policies and strategies	3.8550	0.51637	0.0550	Agreement
Organizational	Organizational culture supportive of innovation	3.3450	0.45771	0.0450	Agreement
Organizational	Investment in digital infrastructure	4.1500	0.48279	−0.0833	Agreement

All 26 indicators reached the predefined level of agreement in the second Delphi round. The standard deviations were also considerably smaller than those observed in the first round, indicating reduced response dispersion and greater convergence among expert judgments. For most indicators, the differences between first- and second-round means were small, indicating that experts' evaluations had become relatively stable.

Within the educational dimension, intelligent support remained the highest-rated component (M = 4.5950), followed by quality and currency of content (M = 4.3075) and intelligent and continuous feedback (M = 4.2150). Personalized learning remained the lowest-rated educational component (M = 3.1075), although it nevertheless reached the required level of agreement and was retained in the final model.

Within the technological dimension, artificial intelligence tools (M = 4.3825) and security and privacy (M = 4.3775) received the highest evaluations. Infrastructure and internet access (M = 4.1775) and stable and user-friendly systems (M = 4.1450) also remained highly rated. The small mean differences across the Delphi rounds demonstrated substantial stability in the technological judgments.

Learning motivation again emerged as the strongest psychological component (M = 4.5500). Active student participation obtained a mean of 3.7850, whereas reduction of technology anxiety remained lower (M = 3.3475), although the considerably lower standard deviation in the second round indicated greater convergence among experts.

Among social components, group interaction increased markedly to M = 4.1900, representing the largest positive mean change across the Delphi indicators (+0.5693). Educational equity and equal access reached M = 3.8975, while sense of belonging received M = 3.5650. These findings confirmed that social interaction and equitable participation remained relevant dimensions of the final model.

Within the managerial dimension, faculty support and professional development received the highest mean (M = 4.2625), followed by optimal resource allocation (M = 4.1950) and data-driven decision-making (M = 4.1300). Faculty readiness and acceptance was the highest-rated human component (M = 4.3375), while students' digital skills and attitudes toward intelligent learning obtained means of 3.8975 and 3.9525, respectively.

Within the organizational dimension, investment in digital infrastructure remained the most highly rated component (M = 4.1500). Macro-level policies and strategies obtained M = 3.8550, whereas organizational culture supportive of innovation remained the lowest-rated component (M = 3.3450). Nevertheless, all three organizational components reached agreement and were retained.

The second-round Kendall coefficient increased substantially to W = 0.715, with $\chi^2 = 747.653$ and $p < .001$. This value indicated strong expert consensus and represented a considerable improvement over the first-round coefficient of 0.147. The statistically significant increase in agreement, together with the reduction in standard deviations and stability of mean scores, demonstrated that the iterative Delphi process successfully reduced differences in expert judgments. Because a strong and stable level of consensus had been achieved for all 26 indicators, an additional Delphi round was not considered necessary.

Following completion of the Delphi process, seven major dimensions and 26 components were retained in the conceptual model. These dimensions and their corresponding codes are presented in Table 4.

Table 4

Final Dimensions and Components of AI-Based Virtual Education Effectiveness

Dimension	Dimension Code	Component	Component Code
Educational	C1	Effective instructional design	C11
Educational	C1	Instructor–student interaction	C12
Educational	C1	Intelligent and continuous feedback	C13
Educational	C1	Quality and currency of content	C14
Educational	C1	Intelligent assessment	C15
Educational	C1	Personalized learning	C16
Educational	C1	Intelligent support	C17
Technological	C2	Infrastructure and internet access	C21
Technological	C2	Stable and user-friendly systems	C22
Technological	C2	Artificial intelligence tools	C23
Technological	C2	Security and privacy	C24
Psychological	C3	Learning motivation	C31
Psychological	C3	Active student participation	C32
Psychological	C3	Reduction of technology anxiety	C33
Social	C4	Group interaction	C41
Social	C4	Sense of belonging	C42
Social	C4	Educational equity and equal access	C43
Managerial	C5	Data-driven decision-making	C51
Managerial	C5	Optimal resource allocation	C52
Managerial	C5	Faculty support and professional development	C53
Human	C6	Faculty readiness and acceptance	C61
Human	C6	Students' digital skills	C62
Human	C6	Attitude toward intelligent learning	C63
Organizational	C7	Macro-level policies and strategies	C71
Organizational	C7	Organizational culture supportive of innovation	C72
Organizational	C7	Investment in digital infrastructure	C73

After the Delphi validation, AHP was used to quantify expert judgments and establish the relative priorities of the seven main dimensions. Pairwise comparisons were synthesized using Expert Choice. Before interpreting the priorities, the logical consistency of the pairwise comparison matrix was evaluated. The inconsistency ratio was 0.00051, which was substantially below the conventional threshold of 0.10. Accordingly, the pairwise judgments demonstrated an exceptionally high level of internal consistency, and the resulting priorities were considered suitable for interpretation.

The final AHP priorities obtained from the uploaded Expert Choice output are presented in Table 5.

Table 5

AHP Ranking of the Main Dimensions

Rank	Main Dimension	AHP Weight	Percentage of Total Weight
1	Managerial	0.181	18.1%
2	Technological	0.173	17.3%

3	Human	0.161	16.1%
4	Social	0.148	14.8%
5	Psychological	0.141	14.1%
6	Educational	0.103	10.3%
7	Organizational	0.093	9.3%

The managerial dimension received the highest priority, with a relative weight of 0.181. The technological dimension followed closely with a weight of 0.173, while the human dimension ranked third with a weight of 0.161. Together, these three dimensions accounted for 51.5% of the total AHP weight, indicating that expert judgments concentrated more than half of the total relative importance on managerial capacity, technological readiness, and human resources.

The social dimension ranked fourth with a weight of 0.148, followed by the psychological dimension with a weight of 0.141. These findings indicated that social interaction, access, motivational conditions, psychological readiness, and user acceptance also represented substantial contributors to the effectiveness of AI-supported virtual education.

The educational dimension obtained a weight of 0.103 and ranked sixth, while the organizational dimension ranked seventh with a weight of 0.093. These rankings do not imply that educational and organizational components were unimportant; rather, within the comparative AHP structure, experts assigned greater relative priority to managerial, technological, and human prerequisites. Thus, the AHP findings suggested that improvement of AI-supported virtual education should initially emphasize management and governance processes, technological infrastructure, and faculty and student capabilities, while educational and organizational mechanisms remain integral components of the broader system.

Following the Delphi and AHP stages, the empirical adequacy of the seven-dimensional measurement model was examined using first- and second-order confirmatory factor analysis within PLS-SEM. At the first-order level, the 26 observed indicators were linked to their respective latent dimensions. At the second-order level, the seven dimensions were modeled as components of the higher-order construct of virtual education using artificial intelligence.

The complete standardized factor loadings, t statistics, and significance levels are reported in Table 6.

Table 6

Results of First- and Second-Order Confirmatory Factor Analysis

Indicator / Dimension	First-Order Loading	t	p	Second-Order Loading	t	p
Q1 ← Educational	0.682	13.140	< .001	0.796	26.410	< .001
Q2 ← Educational	0.827	26.782	< .001	—	—	—
Q3 ← Educational	0.863	35.942	< .001	—	—	—
Q4 ← Educational	0.851	28.342	< .001	—	—	—
Q5 ← Educational	0.854	29.112	< .001	—	—	—
Q6 ← Educational	0.665	10.032	< .001	—	—	—
Q7 ← Educational	0.821	30.114	< .001	—	—	—
Q8 ← Technological	0.823	18.366	< .001	0.840	38.739	< .001
Q9 ← Technological	0.852	28.057	< .001	—	—	—
Q10 ← Technological	0.873	31.440	< .001	—	—	—
Q11 ← Technological	0.825	27.528	< .001	—	—	—
Q12 ← Psychological	0.888	49.261	< .001	0.827	24.505	< .001
Q13 ← Psychological	0.871	34.806	< .001	—	—	—
Q14 ← Psychological	0.716	13.689	< .001	—	—	—
Q15 ← Social	0.797	16.884	< .001	0.836	25.183	< .001
Q16 ← Social	0.863	34.733	< .001	—	—	—
Q17 ← Social	0.761	15.015	< .001	—	—	—
Q18 ← Managerial	0.859	27.843	< .001	0.787	22.619	< .001
Q19 ← Managerial	0.832	28.855	< .001	—	—	—
Q20 ← Managerial	0.799	28.929	< .001	—	—	—
Q21 ← Human	0.824	26.447	< .001	0.799	26.300	< .001

Q22 ← Human	0.823	25.550	< .001	—	—	—
Q23 ← Human	0.764	12.238	< .001	—	—	—
Q24 ← Organizational	0.722	14.514	< .001	0.784	25.642	< .001
Q25 ← Organizational	0.882	42.050	< .001	—	—	—
Q26 ← Organizational	0.855	40.653	< .001	—	—	—

At the first-order level, all standardized factor loadings exceeded 0.60. Educational indicators ranged from 0.665 to 0.863, technological indicators from 0.823 to 0.873, psychological indicators from 0.716 to 0.888, social indicators from 0.761 to 0.863, managerial indicators from 0.799 to 0.859, human indicators from 0.764 to 0.824, and organizational indicators from 0.722 to 0.882. These results indicated that all observed indicators were sufficiently associated with their intended first-order constructs.

The educational indicators demonstrated adequate to strong loadings, with Q3 showing the largest educational loading at 0.863. The technological indicators were particularly homogeneous, with loadings concentrated between 0.823 and 0.873. Within the psychological dimension, Q12 displayed the highest first-order loading in the entire model at 0.888. The social and managerial dimensions also showed consistently strong indicator loadings, while the human and organizational indicators remained well above the minimum acceptable level.

The t statistics provided additional evidence supporting the measurement relationships. Within the educational dimension, t values ranged from 10.032 to 35.942; technological indicators ranged from 18.366 to 31.440; psychological indicators ranged from 13.689 to 49.261; social indicators ranged from 15.015 to 34.733; managerial indicators ranged from 27.843 to 28.929; human indicators ranged from 12.238 to 26.447; and organizational indicators ranged from 14.514 to 42.050. Every first-order t statistic was well above the critical value of 1.96, and all corresponding p values were below .001. Thus, the null hypothesis of a zero loading was rejected for every indicator, and no observed variable required elimination on the basis of statistical insignificance.

The second-order analysis also supported the hierarchical structure of the model. The standardized loading of the technological dimension on the overall construct was the largest at 0.840, followed by the social dimension at 0.836 and the psychological dimension at 0.827. The human dimension loaded at 0.799, the educational dimension at 0.796, the managerial dimension at 0.787, and the organizational dimension at 0.784. All second-order loadings were therefore positive and comparatively high.

The corresponding second-order t values ranged from 22.619 to 38.739. The strongest statistical evidence was observed for the technological dimension, $t = 38.739$, followed by the educational, human, organizational, social, psychological, and managerial dimensions, all of which remained substantially above the critical threshold. All second-order relationships were significant at $p < .001$. Consequently, each of the seven first-order dimensions made a statistically significant contribution to the higher-order construct of AI-based virtual education effectiveness.

The combined first- and second-order CFA results therefore supported the proposed hierarchical measurement model. No weak or nonsignificant pathway was identified, and the empirical findings supported retention of all seven dimensions and all 26 observed indicators.

Internal consistency reliability was examined using Cronbach's alpha, rho_A, and composite reliability. Values above 0.70 were regarded as acceptable. Convergent validity was evaluated through the average variance extracted (AVE), with values of at least 0.50 indicating that a construct explained at least half of the variance in its indicators. Table 7 summarizes the results.

Table 7

Reliability and Convergent Validity of the Study Constructs

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Educational	0.903	0.905	0.924	0.638
Social	0.734	0.746	0.849	0.653
Human	0.726	0.727	0.846	0.647
Psychological	0.767	0.785	0.867	0.686
Organizational	0.757	0.769	0.862	0.677
Technological	0.865	0.865	0.908	0.712
Managerial	0.775	0.774	0.869	0.689

Cronbach's alpha ranged from 0.726 for the human dimension to 0.903 for the educational dimension. Accordingly, every construct exceeded the minimum reliability criterion of 0.70. The educational construct demonstrated particularly strong internal consistency, with $\alpha = 0.903$, rho_A = 0.905, and CR = 0.924. The technological construct similarly demonstrated high reliability, with $\alpha = 0.865$, rho_A = 0.865, and CR = 0.908.

The psychological dimension showed acceptable to strong reliability, with $\alpha = 0.767$, rho_A = 0.785, and CR = 0.867. The managerial dimension produced $\alpha = 0.775$, rho_A = 0.774, and CR = 0.869. Although the social and human dimensions had comparatively lower Cronbach's alpha values, both remained above the acceptable criterion. The social dimension produced $\alpha = 0.734$, rho_A = 0.746, and CR = 0.849, whereas the human dimension produced $\alpha = 0.726$, rho_A = 0.727, and CR = 0.846. The organizational dimension also demonstrated satisfactory internal consistency, with $\alpha = 0.757$, rho_A = 0.769, and CR = 0.862. Overall, no construct demonstrated a reliability problem.

The AVE values ranged from 0.638 to 0.712, and all were above the minimum criterion of 0.50. The technological construct achieved the highest AVE at 0.712, followed by the managerial construct at 0.689, psychological at 0.686, organizational at 0.677, social at 0.653, human at 0.647, and educational at 0.638. Thus, each construct explained more than half of the variance in its respective indicators. Composite reliability was also higher than AVE for every construct, providing further evidence of satisfactory convergent validity.

Discriminant validity was assessed using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations (HTMT). Under the Fornell–Larcker criterion, the square root of AVE for each construct should exceed its correlations with the other constructs. For HTMT, values below 0.90 were used as evidence of acceptable discriminant validity. To present both assessments concisely, Table 8 reports the square roots of AVE on the diagonal, construct correlations below the diagonal, and HTMT coefficients above the diagonal.

Table 8

Discriminant Validity Based on the Fornell–Larcker Criterion and HTMT

Construct	Educational	Social	Human	Psychological	Organizational	Technological	Managerial
Educational	0.799	0.778	0.669	0.769	0.697	0.899	0.643
Social	0.633	0.808	0.824	0.867	0.738	0.867	0.867
Human	0.538	0.606	0.804	0.794	0.834	0.718	0.852
Psychological	0.649	0.723	0.590	0.828	0.758	0.868	0.733
Organizational	0.573	0.554	0.615	0.583	0.823	0.768	0.749
Technological	0.794	0.694	0.568	0.721	0.618	0.844	0.723
Managerial	0.540	0.661	0.644	0.570	0.572	0.594	0.830

The Fornell–Larcker results demonstrated that the square root of AVE for every construct exceeded its correlations with the other constructs. For the educational construct, the square root of AVE was 0.799, which exceeded its correlations with the social (0.633), human (0.538), psychological (0.649), organizational (0.573), technological (0.794), and managerial (0.540) dimensions. Although the correlation between educational and technological dimensions was relatively high at 0.794, it remained slightly below the educational square root of AVE of 0.799.

For the social dimension, the diagonal value of 0.808 exceeded all corresponding interconstruct correlations, including those with psychological (0.723), technological (0.694), and managerial (0.661) dimensions. Similarly, the human dimension had a square root of AVE of 0.804, exceeding its highest observed correlations with managerial (0.644) and organizational (0.615) dimensions.

The psychological construct produced a diagonal value of 0.828, which was greater than its correlations with the social (0.723), technological (0.721), human (0.590), organizational (0.583), managerial (0.570), and educational (0.649) constructs. The organizational construct also satisfied the criterion, with a square root of AVE of 0.823. For the technological construct, the diagonal value of 0.844 exceeded its strongest correlation, which occurred with the educational dimension at 0.794. Finally, the managerial construct had a diagonal value of 0.830, exceeding all of its interconstruct correlations. These results supported discriminant validity according to the Fornell–Larcker criterion.

The HTMT analysis provided further evidence of construct distinctiveness. All HTMT coefficients remained below 0.90. The educational–technological relationship produced the highest HTMT value at 0.899, which was very close to, but still below, the 0.90 criterion. Other comparatively high coefficients included technological–psychological at 0.868, social–psychological at 0.867, social–technological at 0.867, and social–managerial at 0.867. The human–managerial relationship produced an HTMT value of 0.852, while the human–organizational relationship was 0.834. None of the pairwise relationships exceeded the specified 0.90 threshold. Thus, despite meaningful conceptual associations among several dimensions, the constructs retained adequate empirical distinctiveness.

The overall measurement results demonstrated satisfactory internal consistency, convergent validity, discriminant validity, and statistical significance of the indicator loadings. Cronbach's alpha, rho_A, and composite reliability exceeded the accepted minimum values for all seven constructs. Likewise, every AVE value exceeded 0.50, all first-order standardized factor loadings exceeded 0.60, and all first- and second-order t statistics exceeded 1.96 with $p < .001$.

For overall model evaluation, the Goodness-of-Fit index and standardized root mean square residual were considered as supplementary criteria. GOF values of approximately 0.01, 0.25, and 0.36 correspond to weak, moderate, and strong overall fit, respectively, while an SRMR below 0.08 is generally interpreted as evidence of satisfactory fit, with values up to approximately 0.10 sometimes considered acceptable. Numerical GOF and SRMR estimates were not included in the supplied statistical output; therefore, no additional numerical claim regarding these indices is made here.

The results of the standardized loading analysis showed that the measurement model performed consistently across both hierarchical levels. At the first-order level, all 26 observed indicators adequately represented their intended dimensions. At the second-order level, all seven dimensions contributed significantly to the overall construct. The second-order factor loadings were relatively homogeneous, ranging from 0.784 to 0.840, indicating that the overarching construct of AI-based virtual education effectiveness was multidimensional rather than being dominated exclusively by a single dimension.

An important distinction emerged between the AHP and CFA findings. In AHP, the managerial dimension received the greatest relative priority based on experts' comparative judgments, followed by technological and human dimensions. In the second-order CFA, however, the technological dimension produced the strongest standardized association with the higher-order construct, followed by the social and psychological dimensions. These findings are not contradictory because the two analyses address different questions. AHP represents experts' judgments concerning relative strategic priority, whereas second-order CFA reflects the empirical strength with which each dimension represents the higher-order latent construct.

Figure 1

Model with Beta Values

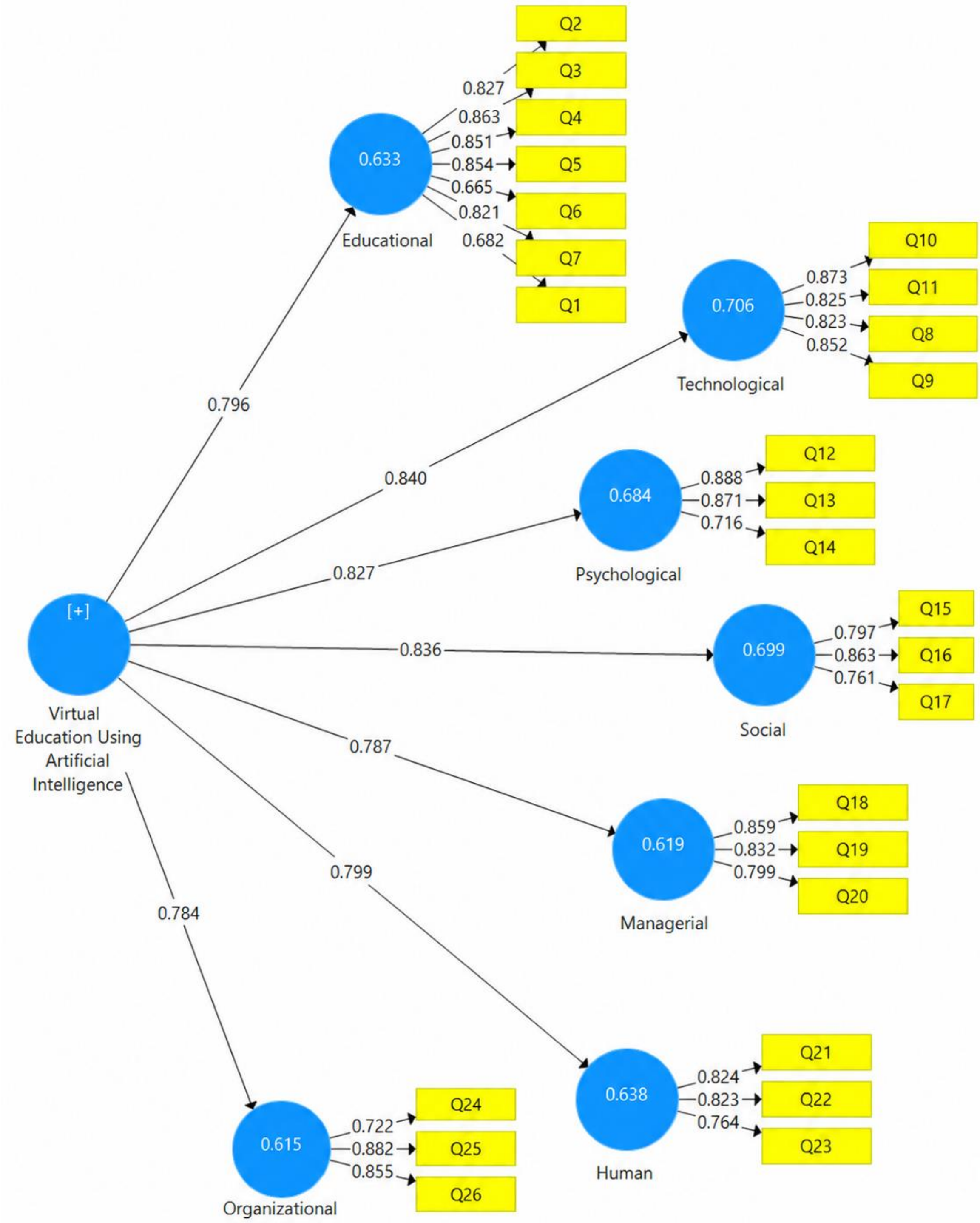
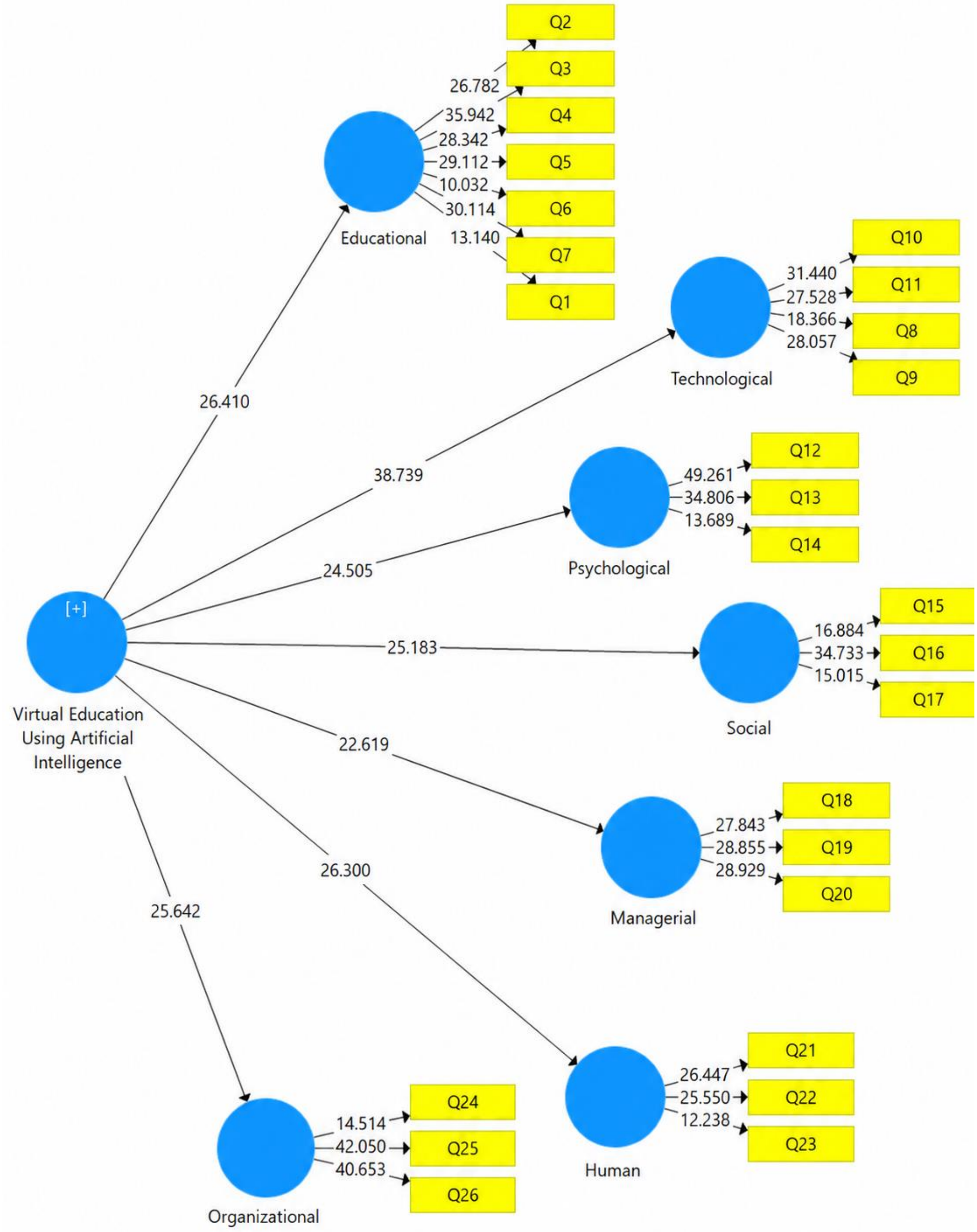


Figure 2

Model with T-Values



Discussion and Conclusion

The present study investigated the factors affecting the effectiveness of virtual education using artificial intelligence in the educational system of Islamic Azad Universities in West Azerbaijan Province through an integrated qualitative–quantitative framework. The findings demonstrated that the effectiveness of AI-supported virtual education is a multidimensional phenomenon consisting of seven interrelated dimensions: educational, technological, psychological, social, managerial, human, and organizational. Twenty-six components were initially identified and subsequently validated through two rounds of Delphi analysis. The first Delphi round revealed relatively limited agreement among experts, with Kendall's coefficient of concordance equal to 0.147, although this level of agreement was statistically significant. In the second round, expert convergence increased substantially, and Kendall's W reached 0.715, indicating strong consensus regarding the relevance of the identified components. The AHP results further showed that the managerial dimension had the highest priority with a weight of 0.181, followed by technological factors with 0.173 and human factors with 0.161. Social, psychological, educational, and organizational dimensions received weights of 0.148, 0.141, 0.103, and 0.093, respectively. Finally, PLS-based confirmatory factor analysis confirmed the reliability and validity of the proposed model, with all first-order and second-order factor loadings being statistically significant and all reliability and validity indices falling within acceptable ranges.

The strong expert consensus obtained in the second Delphi round indicates that effective virtual education based on AI cannot be adequately explained by a single technological or pedagogical variable. Instead, it appears to depend on the coordinated functioning of multiple institutional, human, technological, and educational factors. This multidimensional interpretation is consistent with contemporary literature portraying AI integration in higher education as an ecosystem-level transformation rather than the simple introduction of a new technological tool. Ruano-Borbalan argues that the transformative effects of AI extend across teaching, governance, institutional structures, and student experiences, requiring a broad reconsideration of higher education practices [2]. Similarly, Dubey emphasizes that successful AI integration requires alignment among infrastructure, educational practice, institutional support, and stakeholder readiness [1]. Aslam and colleagues likewise describe adaptive learning, intelligent tutoring, and academic analytics as interconnected components of AI-supported university education rather than isolated applications [3]. Therefore, the convergence of experts around seven dimensions in the present research supports the view that the effectiveness of AI-based virtual education emerges from interactions among several complementary subsystems.

The most important finding of the AHP analysis was the first-place ranking of the managerial dimension. With a relative weight of 0.181, managerial factors were considered more important than any other dimension in determining the effectiveness of AI-supported virtual education. This result suggests that technological availability alone does not ensure successful implementation; rather, managerial decision-making, strategic coordination, resource allocation, faculty support, and professional development provide the conditions under which AI technologies can be effectively incorporated into academic processes. This finding strongly aligns with research emphasizing the central role of leadership in AI transformation. Sposato's taxonomy of artificial intelligence in educational leadership demonstrates that AI adoption introduces new responsibilities for leaders in planning, governance, decision-making, organizational learning, and change management [26]. Kabanda similarly identifies leadership dynamics as an essential element in integrating AI into academic processes [20]. Research on responsible strategic leadership also indicates that institutional leaders must coordinate academic and administrative uses of AI while establishing structures for accountability, resource allocation, and sustainable implementation [27, 28]. Thus, the managerial priority identified in the present study may reflect experts' recognition that the major challenge is not simply obtaining AI tools but managing their integration strategically.

The specific managerial components identified in the study further reinforce this interpretation. Faculty support and professional development received the highest mean within the managerial dimension during the second Delphi round, followed by optimal resource allocation and data-driven decision-making. These findings suggest that university leadership must simultaneously empower instructors, allocate technological and financial resources efficiently, and use educational data to guide policy and implementation. This interpretation is consistent with Tahir et al., who emphasize the importance of AI as a mechanism for supporting higher education teachers rather than merely replacing or automating their instructional activities [6]. Kohnke similarly argues that AI-related teacher education should enhance both pre-service and in-service professional development, enabling instructors to integrate new technologies meaningfully into pedagogical practice [29]. In addition, Tan et al. show that AI competency influences teaching performance through technological pedagogical content knowledge, highlighting that professional development must involve more than technical training and should instead integrate pedagogical, technological, and disciplinary competencies [7].

The technological dimension ranked second in the AHP analysis, with a weight of 0.173, and also demonstrated the strongest second-order factor loading in the empirical measurement model at 0.840. This dual finding underscores the foundational role of technological conditions in both expert prioritization and statistical representation of the higher-order construct. Within this dimension, artificial intelligence tools and security and privacy received the highest ratings, while infrastructure and internet access and stable user-friendly systems were also strongly endorsed. These results suggest that effective AI-supported virtual education requires more than mere internet connectivity. Universities need reliable platforms, accessible intelligent applications, adequate computing capacity, secure data environments, and technology that can be incorporated seamlessly into instructional processes. Chegini et al. similarly report that AI can improve teaching and learning experiences in higher education when appropriate technological conditions are available [21]. The findings also align with Sajja et al., who demonstrated the potential of AI-enabled intelligent assistants for personalized and adaptive learning, a function that inherently depends on robust technological architecture [4]. Hernandez-Herrera et al. likewise identify adaptive AI-based learning as an important mechanism for personalizing higher education, but such systems require stable and sufficiently advanced digital infrastructure [5].

The emphasis placed on security and privacy is also noteworthy. AI-supported learning environments frequently rely on extensive educational data, including performance records, behavioral interactions, communication patterns, and potentially sensitive user information. Consequently, the effectiveness of these systems partly depends on students' and faculty members' confidence that their information is appropriately protected. The present findings are consistent with growing attention to AI governance and ethics in higher education. Eissa highlights the importance of adaptable institutional governance structures capable of regulating AI implementation and responding to emerging risks [24]. McDonald et al. similarly show that higher education institutions are increasingly developing policies and guidelines governing generative AI use, reflecting institutional concerns regarding responsibility, transparency, academic integrity, and acceptable use [25]. Zhang's analysis of AI ethics education further supports the necessity of embedding ethical understanding into professional higher education programs rather than treating ethics as separate from technological competence [23]. Therefore, technological effectiveness must be interpreted as including security, privacy, governance, and responsible use, not merely technical performance.

The human dimension was ranked third, with an AHP weight of 0.161, confirming that human readiness constitutes another major prerequisite for AI-supported virtual education. Among its components, faculty readiness and acceptance received the strongest expert endorsement. This result suggests that even highly sophisticated educational technologies are unlikely to achieve their intended effects unless instructors are willing and able to use them. Faculty members must understand AI tools, perceive them as useful, possess appropriate digital skills, and be confident in incorporating them into teaching. Faculty experiences reported by Asgarova et al. similarly demonstrate that generative AI integration requires instructors to adapt curricula, reconsider pedagogical practices, and negotiate practical and ethical concerns [9]. Walter also emphasizes that AI literacy, prompt engineering, and critical thinking have become essential competencies in contemporary education [11]. The present findings therefore reinforce the argument that human capability is not peripheral to AI implementation but constitutes one of its central determinants.

Student-related human competencies were also retained, particularly digital skills and attitudes toward intelligent learning. The importance of these factors aligns with Wang et al., who found that AI literacy in higher education is associated with self-regulated learning processes and need satisfaction [12]. Hosseini likewise reports that AI literacy can contribute to higher-order thinking through behavioral engagement and peer interaction [13]. These findings suggest that students require both technical competence and active learning skills to benefit meaningfully from AI. AI should therefore support students' autonomy and cognitive engagement rather than encourage passive dependence. This interpretation is also compatible with Walter's emphasis on critical AI literacy and with concerns surrounding students' responsible use of generative systems [11]. Accordingly, strengthening students' ability to evaluate, question, and appropriately use AI-generated information appears to be an important aspect of effective virtual education.

The social dimension ranked fourth in AHP and showed the second-highest second-order loading in the measurement model at 0.836. Group interaction was the strongest social component in the second Delphi round, followed by educational equity and equal access and sense of belonging. These findings demonstrate that technologically mediated learning remains fundamentally social. AI may individualize learning, but excessive individualization without meaningful peer and instructor interaction may weaken the educational experience. Schonberger's work on ChatGPT and interactive higher education similarly emphasizes the potential of AI to strengthen interactive learning and engagement rather than simply automate content delivery [17]. Faraon et al. further demonstrate that students' intention to use ChatGPT differs across cultural and educational contexts, suggesting that social norms and learning environments influence acceptance of AI [18]. The relatively strong loading of the social dimension therefore indicates that virtual education effectiveness depends partly on whether AI enhances rather than reduces meaningful social participation.

The emphasis on educational equity and equal access also corresponds with broader concerns regarding inclusiveness in AI-supported higher education. Nwokocha et al. argue that AI-based educational ecosystems should be designed around inclusion, ethics, and employability and should avoid intensifying existing educational inequalities [31]. Differences in internet access, technological resources, digital literacy, and familiarity with AI may otherwise create unequal opportunities for participation. Zamroni et al. similarly emphasize the use of AI to improve job-ready graduate skills, but such benefits can only be realized when students have meaningful access to appropriate learning resources [15]. The present study therefore suggests that accessibility and equity should be treated as indicators of effectiveness rather than as secondary implementation concerns.

The psychological dimension ranked fifth in AHP but demonstrated a strong second-order factor loading of 0.827. Learning motivation was its most highly rated component and one of the strongest individual indicators in the Delphi analysis. This result suggests that AI technologies contribute to effective virtual education only when they sustain students' motivation, participation, and psychological readiness. Personalized feedback, intelligent tutoring, and adaptive learning may increase students' sense of competence and relevance when properly designed. Hernandez-Herrera et al. emphasize the potential of adaptive and personalized AI-based learning to respond to students' individual needs [5], while Terblanche and Tau demonstrate that AI chatbot coaching can support goal attainment and developmental processes [16]. At the same time, the retention of technology anxiety as a component indicates that AI may also generate psychological challenges. This is especially relevant because anxiety and other psychological difficulties can influence academic functioning among university students [19]. Thus, AI-based virtual education should be designed to reduce uncertainty and cognitive burden rather than intensify them.

Although the educational dimension ranked sixth in the AHP analysis, this should not be interpreted as evidence of limited pedagogical importance. The educational dimension was strongly supported by the measurement model, with a second-order loading of 0.796 and excellent reliability. Intelligent support, quality and currency of content, and continuous intelligent feedback were particularly highly rated. These results indicate that the experts viewed pedagogical quality as essential but may have regarded managerial, technological, and human capacities as immediate prerequisites for achieving it. Research consistently demonstrates the educational potential of AI for adaptive instruction, feedback, assessment, and personalization [3, 4]. Generative AI is also increasingly influencing academic writing and assessment, requiring universities to redesign learning tasks around appropriate and responsible AI use [8, 10]. Zheng's work further demonstrates that AI can contribute to curriculum design in specialized areas of higher education [30]. Therefore, the lower AHP priority of the educational dimension is better understood as reflecting the experts' perception that pedagogical innovation depends on stronger enabling conditions.

The organizational dimension ranked seventh in the AHP analysis, although it remained statistically significant in the second-order model with a loading of 0.784. Investment in digital infrastructure was the strongest organizational component, whereas an innovation-supportive organizational culture received a comparatively lower Delphi mean. These findings may reflect the institutional reality that universities often prioritize tangible technological investments while cultural change develops more gradually. Nevertheless, organizational culture and policy remain essential for sustaining AI implementation. Institutional policies shape acceptable AI use, academic integrity expectations, staff responsibilities, and implementation boundaries [25]. Responsible leadership likewise requires alignment between organizational strategy and technological innovation [27]. The results therefore indicate that organizational structures may not have been perceived as the most urgent priority, but they remain necessary for institutionalizing AI-supported virtual learning over time.

Finally, the psychometric findings strongly supported the proposed model. All first-order factor loadings exceeded 0.60, all second-order loadings were positive and significant, Cronbach's alpha values ranged from 0.726 to 0.903, composite reliability ranged from 0.846 to 0.924, and AVE values ranged from 0.638 to 0.712. Moreover, both the Fornell–Larcker criterion and HTMT supported discriminant validity. These results indicate that the seven dimensions are related but empirically distinguishable components of a broader construct. The combination of strong Delphi consensus, an exceptionally low AHP inconsistency ratio of 0.00051, and satisfactory PLS-SEM measurement properties provides convergent methodological support for the proposed model. Overall, the findings suggest that effective AI-supported virtual education requires the simultaneous development of leadership, technology, human competency, social interaction, psychological readiness, instructional quality, and organizational capacity rather than isolated investment in AI applications.

Several limitations should be considered when interpreting the findings. First, the study was conducted within Islamic Azad Universities in West Azerbaijan Province, and the institutional, technological, socioeconomic, and cultural conditions of this setting may differ from those of other universities and regions. Second, the qualitative stage relied on a relatively small expert group selected through purposive and snowball sampling, which was appropriate for in-depth model development but may have favored individuals who were particularly engaged with virtual education and technological innovation. Third, convenience sampling was used during the quantitative stage, limiting the representativeness of the faculty sample. The research was also based largely on self-reported expert and faculty judgments rather than objective indicators of student learning outcomes, actual AI usage, platform performance, or long-term institutional change. In addition, the cross-sectional nature of the quantitative phase did not allow examination of how the relative importance of the identified dimensions may change as AI tools, university policies, and users' competencies evolve over time.

Future studies should replicate the model across different provinces, public universities, medical universities, technical institutions, and private higher education settings to determine its generalizability and identify context-specific differences. Larger probability-based samples would strengthen external validity, while longitudinal research could examine how faculty readiness, student AI literacy, institutional policies, and technological infrastructure change as AI becomes more established in higher education. Future investigations could also incorporate student perspectives alongside those of faculty members and administrators and could compare perceptions across disciplines, academic ranks, and levels of technological experience. Experimental and quasi-experimental studies are needed to connect the identified dimensions with measurable educational outcomes such as achievement, retention, engagement, self-regulation, satisfaction, and digital competence. Researchers could additionally employ multigroup structural equation modeling, longitudinal PLS analysis, or configurational approaches to determine whether different combinations of managerial, technological, human, and educational conditions produce comparable levels of virtual education effectiveness.

Islamic Azad Universities and similar higher education institutions should approach AI-supported virtual education as a coordinated institutional transformation rather than as the acquisition of individual software tools. Because managerial, technological, and human dimensions emerged as the strongest priorities, university leaders should first establish clear AI strategies, define governance responsibilities, allocate sustained financial resources, and develop continuous professional development programs for faculty members. Reliable internet connectivity, stable learning platforms, secure data infrastructures, and accessible AI applications should be strengthened simultaneously. Faculty development should combine technical AI literacy with instructional design, assessment redesign, ethical decision-making, and critical evaluation of AI-generated content. Students should receive structured training in digital and AI literacy, self-regulated learning, responsible use, and critical thinking. Institutions should also protect opportunities for instructor–student and peer interaction, ensure equitable access to technological resources, monitor technology-related anxiety and exclusion, and regularly evaluate the effectiveness of AI initiatives through educational outcomes rather than merely through rates of technology adoption.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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