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Development and Validation of a Model for AI-Based Educational Interactions in Secondary Schools in Tehran

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ABSTRACT

Purpose: This study aimed to develop and validate a comprehensive model of artificial intelligence-based educational interactions for secondary schools in Tehran.

Methods and Materials: An exploratory mixed-methods design was employed. In the qualitative phase, thematic analysis of theoretical literature and semi-structured interviews with 14 experts in educational management and communication sciences, selected through purposive and snowball sampling until theoretical saturation, was conducted using MAXQDA. In the quantitative phase, a researcher-developed 91-item questionnaire was administered to 361 secondary school students selected through stratified random sampling from Tehran public schools. Data were analyzed using SPSS and partial least squares structural equation modeling (PLS-SEM) in SmartPLS. Model reliability and convergent validity were assessed using Cronbach's alpha, composite reliability, average variance extracted, factor loadings, and bootstrapping. The final model was additionally validated by 30 experts.

Findings: One-sample t-tests showed that data-driven school–parent interactions were significantly above the theoretical midpoint ($M = 3.6146$, $t = 11.031$, $p < .001$), whereas all other dimensions were significantly below it ($p < .001$). PLS-SEM results indicated that all component and indicator t-values exceeded 1.96 and all construct reliability coefficients exceeded .70, while AVE values exceeded .50. The endogenous construct demonstrated substantial explanatory power ($R^2 = .785$). Second-order loadings showed that quality of smart educational content had the strongest association with the overall construct ($\beta = .928$, $t = 46.153$, $p < .001$), followed by evaluation and continuous improvement ($\beta = .867$), whereas technical infrastructure and AI platform had the lowest significant loading ($\beta = .770$). Expert validation further showed that all evaluated model dimensions significantly exceeded the criterion midpoint ($p < .001$).

Conclusion: The validated model indicates that effective AI-based educational interactions depend primarily on high-quality smart educational content, continuous evaluation, multidimensional interaction, and teacher support, while technological infrastructure serves as an essential enabling foundation. Accordingly, successful AI integration in secondary education should be approached as a comprehensive pedagogical transformation rather than merely a technological intervention.

Keywords: *Artificial Intelligence; Educational Interactions; Secondary Education; Smart Learning; PLS-SEM; Tehran.*

1. Introduction

The accelerating digital transformation of educational systems has fundamentally altered the conditions under which teaching, learning, communication, assessment, and educational decision-making occur. Among contemporary technologies, artificial intelligence (AI) has acquired particular importance because it extends beyond the digitization of conventional instructional practices and introduces capabilities for automated reasoning, adaptive support, prediction, personalization, real-time feedback, and data-informed interaction. Earlier reviews of AI applications in education demonstrated that the field was already moving toward intelligent tutoring, profiling and prediction, adaptive systems, and automated assessment, while also revealing a relative scarcity of studies centered on teachers, pedagogical relationships, and the organizational conditions of implementation (Zawacki-Richter et al., 2019). More recent research has expanded this perspective by conceptualizing AI as a technology capable of reshaping teaching and learning processes rather than functioning merely as an additional instructional device (Chan & Lo, 2023). From this standpoint, the educational significance of AI lies not only in its computational power but also in its capacity to reorganize how educational actors communicate, respond to one another, exchange information, and construct learning experiences. Accordingly, AI-supported education increasingly requires attention to the quality and architecture of educational interactions as a central component of technology-enhanced learning.

Educational interaction is a multidimensional construct involving cognitive, behavioral, emotional, social, and communicative processes through which learners engage with teachers, peers, learning content, families, institutional structures, and technological environments. The effectiveness of learning cannot therefore be reduced to content delivery or academic achievement alone. Research emphasizing the interrelationship among cognitive, behavioral, and emotional aspects of educational interaction suggests that meaningful learning depends on the simultaneous engagement of multiple dimensions of the learner's educational experience (Azizi et al., 2021). Likewise, the purposeful integration of traditional and digital communication tools has been associated with richer opportunities for engagement and continuity of communication across learning settings (Heydari et al., 2023). In technology-mediated environments, interaction becomes even more complex because educational communication is no longer exclusively human-to-human; rather, it may involve human–AI interaction, AI-mediated teacher–student communication, algorithmically supported peer collaboration, and data-driven communication between schools and families. Research on the dimensions of interaction in AI-assisted learning environments has therefore emphasized the necessity of examining educational interaction as an integrated system rather than as a single teacher–student relationship (Chou & Chang, 2024). This multidimensional view provides an important conceptual basis for designing educational systems in which AI strengthens, rather than fragments, human relationships.

One of the most frequently discussed affordances of AI is its ability to personalize learning. Conventional classroom instruction is often constrained by heterogeneous learner abilities, differences in prior knowledge, limited instructional time, and the difficulty of providing individualized support to large numbers of students. Technology-supported personalized learning can respond to these limitations by adapting learning pathways, resources, pace, and instructional tasks to individual learner characteristics (Zhang, 2021). Within school settings, AI can further support personalization by identifying learning patterns, diagnosing strengths and weaknesses, recommending appropriate content, and dynamically adapting educational activities (Faghfoori et al., 2023). These capabilities may enhance the quality of teacher–student interaction because teachers can obtain more detailed evidence about learners' needs and direct their professional attention toward students requiring more intensive or specialized support. Studies of AI-supported educational facilitation similarly indicate that intelligent systems can strengthen multilateral relationships within learning environments by connecting learners, teachers, content, and other stakeholders through responsive and data-informed mechanisms (Nasiriyan & Amani, 2022). Thus, personalization is not only an instructional technique but also an interactional process through which AI may support more responsive and differentiated educational relationships.

Real-time feedback represents another major mechanism through which AI can transform educational interaction. The pedagogical value of feedback depends substantially on its timing, specificity, relevance, and capacity to guide subsequent learning. AI systems can continuously process learner responses and behavioral data, identify errors or performance changes, and provide immediate instructional recommendations. Evidence concerning real-time AI

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feedback in STEM education has shown the potential of such mechanisms to improve student performance by reducing delays between learner action and corrective guidance (Garcia & Rahman, 2025). Generative AI has further extended interactive feedback possibilities by supporting dialogue, simulation, scaffolding, and game-based learning. For example, research on role-playing educational games using generative AI has illustrated how AI can act as scaffolding for immediate feedback while sustaining learner engagement within interactive activities (Chien et al., 2025). Students' perceptions of conversational AI also indicate that the educational usefulness of such systems is closely connected to the quality, responsiveness, and contextual appropriateness of interaction (Singh & Gonzalez, 2024). These developments demonstrate that AI-mediated feedback should not be understood solely as automated correction; it can become an interactive component of learning capable of sustaining dialogue, motivation, reflection, and iterative improvement.

The growing role of AI also changes the professional position of teachers. Concerns that automation could diminish the importance of teachers overlook the fundamentally pedagogical and relational functions that teachers perform. Contemporary models increasingly conceptualize AI as a partner or supporting system that can augment teacher judgment rather than replace professional agency. Research on teacher–AI collaboration in adaptive learning emphasizes emerging forms of cooperation in which teachers and intelligent systems jointly support personalization, instructional decision-making, and targeted interventions (Smith & Taylor, 2025). Studies focused specifically on secondary schools in Tehran have likewise suggested that AI can substantially influence teacher–student educational interaction, provided that technological integration is aligned with pedagogical objectives and existing school conditions (Karimi & Sohrabi, 2020). More recent research on smart learning systems has further emphasized that successful implementation depends on factors extending beyond technology itself and that the quality of teacher–student interaction remains a critical outcome of smart educational environments (Abdollahi & Rahmani, 2024). Consequently, any model of AI-based educational interaction should retain the teacher as an active pedagogical agent while specifying how AI can support diagnosis, communication, instructional design, assessment, and learner guidance.

Peer interaction constitutes another essential domain of AI-supported education. Student–student interaction contributes to collaborative learning, social development, knowledge co-construction, mutual support, and the development of communication and problem-solving competencies. AI-enhanced learning environments can facilitate peer interaction by recommending collaborative partners, forming groups based on learning characteristics, supporting online discussion, providing shared tasks, and monitoring patterns of participation. Models proposed for smart schools have identified multiple AI components capable of influencing educational interactions and have emphasized the need to integrate such components within coherent conceptual structures (Nasiri et al., 2023). Research on motivation and self-regulated learning in learning management systems also demonstrates that effective technology-supported learning requires active learner engagement and self-regulatory processes rather than passive exposure to digital resources (Mustapha et al., 2023). Therefore, AI-supported peer environments should be designed not merely to increase the volume of digital communication but to foster purposeful, collaborative, motivational, and academically meaningful interaction. Such a perspective is particularly important for adolescents, for whom peer relationships constitute a major dimension of school experience.

Educational interaction also extends beyond the classroom to communication between schools and families. Digital platforms can support continuous information exchange concerning student progress, attendance, learning difficulties, assignments, and support strategies. Studies of parent–student communication in virtual education have shown that digital environments can modify family involvement in learning and create new patterns of educational communication (Pourghaffar & Jafarzadeh Dashbolagh, 2021). Electronic data exchange may further enhance the efficiency and continuity of information flows within educational systems by facilitating access to timely educational information across institutional and stakeholder boundaries (Meer, 2025). In AI-based environments, these functions can be expanded through personalized progress reports, early-warning systems, automated responses, predictive notifications, and recommendation systems. Nevertheless, the value of such mechanisms depends on whether data are translated into understandable and actionable communication rather than becoming a source of excessive monitoring or informational overload. For this reason, school–parent interaction should be explicitly incorporated into models of AI-based educational interaction rather than treated as a peripheral administrative function.

A related development is the increasing use of educational big data and learning analytics. AI systems generate and process extensive data concerning learner behavior, achievement, participation, interaction patterns, engagement, and progression. Learning analytics can transform these data into information that supports prediction, early intervention, instructional adjustment, and evaluation. Bibliometric research on educational big data and learning analytics indicates substantial scholarly growth in the use of data-intensive approaches for understanding and improving educational processes (Samsul et al., 2023). Technology-mediated interaction analysis is also evolving methodologically, with emerging approaches capable of capturing increasingly complex patterns of educational activity and communication (Davidsen & Steier, 2025). Such analytic capacities can help schools identify students at risk of academic decline, recognize patterns of disengagement, detect learning obstacles, and evaluate the effectiveness of instructional interventions. At the same time, educational outcomes are influenced by broader family and socioeconomic conditions, and recent evidence concerning interactions between family socioeconomic status and individual propensities underscores the continuing importance of contextual heterogeneity in educational achievement (Ghirardi & Bernardi, 2025). AI-based educational analytics must therefore be interpreted within students' social and educational contexts rather than assuming that algorithmically detected patterns are independent of structural differences.

The expansion of AI in educational settings also raises significant ethical, social, and governance concerns. AI-supported interaction relies on the collection, processing, and often long-term storage of student data, which creates questions regarding privacy, consent, transparency, security, algorithmic bias, explainability, and equitable access. Research focused on the ethical dimensions of AI-driven interaction in K–12 education has emphasized that the benefits of AI must be balanced against risks associated with data governance, discriminatory outcomes, digital inequality, and insufficient stakeholder participation (Walsh & Lee, 2025). Broader analyses of AI in education similarly stress that technological innovation requires a pedagogically and ethically grounded approach to implementation (Holmes et al., 2024). These concerns are particularly salient in secondary education because students are minors and may have limited capacity to understand the consequences of automated data processing. Moreover, disparities in access to devices, connectivity, digital literacy, and supportive learning environments can reproduce or intensify pre-existing educational inequalities. Consequently, models of AI-based educational interaction should incorporate not only instructional efficiency but also security, fairness, accessibility, ethical oversight, and human accountability.

These challenges became especially visible during and after the COVID-19 pandemic, when educational systems rapidly expanded virtual and blended learning. In Iran, the pandemic accelerated the adoption of digital education and revealed both opportunities and structural limitations. Research examining the pandemic as an opportunity for information technology development highlighted the expanded role of virtual education in maintaining educational continuity (Atashi et al., 2021). At the same time, studies of students lacking adequate virtual education equipment demonstrated the psychological and academic consequences of unequal technological access and underscored the need for supportive interventions (Ghanbari Hamidabadi et al., 2021). Teachers' lived experiences during the early period of virtual teaching revealed practical difficulties associated with rapid transitions to online instruction, including technological, pedagogical, and interactional challenges (Hasani et al., 2021). Teachers' concerns regarding virtual education in secondary schools have also demonstrated that implementation problems cannot be resolved exclusively by supplying technical platforms (Ahmadi, 2022). Post-pandemic analyses have continued to identify structural weaknesses in virtual and blended education, indicating the need for more sustainable, integrated, and resilient educational arrangements (Zaidi et al., 2023).

The Iranian experience with the SHAD platform similarly demonstrates that technological availability alone does not guarantee effective smart educational interaction. Evaluation of SHAD and smart educational interactions in Tehran schools identified challenges affecting the quality and continuity of technology-mediated education (Alizadeh, 2021). Qualitative research on the opportunities and challenges of AI implementation in secondary-school educational interactions has likewise emphasized the simultaneous presence of considerable pedagogical potential and contextual barriers (Mirzaei & Eftekhari, 2021). These findings are consistent with broader arguments that educational systems require localized approaches rather than direct transplantation of technological models developed in different institutional and cultural contexts. Personalized and

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technology-based learning in the AI era therefore necessitates indigenous models responsive to national curricula, cultural expectations, organizational capacities, infrastructure, and educational values (Shakeri & Asgari, 2024). Governmental and institutional support also matters because digital capability development can contribute to organizational resilience and adaptation within educational organizations (Dehghan & Jalalian, 2025). Accordingly, the development of AI-based educational interaction in Tehran secondary schools requires simultaneous attention to pedagogical, organizational, technological, cultural, and policy conditions.

Recent Iranian research has begun to address this need by proposing conceptualizations of AI-supported educational interaction. Studies on artificial intelligence and the future of educational interactions in Iranian secondary schools have emphasized the movement from theoretical potential toward practical implementation and the need to reconceptualize educational relationships in intelligent environments (Rastegar & Soleymani, 2024). A parallel body of research under the same broad thematic focus has similarly highlighted the transformative potential of AI for future interaction patterns in secondary education (Rastegar & Soleimani, 2024). Research specifically devoted to designing AI-based educational interaction models in smart learning environments has advanced the field by identifying structures through which AI can support dynamic and adaptive educational relationships (Jafari & Naderi, 2024). These studies represent important steps toward model development; however, educational interaction remains sufficiently complex that a comprehensive framework must integrate teacher–student interaction, peer interaction, school–parent communication, intelligent educational content, technical infrastructure, educational analytics, teacher support, and continuous evaluation within a single empirically validated structure. Without such integration, AI initiatives may remain fragmented across isolated applications, platforms, or administrative functions.

The need for an integrated model is further reinforced by the rapid development of AI capabilities and the increasing dependence of education systems on digital communication. AI now operates within an ecosystem that includes learning management systems, adaptive platforms, conversational agents, predictive analytics, smart content, automated assessment, and educational data exchange. Research on successful smart learning implementation shows that the effectiveness of these technologies depends on coordinated organizational and pedagogical conditions (Abdollahi & Rahmani, 2024), while studies of AI-assisted educational interaction indicate that interaction quality itself should be treated as a multidimensional outcome of system design (Chou & Chang, 2024). The growing availability of AI-generated feedback and interactive generative applications adds further urgency to the development of structured educational models (Chien et al., 2025; Garcia & Rahman, 2025). At the same time, the promises of AI must be considered alongside limitations related to teacher preparedness, infrastructure, data governance, educational equity, and the social context of schooling (Holmes et al., 2024; Walsh & Lee, 2025). Thus, an effective model should not merely identify technologies that can be introduced into schools; it should explain the interactional architecture through which those technologies contribute to meaningful educational relationships and continuous improvement.

In this context, Tehran secondary schools provide an important setting for model development because they combine extensive educational demand, heterogeneous student populations, prior experience with large-scale virtual education, and increasing pressure to adopt intelligent educational technologies. Existing evidence indicates that effective integration requires attention to both technical systems and human relationships, including the ways teachers use AI-supported information, students interact with intelligent tools and peers, parents receive and respond to educational data, and schools continuously evaluate interaction quality. The literature also indicates that the effectiveness of digital education depends on meaningful communication rather than technological presence alone (Heydari et al., 2023), that AI can strengthen adaptive and personalized learning when appropriately integrated into teaching (Smith & Taylor, 2025), and that smart educational systems require systematic models that are contextually relevant and empirically validated (Nasiri et al., 2023; Shakeri & Asgari, 2024). Accordingly, the unresolved challenge is to formulate a coherent framework that captures the multidimensional nature of AI-based educational interaction and determines the relative importance of its constituent dimensions and components within the specific context of Tehran's secondary schools.

Therefore, this study aimed to develop and validate a comprehensive model of AI-based educational interactions in secondary schools in Tehran.

2. Methods and Materials

Given the nature of the study, an exploratory mixed-methods (qualitative–quantitative) approach was employed. The qualitative phase utilized thematic analysis, while the quantitative phase adopted a descriptive-survey design. The primary research instruments included semi-structured interviews and a researcher-developed questionnaire, with data processing and modeling conducted via MAXQDA, SPSS, and SmartPLS software packages.

In the qualitative phase, indicators (basic themes), components (organizing themes), and dimensions (global themes) were identified through thematic analysis based on the theoretical framework, literature review, and semi-structured interviews. The study participants comprised faculty members specializing in Educational Management and Communication Sciences, as well as experienced subject-matter experts possessing relevant academic credentials, publications (books and peer-reviewed articles), and teaching records in the field. Inclusion criteria required experts to have at least three years of academic and university experience in educational management or communication sciences. Qualitative data collection was conducted via semi-structured interviews using a purposive, non-probability snowball sampling strategy. Sampling continued until theoretical saturation was reached, resulting in a final qualitative sample of 14 experts. Interviews were conducted between the summer and autumn of 2025. Instrument validity was confirmed by subject-matter experts, and qualitative reliability was established through the intra-coder reliability coefficient (0.80). Additionally, data trustworthiness was assessed using interpretive research criteria—namely, credibility, dependability, confirmability, and transferability—alongside theoretical criteria including generality, fit, understandability, and control.

In the quantitative phase, a descriptive-survey method was employed. The data collection instrument was a researcher-developed questionnaire designed according to the findings of the qualitative thematic analysis. A stratified random sampling technique was utilized (Table 1). The target statistical population comprised secondary school students from public schools across Tehran, with a total sample size of 361 students calculated based on Cochran's formula. Descriptive statistical analysis was carried out using SPSS, and structural equation modeling (PLS-SEM) was performed using SmartPLS to assess model fit and path coefficients.

Table 1

Quantitative Sample Size Allocation Using Stratified Sampling Across Educational Districts

District	Total Population (N_i)	Allocation Formula (N_i × Sampling Ratio)	Sample Size (n_i)
District 1	695	695 × 0.067	47
District 6	893	893 × 0.067	60
District 9	1,104	1,104 × 0.067	74
District 13	706	706 × 0.067	47
District 16	948	948 × 0.067	64
District 19	1,024	1,024 × 0.067	69
Total	5,370	5,370 × 0.067	361

3. Findings and Results

To answer the question of "What are the factors affecting the model of AI-based educational interactions (case study: secondary schools in Tehran)?", the list of responses for each question—finalized after reviewing the literature and coding by the researcher along with 4 statistics specialists and domain experts—is presented in Table 2. In this section, 8 dimensions and 19 components were identified for 91 indicators.

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Table 2

Final List of Basic, Organizing, and Overarching Themes Obtained Through Semi-Structured Interview Technique

Row	Overarching Themes (Dimensions)	Organizing Themes (Components)	Basic Themes (Indicators)	Code	Interviewee Code
1	AI-based Teacher–Student Interactions	Personalization of the Learning Process	Adapting course content to the learner's progress level	S1	I4, I2, I8, I15, I9
2			Providing smart assignments tailored to individual needs	S2	I8, I2, I19, I1
3			Automatic detection of strengths and weaknesses	S3	I11, I1, I3, I8, I6
4			Redirecting learning path based on real-time responses	S4	I6, I9, I3, I21
5			Providing different learning scenarios for a single objective	S5	I2, I1, I10, I7
6		Real-time Feedback	Delivering instant feedback using AI	S6	I5, I8, I7, I6, I4
7			Automatic analysis of responses and provision of improvement suggestions	S7	I5, I6, I4, I13
8			Visual display of learning progress	S8	I1, I2, I11, I7, I10
9			Alerting the teacher in case of a sudden performance drop	S9	I2, I6, I10, I9
10			Enabling intelligent dialogue with students for problem-solving	S10	I11, I9, I10, I4, I5
11		Smart Motivation & Encouragement (New)	Delivering smart motivational messages upon performance decline	S11	I6, I1, I2
12			Recording and displaying academic achievements	S12	I11, I7, I10, I3, I8
13			Suggesting engaging learning challenges with rewards	S13	I8, I3, I5, I4, I2
14			Providing self-confidence-enhancing activities	S14	I4, I3, I2, I8, I6
15	Student–Student Interactions in Smart Environment	Online Collaborative Learning	Automatic formation of study groups based on level & interest	S15	I3, I9, I5, I4, I2
16			Suggesting suitable classmates for collaboration	S16	I5, I8, I7, I6, I4
17			Using chatbots to simulate group discussions	S17	I2, I6, I7, I9
18			System-generated group projects	S18	I11, I9, I3, I4, I5
19			Measuring students' participation in teamwork	S19	I6, I5, I2
20		Conflict Resolution with AI Support	Detecting signs of online conflict	S20	I9, I7, I10, I3, I8
21			System-provided compromise solutions	S21	I8, I3, I5, I4, I2
22			Recording and analyzing dialogue trends	S22	I4, I3, I5, I9, I6
23			Suggesting new roles to reduce tension	S23	I10, I6, I5, I1, I7
24			Creating anonymous dialogue spaces for expressing problems	S24	I3, I11, I5
25		Healthy Competitive Learning with AI (New)	Creating student performance leaderboards	S25	I9, I5, I4, I2, I11
26			Announcing weekly winners of learning activities	S26	I3, I4, I11, I5
27			Designing competitive group educational games	S27	I10, I8, I3
28			Sending automatic congratulatory messages to top performers	S28	I10, I9, I1, I16, I21
29	Data-based School–Parent Interactions	Smart Academic Progress Reporting	Sending personalized reports to parents	S29	I6, I8, I10, I3, I4
30			Early warning of poor performance	S30	I10, I8, I1, I13, I4
31			Suggesting supportive home-based activities	S31	I3, I1, I5, I14, I6

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32			Analyzing monthly progress trends	S32	I22, I16, I10, I9
33			Comparing student performance with class average	S33	I11, I19, I10, I14, I5
34		Interactive Communication Channel	Creating an intelligent parent portal	S34	I6, I1, I2
35			Live chat with teachers featuring automatic translation	S35	I11, I7, I10, I3, I8
36			Automated responses to frequently asked questions	S36	I8, I3, I5, I4, I2
37			Sending short educational videos to parents	S37	I4, I3, I2, I8, I6
38			Logging conversation histories for future reference	S38	I3, I9, I5, I4, I2
39	Technical Infrastructure & AI Platform	System Stability & Security	Response speed under 2 seconds	S39	I5, I8, I7, I16, I4
40			Data security level compliant with ISO/IEC 27001	S40	I5, I11, I14, I13
41			Multimedia content support	S41	I1, I2, I9, I7, I5
42			Multi-factor user authentication	S42	I8, I7, I11, I15
43			Rapid data recovery capability in crisis situations	S43	I10, I6, I5, I1, I7
44		Data Integration	Connection to the smart attendance system	S44	I3, I11, I5
45			Combining educational and psychological data	S45	I9, I5, I4, I2, I11
46			Providing an analytical dashboard	S46	I3, I4, I11, I5
47			Synchronization with national e-learning platforms	S47	I10, I8, I3
48			Cloud storage for simultaneous access by all stakeholders	S48	I10, I9, I1, I6, I11
49	Quality of Smart Educational Content	Digital Resource Richness	Availability of video-based and interactive content	S49	I6, I8, I22, I3, I14
50			Data-driven content updating	S50	I10, I8, I1, I3, I4
51			Continuous quality assessment of content	S51	I4, I2, I8, I15, I9
52			Adding alternative learning pathways	S52	I8, I2, I19, I1
53			AI-assisted production of interactive content	S53	I11, I1, I3, I8, I6
54		Alignment with Educational Standards	Compliance with the national curriculum	S54	I6, I9, I3, I21
55			Alignment with 21st-century skills standards	S55	I2, I1, I10, I7
56			Coverage of Bloom's cognitive levels	S56	I5, I8, I7, I6, I4
57			Conformity with future occupational needs	S57	I5, I6, I4, I13
58			Consistency with international e-learning standards	S58	I1, I2, I11, I7, I10
59		Compatibility with Student Learning Styles (New)	Identifying learning styles based on image, sound, or text	S59	I2, I6, I10, I9
60			Providing lesson formats matching individual learning styles	S60	I11, I9, I10, I4, I5
61			Changing instructional approach upon declining engagement	S61	I6, I1, I2
62			Combining multiple methods to enhance learning	S62	I11, I7, I10, I3, I8
63	Educational Data Analytics	Predictive Analytics	Predicting academic decline	S63	I8, I3, I5, I4, I2
64			Predicting the need for intervention	S64	I4, I3, I2, I8, I6
65			Predicting the probability of dropout	S65	I3, I9, I5, I4, I2
66			Identifying special talents	S66	I5, I8, I7, I6, I4
67			Analyzing student motivation based on behavioral data	S67	I2, I6, I7, I9
68		Deep Learning Analytics	Analyzing concentration patterns	S68	I11, I9, I3, I4, I5
69			Analyzing study habits	S69	I6, I5, I2
70			Assessing progress changes throughout the semester	S70	I9, I7, I10, I3, I8
71			Identifying learning obstacles	S71	I8, I3, I5, I4, I2
72			Measuring engagement with digital content	S72	I4, I3, I5, I9, I6

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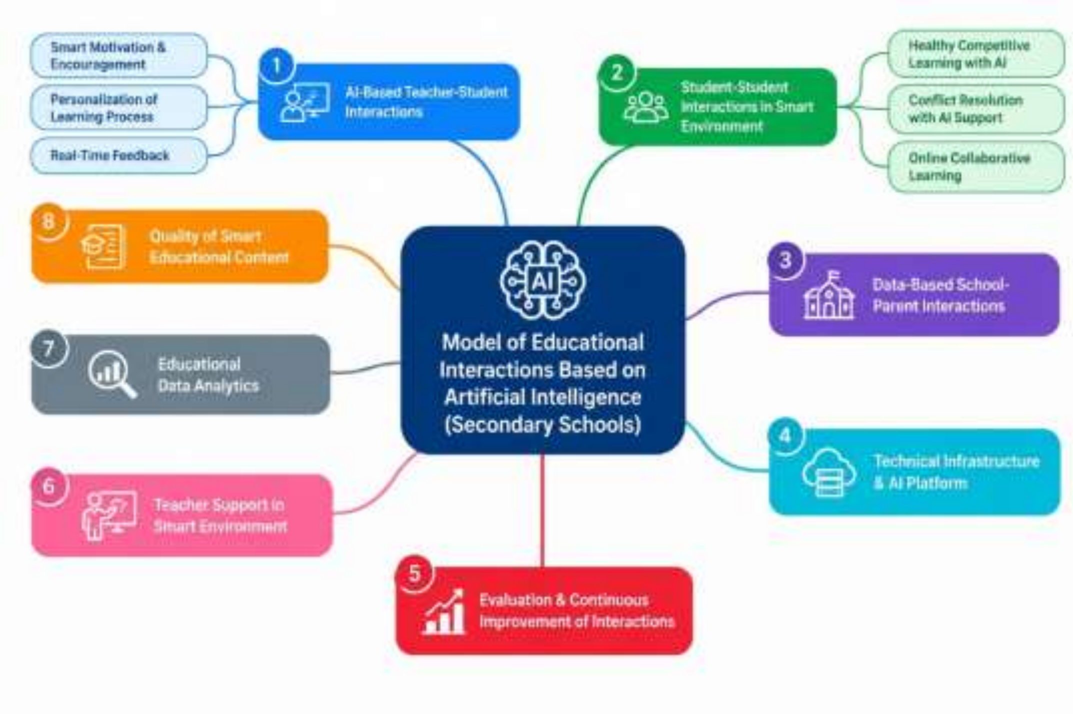
73	Teacher Support in Smart Environment	Teacher Training for AI Usage	Holding in-person workshops	S73	I10, I6, I5, I1, I7
74			Providing instructional videos	S74	I3, I11, I5
75			Step-by-step guides on the platform	S75	I9, I5, I4, I2, I11
76			Online support by the technical team	S76	I3, I4, I11, I5
77			Sharing successful smart teaching examples	S77	I10, I8, I3
78		Intelligent Teaching Assistant	Suggesting resources according to lesson topic	S78	I10, I9, I1, I16, I21
79			Automatic question generation	S79	I6, I8, I10, I3, I4
80			Automatic design of interactive activities	S80	I10, I8, I1, I13, I4
81			Suggesting diverse assessment methods	S81	I3, I1, I5, I14, I6
82			Creating weekly teaching schedules	S82	I4, I2, I8, I15, I9
83	Evaluation & Improvement of Educational Interactions	Monitoring Interaction Quality	Measuring student participation	S83	I8, I2, I19, I1
84			Evaluating quality of teacher–student communication	S84	I11, I1, I3, I8, I6
85			Measuring parent satisfaction	S85	I6, I9, I3, I21
86			Measuring feedback turnaround speed	S86	I2, I1, I10, I7
87			Assessing impact of smart instruction on test outcomes	S87	I5, I8, I7, I6, I4
88		ML-based Improvement	Updating algorithms	S88	I5, I6, I4, I13
89			Automatic adjustment of exercise difficulty	S89	I1, I2, I11, I7, I10
90			Optimizing communication methods	S90	I2, I6, I10, I9
91			Suggesting educational innovations based on data	S91	I11, I9, I10, I4, I5

Figure 1

A conceptual model of AI-driven educational interactions among secondary school students in Tehran



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Answer to Question 2: What is the current status of the dimensions and components of AI-based educational interactions in secondary schools in Tehran?

To examine the status of each research dimension, respondents' perspectives were analyzed using a **one-sample t-test** (against the theoretical midpoint of 3.00 on a 5-point Likert scale). A summary of the one-sample t-test results based on the mean scores is presented in **Table 3**.

Table 3

Summary of One-Sample t-Test Results for the Dimensions of AI-Based Educational Interactions (Tehran Secondary Schools)

Research Variables / Dimensions	Mean	t-value	Sig. (p-value)	95% Confidence Interval (Lower Limit)	95% Confidence Interval (Upper Limit)
AI-Based Teacher–Student Interactions	2.8403	-9.538	0.000	-0.410	-0.270
Student–Student Interactions in Smart Environment	2.4800	-12.047	0.000	-0.568	-0.409
Data-Driven School–Parent Interactions	3.6146	11.031	0.000	0.355	0.510
Technical Infrastructure & AI Platform	2.7380	-14.151	0.000	-0.600	-0.454
Quality of Smart Educational Content	2.6700	-8.084	0.000	-0.479	-0.292
Educational Data Analytics	2.7227	-13.684	0.000	-0.611	-0.458
Teacher Support in Smart Environment	2.9524	-12.529	0.000	-0.604	-0.253
Evaluation & Continuous Improvement of Interactions	2.9022	-19.828	0.000	-0.711	-0.111

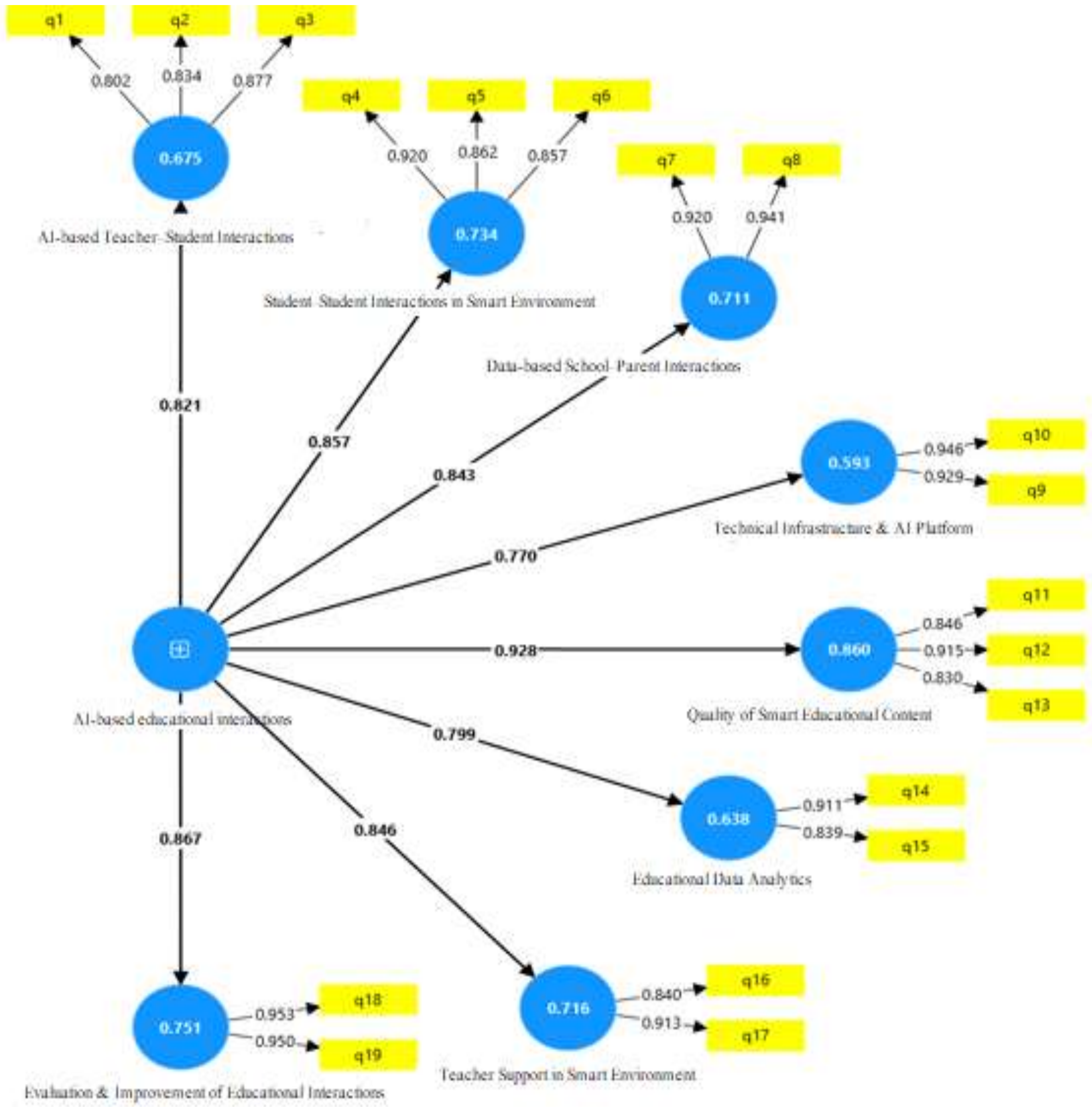
The mean perspective of the respondents regarding the dimensions was analyzed. With the exception of *"Data-Driven School–Parent Interactions"* (Mean = 3.6146, $t = 11.031, p < .001$), all other dimensions yielded mean scores significantly below the theoretical midpoint of 3.00, with p-values equal to 0.000(less than the $.05$alpha level) and absolute t-statistics exceeding the critical threshold of 1.96. Furthermore, the confidence interval bounds confirm these significant deviations. Based on these statistical findings, with a 95% confidence level, it can be concluded that while these dimensions exist to a moderate extent in current practice, they fall substantially short of the optimal desired level (means of 4.00 to 5.00), highlighting critical areas requiring pedagogical and infrastructural reinforcement.

Answer to Question 3: What is the prioritization of the dimensions and components of AI-based educational interactions in secondary schools in Tehran?

To address this question, questionnaires were distributed to the main sample of 361 participants, and the resulting data were analyzed using Structural Equation Modeling (SEM) to establish the path coefficients, factor loadings, and structural hierarchy of the dimensions.

Figure 2

Partial Least Squares Outer Model (Measurement Model)



According to the results of the measurement model illustrated in Figure 2, the outer loadings observed across all items exceeded the threshold of 0.3, indicating an acceptable correlation between the observed (manifest) variables and their corresponding latent constructs.

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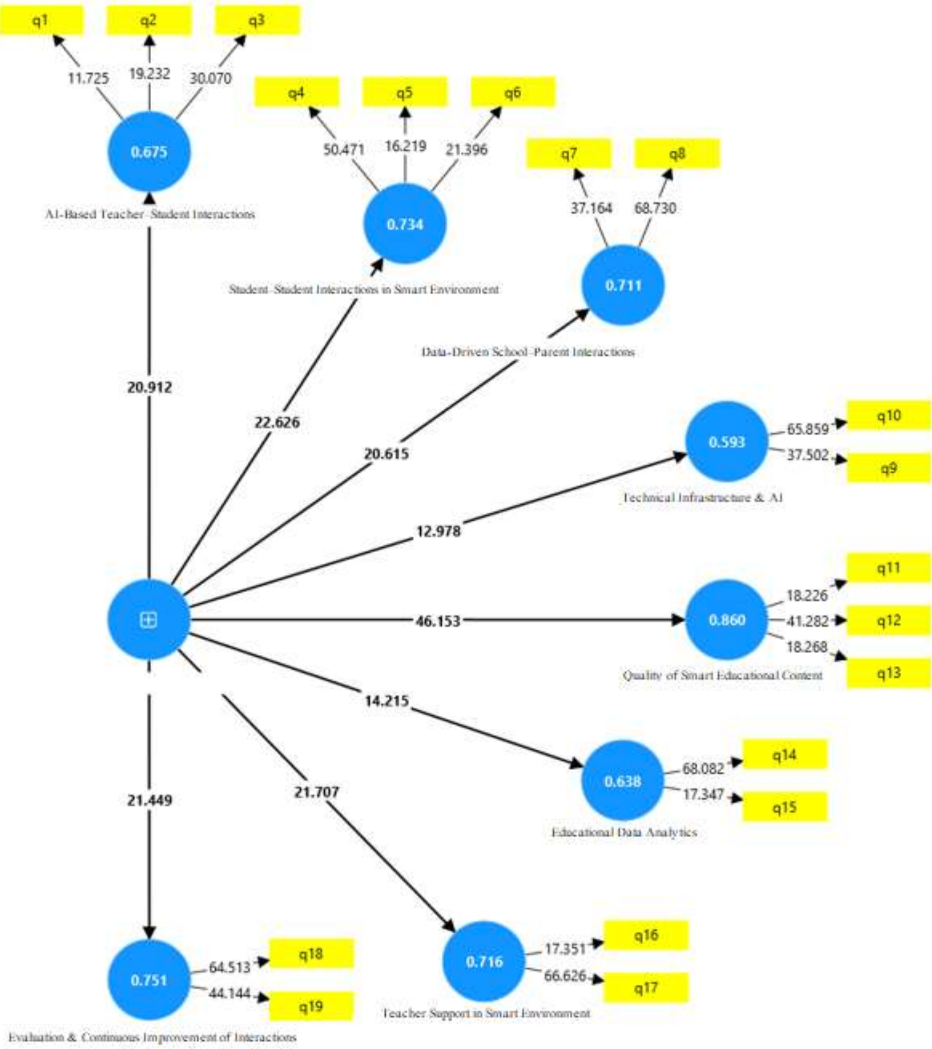
Figure 3

t-value Statistics of the Research Model Using the Bootstrapping Technique



Based on the results obtained from Figure 3, it can be concluded that all components and indicators achieved t-values above 1.96; therefore, these indicators can be reliably employed to assess the fit of the components. Consequently, it can be inferred that each primary construct has been adequately measured, and based on the findings derived from this scale, the ranking of the dimensions and components can be pursued.

Furthermore, convergent validity was also computed. The Cronbach's alpha for all variables exceeded the threshold of 0.70, confirming the internal reliability of all constructs. Moreover, the Average Variance Extracted (AVE) consistently exceeded 0.50, thereby verifying convergent validity. Additionally, the Composite Reliability (CR) values were greater than their corresponding AVE values across all constructs.

The R^2 value for the endogenous construct was calculated as 0.785, which—based on the three established criteria—confirms the adequate fit of the structural model. The overall model fit (Goodness of Fit, GOF) was also computed, enabling the researcher—after examining the fit of both the measurement and structural sub-models—to assess the global fit of the entire research model:

$$GOF = \sqrt{0.645 \times 0.709} = \sqrt{0.475} = 0.676$$

In this section, the dimensions and components were ranked based on their factor loadings and are presented separately in Table 4 (each component within its respective dimension) as well as in an overall aggregated ranking.

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Table 4

Prioritization of the Dimensions and Components of AI-Based Educational Interactions (Tehran Secondary Schools)

Dimension	Component	First-Order Loading	Overall Rank	t-value	p-value	Second-Order Loading	Dimension Rank	t-value	p-value
AI-Based Teacher–Student Interactions	Q1	0.802	18	11.725	0.000	0.821	6	20.912	0.000
	Q2	0.834	16	19.232	0.000				
	Q3	0.877	10	30.070	0.000				
Student–Student Interactions in Smart Environment	Q4	0.920	6	50.471	0.000	0.857	3	22.626	0.000
	Q5	0.862	11	16.219	0.000				
	Q6	0.857	12	21.396	0.000				
Data-Driven School–Parent Interactions	Q7	0.920	6	37.164	0.000	0.843	4	20.615	0.000
	Q8	0.941	4	68.730	0.000				
Technical Infrastructure & AI Platform	Q9	0.946	3	65.859	0.000	0.770	8	12.978	0.000
	Q10	0.929	5	37.502	0.000				
Quality of Smart Educational Content	Q11	0.846	13	18.226	0.000	0.928	1	46.153	0.000
	Q12	0.915	7	41.282	0.000				
	Q13	0.830	17	18.268	0.000				
Educational Data Analytics	Q14	0.911	9	68.082	0.000	0.799	7	14.215	0.000
	Q15	0.839	15	17.347	0.000				
Teacher Support in Smart Environment	Q16	0.913	8	17.351	0.000	0.846	5	21.707	0.000
	Q17	0.840	14	66.626	0.000				
Evaluation & Continuous Improvement of Interactions	Q18	0.953	1	64.513	0.000	0.867	2	21.446	0.000
	Q19	0.950	2	44.144	0.000				

An examination of the second-order factor loadings reveals that the dimension of "Quality of Smart Educational Content" (loading = 0.928, t = 46.153) occupies the highest rank of importance, contributing the greatest share to explaining and shaping AI-based educational interactions in secondary schools. It is followed respectively by the dimensions of "Evaluation & Continuous Improvement of Interactions" (loading = 0.867, Rank 2), "Student–Student Interactions in Smart Environment" (loading = 0.857, Rank 3), "Teacher Support in Smart Environment" (loading = 0.846, Rank 4), "Data-Driven School–Parent Interactions" (loading = 0.843, Rank 5), and "AI-Based Teacher–Student Interactions" (loading = 0.821, Rank 6). Finally, the dimensions of "Educational Data Analytics" (loading = 0.799, Rank 7) and "Technical Infrastructure & AI Platform" (loading = 0.770, Rank 8), although statistically significant, exert a comparatively lower coefficient of influence on the overall construct. This suggests that infrastructural elements play primarily an enabling (foundational) role, whereas the core effectiveness of these interactions is contingent upon content quality and process monitoring.

In the assessment of the 19 components, component Q18 (belonging to the dimension of Evaluation & Continuous Improvement), with a loading of 0.953, followed by Q19 with a loading of 0.950, exhibited the highest correlation coefficients with their respective dimension, occupying the first and second ranks among all components. Furthermore, component Q9 (from the Technical Infrastructure dimension) with a loading of 0.946, and Q8 (from the Data-Driven School–Parent Interactions dimension) with a loading of 0.941, ranked subsequently in the model's measurement hierarchy. The lowest first-order loading was assigned to component Q1 (loading = 0.802); nonetheless, since it exceeds the acceptable threshold of 0.70, it still demonstrates a highly acceptable explanatory power.

Answer to the Main Research Question: What is the model of AI-based educational interactions (Case study: Secondary schools in Tehran)?

The model of AI-based educational interactions (Case study: Secondary schools in Tehran), derived from the perspectives of the experts studied in the present research—comprising 8 dimensions, 19 components, and 91 indicators—was developed based on the conducted interviews, the examination of theoretical foundations, and thematic analysis.

Based on the validity and reliability results obtained from the questionnaire, complemented by the findings of library-based research on the relevant literature, a model was structured consisting of a central core and five subordinate sections: (1) Philosophy and General Objectives of the Model; (2) Theoretical Foundations of the Model; (3) Implementation Stages of the Model; (4) Model Evaluation

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System; and (5) Operational Mechanism of the AI-Based Educational Interactions Model in Tehran secondary schools.

A researcher-made questionnaire—comprising 5 dimensions (Philosophy & Objectives, Theoretical Foundations, Evaluation System, Implementation Principles, and Operational Mechanism) measured on a 5-point Likert scale—was employed to assess the internal validity of the model. This questionnaire was administered to 30 experts, and the results concerning the internal validity of the model indicated that all components scored above the Likert midpoint (3), signifying the acceptance of the model.

Across the dimensions of Philosophy The Objectives, Theoretical Foundations, Implementation Principles, the Model Evaluation System, and the Operational Mechanism, the calculated t-statistics were significant at the ** t-statistics were significant at the 0.01 level. Compar Objectives dimension with the population mean demonstrates that these components possess high validity from the experts' standpoint and have been confirmed with 99% confidence.

Table 5

Validation of the Dimensions of the AI-Based Educational Interactions Model (Tehran Secondary Schools)

Validation Type	Component	Mean	Mean Difference	Std. Deviation	t	df	Sig.
External	Philosophy & Objectives	4.07	1.08	0.658	7.456	29	0.000
	Theoretical Foundations	3.83	0.91	0.660	6.875	29	0.000
	Evaluation System	4.06	0.18	0.686	7.616	29	0.000
	Operational Mechanism	4.04	1.08	0.69	8.198	29	0.000

According to the results of Table 5, it can be inferred that the dimension of "Philosophy & Objectives" (Mean = 4.07), followed by the "Operational Mechanism" (Mean = 4.06), the "Evaluation System" (Mean = 4.06), and the "Theoretical Foundations" (Mean = 3.83) constitute, respectively, the most significant dimensions of the model in terms of validation.

4. Discussion and Conclusion

The present study developed and validated a multidimensional model of AI-based educational interactions for secondary schools in Tehran. The qualitative phase identified eight dimensions, 19 components, and 91 indicators, indicating that AI-based educational interaction is not restricted to a single teacher–student relationship or to the use of particular technological applications. Rather, it encompasses AI-based teacher–student interactions, student–student interactions in smart environments, data-driven school–parent interactions, technical infrastructure and AI platforms, quality of smart educational content, educational data analytics, teacher support in smart environments, and evaluation and continuous improvement of interactions. The quantitative findings subsequently supported the structural adequacy of this conceptualization: all components and indicators achieved t-values above 1.96, reliability coefficients exceeded the acceptable threshold, AVE values were above 0.50, and the endogenous construct attained an R^2 of 0.785, indicating substantial explanatory power. This multidimensional structure is consistent with studies arguing that AI should be understood as part of an educational ecosystem that simultaneously affects instructional, communicative, analytical, and organizational processes (Chan & Lo, 2023; Holmes et al., 2024). It also supports the view that educational interaction in AI-assisted learning environments involves several interconnected levels rather than a simple dyadic exchange between teachers and students (Chou & Chang, 2024). Similar Iranian research has emphasized the necessity of conceptual models capable of integrating different AI components affecting educational interactions in smart schools (Nasiri et al., 2023).

Among the eight dimensions, the quality of smart educational content demonstrated the highest second-order loading ($\beta = 0.928$, $t = 46.153$), indicating that content quality made the strongest contribution to the overall construct of AI-based educational interactions. This result suggests that educational AI becomes meaningful only when the content delivered, adapted, or generated by intelligent systems is pedagogically appropriate, responsive to learner needs, aligned with curricular objectives, and capable of supporting different learning pathways. The finding is consistent with the principle of personalized learning, according to which technology should adapt instructional materials and learning experiences to individual characteristics rather than merely digitize standardized instruction (Zhang, 2021). It also accords with research indicating that AI can improve educational interactions by

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personalizing learning materials, identifying learner characteristics, and modifying instructional experiences according to individual progress (Faghfoori et al., 2023). Shakeri and Asgari similarly emphasized that technology-based personalized education requires contextually appropriate and indigenous educational models rather than the simple adoption of generic technological solutions (Shakeri & Asgari, 2024). The prominence of smart content quality in the present model therefore reflects a pedagogical priority: AI systems can facilitate interaction only to the extent that the instructional material with which students interact is relevant, adaptive, understandable, and educationally valuable.

Evaluation and continuous improvement of interactions ranked second with a loading of 0.867, while its two components also occupied the first and second ranks among all first-order components, with loadings of 0.953 and 0.950. This finding highlights the importance of viewing AI-based educational interaction as a dynamic process requiring continuous monitoring, feedback, evaluation, and adjustment. Smart educational systems generate continuous traces of learner participation and performance, making it possible to evaluate interaction quality rather than relying exclusively on periodic achievement measures. This interpretation is supported by the growing literature on educational big data and learning analytics, which demonstrates the increasing importance of data-based monitoring and improvement in technology-supported education (Samsul et al., 2023). Davidsen and Steier likewise emphasized emerging technology-mediated approaches to interaction analysis, through which complex educational processes can be examined in greater detail and over time (Davidsen & Steier, 2025). The finding also aligns with evidence that real-time AI feedback can improve student performance by providing immediate information that can guide subsequent learning activities (Garcia & Rahman, 2025). Accordingly, continuous evaluation in an AI-supported environment should not be regarded merely as a final assessment mechanism; instead, it constitutes a feedback loop through which instructional interactions, learning tasks, and system responses can be progressively optimized.

Student–student interactions in smart environments ranked third ($\beta = 0.857$). This result indicates that AI-based educational interaction cannot be conceptualized solely in terms of learner interaction with a machine or teacher interaction with an intelligent platform. Peer relationships remain an essential component of learning and may be strengthened through AI-supported collaboration, group formation, structured dialogue, conflict management, and healthy competition. The identified indicators in this study included mechanisms such as automatic formation of study groups, recommendation of appropriate classmates for collaboration, AI-supported discussion, system-generated group projects, and intelligent support for conflict resolution. This finding corresponds with the broader understanding of educational interaction as involving behavioral, emotional, social, and cognitive participation (Azizi et al., 2021). It is also compatible with research showing that learner motivation and self-regulated participation are critical for effective use of technology-supported learning environments (Mustapha et al., 2023). Interactive generative AI can further support peer-oriented learning by providing scaffolding, immediate feedback, and engaging educational activities, as demonstrated in research on generative AI-supported role-playing environments (Chien et al., 2025). Therefore, the high importance of student–student interaction suggests that intelligent learning environments should be designed to enhance human collaboration rather than shift students toward isolated interaction with automated systems.

Teacher support in smart environments ranked fourth ($\beta = 0.846$), confirming the continuing centrality of the teacher in AI-mediated education. The model conceptualized teacher support through professional training for AI use and intelligent teaching assistance, including workshops, instructional guidance, technical support, resource recommendations, automatic question generation, interactive activity design, and assistance with assessment. This result supports research that rejects the assumption that AI will simply replace teachers. Instead, contemporary studies conceptualize AI as a complementary partner capable of supporting adaptive instruction while leaving pedagogical interpretation, relational judgment, and instructional leadership with the teacher (Smith & Taylor, 2025). Similar findings have been reported regarding smart learning systems, where implementation success and improvements in teacher–student interaction depend substantially on teacher readiness and organizational support (Abdollahi & Rahmani, 2024). Earlier research in Tehran secondary schools also indicated that AI can influence teacher–student educational interactions when incorporated within a pedagogically appropriate framework (Karimi & Sohrabi, 2020). The present finding is therefore consistent with a human-centered interpretation of educational AI in which teacher competence, digital literacy, and professional

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agency remain essential conditions for successful intelligent interaction.

Data-driven school–parent interactions ranked fifth in the structural model (β = 0.843), yet this dimension produced a particularly noteworthy result in the one-sample t-tests. It was the only dimension whose observed mean was significantly above the theoretical midpoint, with $M = 3.6146$, $t = 11.031$, and $p < .001$; all other dimensions were significantly below the midpoint. This suggests that digital communication between schools and families may currently be more developed or more familiar to respondents than other forms of AI-based interaction. The result can be interpreted in light of the expansion of digital educational communication following the COVID-19 pandemic, during which parents became more directly involved in technology-mediated schooling. Research on parent–student communication in virtual education has shown that digital platforms can expand family participation and create new channels for exchanging educational information (Pourghaffar & Jafarzadeh Dashbolagh, 2021). The experience of SHAD in Iranian schools also normalized forms of online communication involving schools, students, and families, despite recognized limitations in the quality of smart interactions (Alizadeh, 2021). Electronic data exchange can further support educational systems by increasing the efficiency and continuity of information sharing (Meer, 2025). Thus, the comparatively favorable status of school–parent interaction may reflect the institutionalization of digital communication practices that were accelerated during pandemic-era virtual education.

AI-based teacher–student interaction ranked sixth (β = 0.821), while its current status remained significantly below the theoretical midpoint. This combination is important because it indicates that teacher–student interaction is structurally meaningful to the proposed model but remains insufficiently developed in current practice. The finding may reflect the difference between using digital technologies for content transmission and using AI to create genuinely adaptive, responsive, and personalized pedagogical exchanges. Iranian studies of teachers' experiences during virtual education reported substantial challenges in transitioning from conventional instruction to technology-mediated teaching (Hasani et al., 2021), while research on teachers' concerns about virtual education similarly identified pedagogical and technological barriers affecting effective interaction (Ahmadi, 2022). Post-pandemic analyses have further shown that structural weaknesses persisted in virtual and blended educational systems (Zaidi et al., 2023). Conversely, contemporary studies demonstrate that when conversational AI produces natural, context-sensitive responses, students perceive it as more useful for educational activities (Singh & Gonzalez, 2024). Research on AI and the future of educational interactions in Iranian secondary schools also emphasizes the potential movement from static technology use toward more dynamic, multidirectional educational relationships (Rastegar & Soleimani, 2024; Rastegar & Soleymani, 2024). Therefore, strengthening teacher–student AI interaction requires moving beyond basic digital communication toward adaptive feedback, intelligent tutoring, and teacher-guided personalization.

Educational data analytics ranked seventh (β = 0.799). Although its structural contribution was lower than that of content, evaluation, peer interaction, and teacher support, it remained statistically significant and conceptually important. This dimension included predictive analytics and deeper analyses of student concentration, study habits, engagement, learning obstacles, risk of academic decline, and probability of dropout. The relatively lower ranking may indicate that data analytics primarily functions as an enabling and decision-support mechanism rather than as a direct educational interaction experienced by students. Nevertheless, its importance is supported by the expansion of learning analytics research, which has demonstrated the value of educational data for understanding learner behavior and supporting evidence-based intervention (Samsul et al., 2023). AI-supported analytics also complements personalized learning by allowing educational systems to detect individual patterns and adapt instruction accordingly (Zhang, 2021). However, learner data should not be interpreted in isolation from wider contextual differences. Educational outcomes are partly conditioned by family and socioeconomic environments, and research has demonstrated complex interactions between background characteristics and educational selectivity (Ghirardi & Bernardi, 2025). Thus, the analytic dimension of the model should be used to support pedagogical judgment rather than to reduce learners to algorithmically generated risk categories.

Technical infrastructure and the AI platform received the lowest second-order loading (β = 0.770), although the coefficient remained statistically significant and acceptable. This finding should not be interpreted as indicating that infrastructure is unimportant; rather, it suggests that infrastructure functions as a foundational prerequisite whose educational value emerges through higher-level pedagogical processes. Stable platforms, data security, rapid response, multimedia support, authentication, data integration, and cloud-based access are necessary conditions, but they do not independently create meaningful educational interaction. The Iranian experience during emergency virtual education illustrates this distinction. The pandemic expanded technological use and created opportunities for educational continuity (Atashi et al., 2021), but unequal access to devices and virtual learning facilities also generated academic and psychological difficulties (Ghanbari Hamidabadi et al., 2021). Studies of AI implementation in secondary education similarly identify both technological opportunities and infrastructural barriers (Mirzaei & Eftekhari, 2021). Dehghan and Jalalian further demonstrate the importance of digital capabilities and institutional support for strengthening organizational resilience in educational settings (Dehghan & Jalalian, 2025). Hence, infrastructure is indispensable, but its contribution is realized only when it supports high-quality content, capable teachers, effective analytics, and meaningful educational communication.

Finally, the validation phase showed that experts evaluated the main elements of the proposed model significantly above the criterion midpoint, with all validation tests reaching statistical significance at $p < .001$. Philosophy and objectives received the highest mean, followed closely by the operational and evaluation dimensions, while theoretical foundations were also positively validated. This finding demonstrates that experts viewed AI-based educational interaction as requiring more than a technical implementation plan. A coherent philosophy, explicit educational objectives, operational mechanisms, theoretical grounding, and continuous evaluation are all necessary for sustainable adoption. This interpretation is consistent with the call for indigenous and pedagogically grounded models of AI-supported education (Shakeri & Asgari, 2024) and with research emphasizing that AI implementation should simultaneously address educational promises, institutional implications, and responsible integration (Chan & Lo, 2023; Holmes et al., 2024). It also corresponds with ethical analyses of AI-driven interactions in K–12 education, which emphasize privacy, fairness, equitable access, transparency, and stakeholder participation as essential policy considerations rather than secondary technical concerns (Walsh & Lee, 2025). Overall, the findings indicate that AI-based educational interaction in Tehran secondary schools should be understood as a systemic pedagogical transformation in which technology, content, human relationships, analytics, professional capability, ethics, and organizational processes operate as mutually dependent elements.

The study has several limitations that should be considered when interpreting its findings. First, the quantitative phase was conducted among secondary school students in public schools in Tehran; therefore, the findings may not be directly generalizable to private schools, other educational levels, or schools in provinces with substantially different socioeconomic, cultural, and technological conditions. Second, although the qualitative sample reached theoretical saturation and included relevant experts, the number of participants was relatively limited and other stakeholder groups, particularly parents, school principals, teachers from a wider range of subject areas, and technology developers, could have contributed additional perspectives. Third, the quantitative findings were derived primarily from self-report questionnaire data, which may be affected by response tendencies and participants' varying familiarity with AI applications. Fourth, the cross-sectional design captures perceptions at one point in a rapidly changing technological environment and cannot demonstrate how the importance or actual implementation of the model dimensions may change over time. Finally, structural validation confirms the statistical coherence of the proposed model but does not by itself establish its causal effectiveness in improving learning achievement, engagement, educational equity, or other student outcomes.

Future studies should test the proposed model in different geographical regions, school types, and educational levels to assess its external validity and determine whether the relative importance of its dimensions changes across contexts. Longitudinal research would be particularly valuable for examining how AI-based educational interactions evolve as teachers and students gain greater experience with intelligent systems. Quasi-experimental and experimental studies should evaluate whether implementation of specific elements of the model produces measurable improvements in academic achievement, motivation, engagement, self-regulated learning, social interaction, and retention. Multi-group analyses could examine differences according to gender, grade level, digital literacy, socioeconomic status, school resources, and prior AI experience. Future research should also incorporate data from teachers, parents, administrators, and educational technology specialists and combine questionnaire measures with behavioral learning analytics, classroom observations, system log data, and qualitative interviews. Additional studies are recommended to investigate ethical dimensions

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of the model, particularly algorithmic bias, privacy, explainability, student autonomy, and the long-term psychological consequences of continuous data-driven monitoring.

Educational authorities and school administrators should implement AI-based educational interaction gradually through an integrated strategy rather than through isolated acquisition of technological tools. Priority should be given to developing high-quality, curriculum-aligned, adaptive smart content because this dimension exerted the strongest contribution to the proposed model. Schools should establish continuous evaluation and feedback mechanisms capable of monitoring interaction quality and using results to revise instructional processes. Teachers should receive sustained professional development in AI literacy, digital pedagogy, learning analytics, ethical use of student data, and the design of human-centered AI-supported activities. AI platforms should facilitate collaborative student learning, timely teacher–student feedback, and meaningful school–parent communication instead of focusing solely on content delivery or administrative automation. Infrastructure development should ensure stable connectivity, secure authentication, data protection, interoperability, and reliable access for students with differing levels of technological resources. Finally, schools should establish clear governance procedures defining human responsibility for AI-supported decisions so that intelligent systems remain tools for strengthening professional judgment, educational equity, and human interaction rather than substitutes for them.

Authors' Contributions

Authors equally contributed to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in studies involving human participants were under the ethical standards of the institutional and, or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

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