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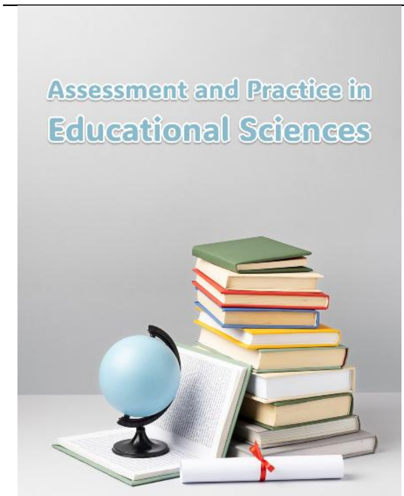

Presenting an Artificial Intelligence Model in School Management in Iraq

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ABSTRACT

This study aimed to design and validate a localized artificial intelligence (AI)-based school management model for use in Iraq's educational system. The research employed a sequential exploratory mixed-methods design. In the qualitative phase, semi-structured interviews were conducted with 15 educational experts, school principals, teachers, and IT specialists to explore the foundational dimensions of AI implementation in school management. Data were analyzed using the systematic grounded theory approach, including open, axial, and selective coding. In the quantitative phase, a researcher-made questionnaire based on the qualitative findings was distributed to 450 school administrators and leading teachers across selected Iraqi provinces. Confirmatory factor analysis (CFA), reliability testing (Cronbach's alpha and composite reliability), convergent validity (AVE), predictive relevance (Q^2), and structural equation modeling (SEM) were performed using SPSS-27 and SmartPLS-3. The CFA confirmed the structural integrity of the six core dimensions: causal conditions, contextual conditions, intervening conditions, the core phenomenon (AI implementation), strategic actions, and outcomes. All constructs demonstrated strong factor loadings (>0.70), high reliability (CR > 0.90), and acceptable convergent validity (AVE > 0.60). Path analysis revealed that causal conditions significantly predicted AI implementation in school management ($\beta = 0.963$, $R^2 = 0.928$). AI implementation strongly predicted strategic actions ($\beta = 0.416$), which in turn significantly influenced educational outcomes ($\beta = 0.971$, $R^2 = 0.943$). Contextual and intervening conditions also showed significant positive effects on strategy development ($\beta = 0.560$ and $\beta = 0.452$, respectively). The validated model offers a robust and context-sensitive framework for guiding AI integration in Iraqi school management systems. It emphasizes the importance of infrastructure, ethical readiness, professional development, and strategic planning. This model can inform policy formulation, capacity-building initiatives, and future research in the field of AI-enabled educational governance.

Keywords: Artificial Intelligence, School Management, Iraq, Educational Technology, Structural Equation Modeling, Grounded Theory, Educational Leadership, Digital Transformation.

Introduction

The integration of artificial intelligence (AI) into educational systems represents one of the most transformative developments in the 21st-century learning environment. As schools worldwide grapple with challenges of quality, equity, administrative efficiency, and digital modernization, AI is increasingly viewed not as a futuristic novelty but as a strategic necessity. In contexts like Iraq—where post-conflict reconstruction, educational disparity, and resource limitations prevail—the role of AI can be especially pivotal in reimagining how schools are managed and how learning is delivered. Artificial intelligence offers a promising framework for automating administrative processes, supporting personalized instruction, enhancing teacher productivity, and ensuring data-driven decision-making in schools (1-3).

In school management specifically, the potential of AI lies in streamlining complex administrative tasks, improving teacher support systems, allocating educational resources intelligently, and developing adaptive learning environments that cater to the individual needs of students (4-6). The growing interest in this field is matched by emerging research on AI's implications for pedagogical design, assessment strategies, and leadership practices (7, 8). This transformative potential, however, is accompanied by a set of theoretical, ethical, and practical challenges. Questions about AI literacy among educators, algorithmic bias, ethical decision-making, data privacy, and the digital divide remain critical in determining whether AI becomes a tool for educational inclusion or exclusion (9-11).

The current educational climate in Iraq is marked by a strong push toward modernization, driven by digital globalization and regional policy agendas. However, the lack of cohesive digital infrastructure, uneven teacher training, and minimal integration of emerging technologies in curriculum and school management have created a significant gap between policy intentions and on-ground realities. AI, if implemented thoughtfully and responsibly, could serve as a catalyst for reform by augmenting school leadership functions and fostering adaptive administrative models (12-14). Yet, this integration must be grounded in context-specific models that consider local educational needs, cultural norms, and technological readiness.

Recent advancements in AI capabilities—particularly in natural language processing, predictive analytics, and machine learning—have expanded the spectrum of possible applications in schools. These range from automated attendance systems and intelligent scheduling to AI-driven dashboards that help principals monitor performance metrics in real time (15-17). Furthermore, intelligent tutoring systems and adaptive platforms are increasingly utilized to complement classroom teaching, creating hybrid educational environments that blend human and machine capabilities (18-20). These developments align closely with the Iraqi Ministry of Education's goals to improve institutional accountability and learning outcomes across public schools.

Despite this potential, most school management systems in Iraq still operate under traditional paradigms that are ill-equipped to accommodate the rapid shift toward data-centric and technology-enhanced administration. This lag not only impacts operational efficiency but also hinders student support services and educational equity. There is, therefore, a pressing need for a contextually appropriate AI model tailored to the Iraqi school system—one that integrates cognitive, organizational, and technological components to guide AI deployment at both strategic and operational levels (21-23). Such a model must also promote ethical use and responsible AI leadership, particularly in settings where digital literacy among school staff remains limited (24-26).

A growing body of literature underscores the transformative role of AI in enhancing institutional leadership and teacher decision-making. AI-supported dashboards and data visualization tools have shown promise in supporting principals' real-time judgments regarding resource allocation, curriculum planning, and disciplinary interventions (2, 7, 27). Additionally, intelligent systems can help detect patterns in student behavior, absenteeism, and academic performance, thereby enabling proactive rather than reactive management strategies. Yet, without a structured implementation framework, such tools risk becoming underutilized or misapplied. Thus, any attempt to introduce AI in school management must begin with a foundational understanding of local educational ecosystems and be informed by both global best practices and indigenous innovation (8, 14, 21).

One notable concern that accompanies the digitalization of school management is the need to redefine leadership roles in AI-integrated contexts. School leaders are now required not only to manage people and resources but also to interpret data, oversee technology infrastructures, and ensure ethical AI use. This evolving leadership mandate demands new professional competencies and institutional supports that are often absent in traditional training frameworks (1, 9, 11). For instance, understanding how algorithmic outputs should inform pedagogical decisions or how to balance automated insights with human judgment requires a nuanced and reflexive approach to leadership. Furthermore, educational leaders must be capable of guiding their staff through technological transitions, mitigating resistance, and fostering a culture of continuous learning and digital trust.

AI integration also invites attention to teacher–machine collaboration and the human–AI interface in educational decision-making. As tools like generative AI, recommendation systems, and learning analytics become more prevalent, school administrators and educators must strike a balance between automation and human-centric values. Studies have shown that while AI can reduce administrative burden, its effectiveness heavily depends on human oversight and contextual interpretation (4, 12, 28). Additionally, in the case of Iraq—where schools vary significantly in resources and digital maturity—over-reliance on AI without proper customization may lead to system-wide inequities. Therefore, any AI model proposed for Iraqi schools must adopt a modular, scalable, and culturally sensitive design.

Importantly, AI-driven school management must also address the psychological and ethical implications for educators and learners. As Rezaei and Faghih Abdollahi (16) argue, trust, transparency, and accountability are critical when implementing data-driven systems in education. Concerns around surveillance, job displacement, and decision bias must be acknowledged and addressed within the model framework. Moreover, to avoid the pitfalls of technological determinism, educational stakeholders must remain active agents in AI governance, ensuring that innovation serves pedagogical purpose rather than bureaucratic convenience (5, 13, 29).

This study is situated within this complex landscape of opportunity and constraint. It aims to identify the key components of artificial intelligence applicable to school management and to develop a conceptual model tailored to the Iraqi context.

Methods and Materials

This study employed a sequential exploratory mixed-methods design aimed at identifying the dimensions and components of artificial intelligence (AI) in school management and subsequently proposing an applicable model for the Iraqi educational system. Given its goal to generate both theoretical and practical insights, the research falls within the category of developmental and applied studies. The first phase of the study was qualitative and focused on exploring foundational components of AI integration in school management. Participants in this phase included 18 educational management faculty members, information technology and AI experts, educational researchers, school principals, and experienced teachers in Iraq. These participants were selected using purposive and theoretical sampling strategies, based on their domain expertise, practical involvement in AI-based school initiatives, and deep understanding of educational technology systems. The principle of theoretical saturation determined the final sample size, with data collection ceasing once no new significant information emerged from additional interviews.

In the second, quantitative phase of the study, the findings from the qualitative stage were used to develop a researcher-made questionnaire. This tool was then distributed among high school principals and teachers recognized for their engagement with modern educational technologies across selected provinces in Iraq. A total of 450 completed questionnaires were returned and deemed valid for analysis, exceeding the minimum required sample size of 280 respondents as calculated using the Barclay et al. (1995) formula for structural equation modeling. The sampling strategy ensured statistical reliability and broader generalizability by targeting individuals with practical exposure to AI-enhanced school management practices.

The data collection phase utilized two main instruments: semi-structured interviews for the qualitative stage and a comprehensive researcher-developed questionnaire for the quantitative stage. During the qualitative phase, individual interviews were conducted with key informants selected based on their expertise in educational leadership and AI integration. Each interview lasted approximately 45 minutes and followed a pre-designed protocol of six open-ended questions, developed through literature review and expert consultation. The interview protocol aimed to capture insights into causal conditions, contextual and intervening factors, strategies, and outcomes of AI implementation in school leadership. Ethical standards such as informed consent, confidentiality, voluntary participation, and audio recording with permission were strictly followed throughout the interview process.

The quantitative phase was built upon qualitative insights and aimed to validate and generalize the identified components. The resulting questionnaire consisted of 116 closed-ended items rated on a five-point Likert scale (from "strongly disagree" to "strongly agree") and covered six dimensions: causal conditions, the core phenomenon, contextual conditions, intervening conditions, strategies, and outcomes. The first section collected demographic information, including gender, age, education level, work experience, school type, and familiarity with AI technologies. The second section focused on measuring participants’ awareness, attitudes, and practical engagement with AI applications in school administration. The items were distributed across six theoretical dimensions, with subcategories such as technological infrastructure, teacher training, intelligent content development, learning technologies, cybersecurity, policy frameworks, organizational structures, digital barriers, professional development strategies, and outcome metrics such as school productivity and personalized learning.

In the qualitative phase, data were analyzed using the systematic approach of Grounded Theory as developed by Strauss and Corbin (1990). This approach emphasizes structured coding procedures and conceptual clustering to generate an emergent theory. The analysis followed three major coding phases: open coding, axial coding, and selective coding. During open coding, interview transcripts were segmented and examined line by line and paragraph by paragraph to extract initial concepts. These concepts were then grouped into categories through a process of constant comparison. In axial coding, the researcher identified relationships between core categories and subcategories, organizing them around a central phenomenon. This stage enabled the construction of a preliminary paradigm model linking causal conditions, contextual and intervening factors, strategies, and outcomes. Finally, in the selective coding phase, all major categories were integrated into a coherent theoretical model representing AI application in school management. The central phenomenon was elaborated through its links to various causal and environmental variables, ultimately producing a substantive framework grounded in empirical data.

Simultaneous data collection and analysis ensured theoretical sensitivity and allowed emerging themes to shape the course of the study dynamically. Coding procedures were flexible, iterative, and conducted with analytical rigor, facilitating the emergence of a conceptual model that reflects the complexity of AI-based educational management in Iraq. NVivo software was employed to assist with qualitative data organization and thematic extraction.

For the quantitative phase, data analysis was conducted using SPSS version 27 and SmartPLS version 3. Descriptive statistics such as frequency distributions and means were calculated to characterize the sample and their responses. Inferential analysis included Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to test the fit and validity of the proposed model. The CFA verified the factor structure derived from the qualitative stage, confirming the construct validity of the questionnaire. SEM was employed to assess the causal relationships between identified variables and to evaluate the overall fitness of the model within the AI-in-education framework. These analytical procedures allowed the researcher to test hypotheses derived from the qualitative phase and refine the model based on empirical evidence. The integration of both qualitative insights and quantitative validation provided a robust foundation for the proposed AI-based school management model tailored to the Iraqi educational context.

Findings and Results

In this study, semi-structured interviews were conducted with 15 experts in the fields of educational management and advanced technologies. The analysis of the collected qualitative data was carried out concurrently with the data collection process, following the structured grounded theory methodology, including the three phases of open, axial, and selective coding. Initially, the interview recordings were transcribed verbatim, and the textual data were segmented into smaller meaning units for detailed examination and categorization. During the open coding stage, a total of 116 preliminary codes were identified. After refining and eliminating redundancies, these were distilled into 120 distinct open codes. These codes were then grouped into 32 subcategories and subsequently consolidated into 16 main categories. The selection of categories was guided by the level of conceptual saturation they offered. In the axial coding phase, utilizing the systematic approach of grounded theory, the extracted codes were organized into six overarching thematic clusters: the core phenomenon (application of artificial intelligence in school management), causal conditions, contextual conditions, intervening conditions, strategic actions, and anticipated outcomes. This structured categorization provided the conceptual foundation for the proposed model of AI integration in school administration.

Table 1. Axial Coding and Formation of Main Dimensions

Main Categories	Subcategories
Advanced Technologies in Education	Core Phenomenon
Cybersecurity	
Technological Infrastructure	Causal Conditions
Human Resources	
Intelligent Educational Content Development	
Policies and Regulations	Contextual Conditions
Organizational Factors	
Technological Challenges	Intervening Conditions
Security and Cultural Barriers	
Improvement of Communication Infrastructure	Strategies
Enhancement of Educational Skills	
Reduction of Skill Gaps	
Improvement of Educational Quality	Outcomes
Productivity in School Management	
Data-Driven Feedback for Students	
Integration of Educational Assessment	

The results of the axial coding process, as illustrated in Table 1, demonstrate the structuring of the identified open codes into six major conceptual dimensions, each comprising several relevant subcategories. The central phenomenon emerging from the qualitative data was categorized under "Advanced Technologies in Education," with "Cybersecurity" representing a critical associated theme. The causal conditions were found to include technological infrastructure, human resource capabilities, and the development of intelligent educational content, all of which are foundational for successful AI integration in school management. Contextual conditions encompassed policies, regulations, and organizational factors that shape the institutional environment. Intervening conditions were related to existing technological barriers and cultural-security constraints that might impede AI implementation. Strategic actions were categorized under themes such as enhancing communication infrastructure, improving educational skills, and reducing technological skill gaps. Lastly, anticipated outcomes included improvements in educational quality, increased management productivity, data-informed student feedback, and integration of assessment systems—together forming a comprehensive model of AI-based school management.

In the quantitative phase of the study, data were collected from a sample of 450 respondents, consisting of secondary school principals and leading teachers from various provinces in Iraq who had experience using educational technologies and artificial intelligence tools in school settings. The demographic profile of the participants included both male and female respondents across a wide age range, with varying levels of education and professional experience. Most participants held bachelor's or master's degrees in education or related fields, and their years of service ranged from less than 5 years to over 20 years. Additionally, participants worked in different types of schools—public and private—and reported diverse levels of familiarity with AI applications in educational management, which provided a representative perspective on the practical realities and challenges of implementing AI in Iraqi school leadership.

Table 2. Confirmatory Factor Analysis Results for Questionnaire Items by Construct

Construct	Observed Variables	Factor Loadings	t-Values
Causal Conditions	Q1–Q18	0.79 – 0.90	23.38 – 56.52
Core Phenomenon	Q19–Q34	0.77 – 0.88	17.71 – 53.50
Contextual Conditions	Q35–Q50	0.80 – 0.86	22.02 – 36.41
Intervening Conditions	Q51–Q66	0.78 – 0.88	23.03 – 49.41
Strategies	Q67–Q88	0.78 – 0.87	19.55 – 37.01
Outcomes	Q89–Q116	0.70 – 0.89	21.86 – 47.95

The results of the confirmatory factor analysis, as detailed in Table 2, validate the structural integrity of the questionnaire items across the six theoretical dimensions of the AI-based school management model. All items demonstrated strong and statistically significant factor loadings, with values ranging from 0.70 to 0.90, exceeding the commonly accepted threshold of 0.70. The corresponding t-values also confirmed the significance of these loadings, with all t-values above 17 and many exceeding 30, indicating a high level of reliability and convergent validity. For the causal conditions construct (Q1–Q18), factor loadings ranged between 0.79 and 0.90, showing strong alignment among variables such as infrastructure readiness, human resource competence, and intelligent content development. The core phenomenon dimension (Q19–Q34) also exhibited strong internal consistency, with factor loadings from 0.77 to 0.88, reflecting the depth and consistency in perceptions of AI implementation in school management. Contextual conditions (Q35–Q50) and intervening conditions (Q51–Q66) similarly showed robust item correlations, underscoring the influence of regulatory, organizational, technological, and cultural variables. The strategies component (Q67–Q88) reflected high coherence with loadings between 0.78 and 0.87, validating practical approaches such as communication infrastructure enhancement and teacher training. Lastly, the outcomes construct (Q89–Q116) showed excellent internal reliability, confirming the validity of measuring educational quality, managerial efficiency, data feedback mechanisms, and evaluation integration. Overall, the CFA results provided strong empirical support for the proposed conceptual model.

Table 3. Results of Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE)

Construct / Subconstruct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Causal Conditions	0.959	0.963	0.593
Technological Infrastructure	0.880	0.910	0.627
Hardware	0.758	0.861	0.674
Software	0.801	0.883	0.717
Human Resources	0.887	0.914	0.639
Teacher Training	0.751	0.858	0.668
Technical Support	0.824	0.895	0.740
Intelligent Educational Content Development	0.891	0.917	0.648
Smart Content Production	0.816	0.891	0.732
Content Optimization	0.795	0.880	0.709
Core Phenomenon	0.956	0.961	0.605
Advanced Technologies in Education	0.911	0.928	0.618
Learning Technologies Implementation	0.831	0.887	0.663

Recognition and Analysis Technologies	0.836	0.891	0.671
Cybersecurity	0.918	0.933	0.637
Network Infrastructure Development	0.854	0.901	0.696
Cybersecurity Enhancement	0.852	0.900	0.693
Contextual Conditions	0.956	0.960	0.603
Policies and Regulations	0.910	0.927	0.614
National and International Laws	0.843	0.895	0.680
Support Programs	0.837	0.891	0.673
Organizational Factors	0.923	0.937	0.650
Cultural Attitudes	0.847	0.897	0.686
Organizational Structure	0.852	0.900	0.692
Intervening Conditions	0.957	0.961	0.607
Technological Challenges	0.913	0.930	0.624
Digital Infrastructure Deficiencies	0.821	0.881	0.650
Lack of Technological Support	0.858	0.904	0.701
Security and Cultural Barriers	0.918	0.933	0.637
Security Challenges	0.855	0.902	0.698
Organizational Limitations	0.870	0.911	0.720
Strategies	0.970	0.972	0.611
Communication Infrastructure Improvement	0.916	0.931	0.629
Internet Network Upgrades	0.865	0.908	0.713
Hardware/Software Updates	0.818	0.880	0.648
Educational Skills Enhancement	0.896	0.920	0.657
Student Empowerment	0.819	0.893	0.735
Teacher Training Improvement	0.799	0.882	0.714
Skill Gap Reduction	0.925	0.938	0.656
Basic Skills Strengthening	0.854	0.901	0.695
Advanced Skills Development	0.867	0.909	0.715
Outcomes	0.976	0.978	0.611
Educational Quality Improvement	0.919	0.934	0.641
Personalized Learning	0.870	0.912	0.721
Access to Educational Resources	0.816	0.880	0.648
School Management Productivity	0.925	0.938	0.656
Data Management	0.869	0.911	0.718
Resource Optimization	0.858	0.904	0.702
Data-Driven Feedback for Students	0.896	0.920	0.657
Data Collection and Analysis	0.814	0.889	0.729
Feedback and Educational Reform	0.799	0.882	0.714
Integrated Assessment Systems	0.900	0.923	0.668
Comprehensive Evaluation Systems	0.828	0.897	0.745
Alignment of Evaluation and Teaching	0.812	0.889	0.727

As presented in Table 3, the results of reliability and validity assessments indicate strong psychometric properties across all constructs of the model. Cronbach's alpha values for all main constructs exceed the recommended threshold of 0.70, with values ranging from 0.751 to 0.976, demonstrating excellent internal consistency. Similarly, composite reliability (CR) values ranged between 0.858 and 0.978, confirming the stability of the latent constructs. The Average Variance Extracted (AVE) for all constructs was also above the 0.50 benchmark, ranging from 0.593 to 0.745, indicating adequate convergent validity and that a significant proportion of variance is captured by the latent variables. These findings validate the questionnaire's multidimensional structure and affirm that each set of indicators reliably represents its respective construct—whether causal conditions, the core phenomenon, contextual and intervening conditions, strategies, or outcomes. This robust measurement model provides a strong foundation for further structural modeling and hypothesis testing within the study's AI-based school management framework.

Table 4. CV-Com (Construct Cross-Validated Communality) Results for Endogenous Constructs

Construct / Subconstruct	SSO	SSE	Q^2 (=1−SSE/SSO)

Causal Conditions	341.24	164.55	0.52
Technological Infrastructure	117.85	55.73	0.53
Hardware	65.13	44.91	0.31
Software	53.03	37.43	0.29
Human Resources	109.53	56.06	0.49
Teacher Training	51.72	35.67	0.31
Technical Support	57.68	33.35	0.42
Intelligent Content Development	108.31	57.54	0.47
Smart Content Production	54.74	28.50	0.48
Content Optimization	49.72	29.56	0.41
Core Phenomenon	256.38	128.29	0.50
Advanced Educational Technologies	123.25	69.08	0.44
Learning Technology Implementation	59.56	30.71	0.48
Recognition and Analysis Technologies	80.55	42.91	0.47
Cybersecurity	153.57	75.77	0.51
Network Infrastructure Development	76.33	37.89	0.50
Cybersecurity Enhancement	77.29	39.45	0.49
Contextual Conditions	322.68	170.15	0.47
Policies and Regulations	150.22	88.61	0.41
National and International Laws	71.04	38.79	0.45
Support Programs	93.81	55.69	0.41
Organizational Factors	162.10	81.13	0.50
Cultural Attitudes	59.87	27.68	0.54
Organizational Structure	84.52	50.18	0.41
Intervening Conditions	328.99	161.82	0.51
Technological Challenges	156.22	79.40	0.49
Digital Infrastructure Gaps	68.32	44.11	0.35
Lack of Tech Support	59.96	34.65	0.42
Security and Cultural Barriers	149.02	78.59	0.47
Security Challenges	74.83	44.16	0.41
Organizational Limitations	73.10	30.72	0.58
Strategies	384.70	180.06	0.53
Communication Infrastructure Improvement	133.14	67.35	0.49
Internet Network Upgrade	54.69	29.85	0.45
Hardware/Software Updates	78.53	57.22	0.27
Educational Skills Enhancement	117.35	57.69	0.51
Student Empowerment	40.09	24.29	0.39
Teacher Training Enhancement	49.74	32.31	0.35
Skill Gap Reduction	143.57	69.82	0.51
Basic Skills Strengthening	78.41	37.22	0.53
Advanced Skills Development	57.91	33.60	0.42
Outcomes	521.76	244.86	0.53
Educational Quality Improvement	167.52	80.52	0.52
Personalized Learning	62.01	32.29	0.48
Access to Educational Resources	46.76	37.41	0.20
School Management Productivity	138.37	59.88	0.57
Data Management	75.75	35.61	0.53
Resource Optimization	83.56	47.64	0.43
Data-Driven Student Feedback	101.99	55.59	0.45
Data Collection and Analysis	51.70	35.45	0.31
Feedback and Educational Reform	59.19	30.95	0.48
Educational Assessment Integration	109.41	56.21	0.49
Comprehensive Evaluation Systems	47.23	29.39	0.38
Evaluation and Teaching Alignment	68.98	47.51	0.31

Table 4 presents the results of the CV-Com (Construct Cross-Validated Communality) analysis, used to evaluate the predictive relevance (Q^2) of the latent constructs in the structural model. All major constructs demonstrated acceptable to strong predictive relevance, with Q^2 values ranging between 0.27 and 0.58. The overall Q^2 value for the main constructs—Causal Conditions (0.52), Core Phenomenon (0.50), Contextual Conditions (0.47), Intervening Conditions (0.51), Strategies (0.53), and Outcomes (0.53)—confirmed that the model has high explanatory power and predictive validity. Among the subconstructs, particularly high Q^2 values were observed for Organizational Limitations (0.58), Cultural Attitudes (0.54), Basic Skills Strengthening (0.53), and Data Management (0.53), indicating their strong relevance in explaining the variance in school management outcomes. In contrast, a lower predictive relevance was noted for Access to Educational Resources (0.20) and Hardware/Software Updates (0.27), suggesting these areas may need further investigation or modeling refinement. Overall, the results affirm the model's robustness and capacity to explain and predict AI-driven transformations in educational leadership within Iraqi schools.

Table 5. Mean Communality, Average R^2, and Goodness-of-Fit (GOF) Index

Measure	Value
Mean Communality	0.672
Average R^2	0.908
Goodness-of-Fit (GOF) Index	0.78

As shown in Table 5, the overall model demonstrated strong measurement quality and structural integrity. The average communality value was 0.672, indicating that a substantial proportion of the variance in each indicator is well explained by its corresponding latent construct. The average R^2 value was remarkably high at 0.908, reflecting excellent explanatory power across the endogenous variables in the structural model. Moreover, the Goodness-of-Fit (GOF) index—calculated at 0.78—far exceeds the threshold of 0.36 for large effect sizes in structural equation modeling, as proposed by Tenenhaus et al. (2005). This high GOF value confirms that the model possesses a very strong overall fit, effectively capturing the relationships between constructs related to the application of artificial intelligence in school management.

Table 6. Direct Path Coefficients and Significance Values for Structural Model Hypotheses

Hypothesized Path	Standardized Coefficient (β)	t-Statistic	R^2
Causal Conditions → AI Implementation in School Management	0.963	160.081	0.928
AI Implementation in School Management → Strategies	0.416	35.585	0.709
Contextual Conditions → Strategies	0.560	40.622	—
Intervening Conditions → Strategies	0.452	45.126	—
Strategies → Outcomes	0.971	193.172	0.943

Table 6 illustrates the structural relationships and hypothesis testing results within the proposed model. All hypothesized paths were found to be statistically significant with extremely high t-values, confirming the robustness of the conceptual framework. The strongest path was observed from causal conditions to the implementation of AI in school management ($\beta = 0.963$, $t = 160.081$), explaining 92.8% of the variance in this core construct. Similarly, AI implementation significantly influenced strategic actions ($\beta = 0.416$, $t = 35.585$), which in turn strongly predicted the outcomes ($\beta = 0.971$, $t = 193.172$), accounting for 94.3% of their variance. Additionally, both contextual conditions ($\beta = 0.560$, $t = 40.622$) and intervening conditions ($\beta = 0.452$, $t = 45.126$) demonstrated significant positive effects on the formation of strategies. These results validate the conceptual pathways in the model and underscore the central mediating role of strategies in translating AI-based managerial innovations into tangible school outcomes.

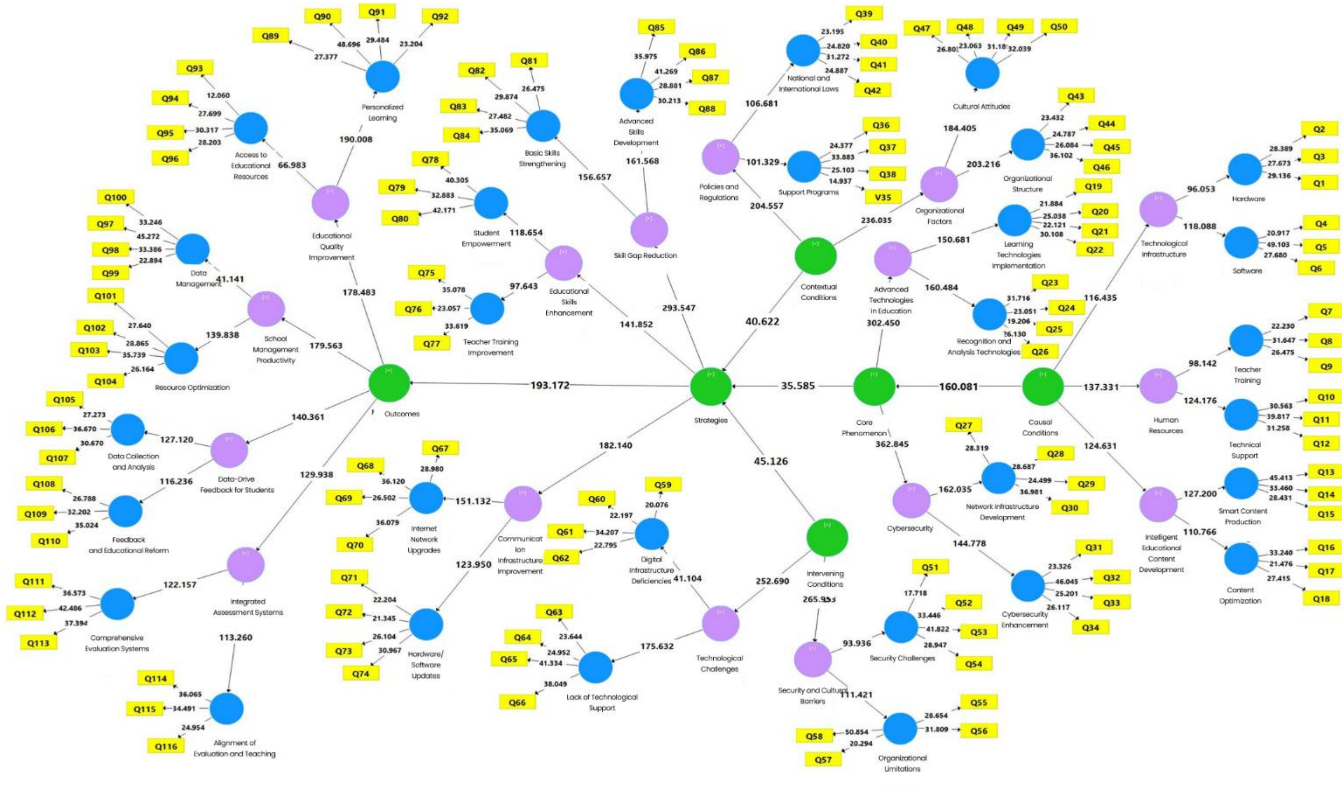

Figure 1. Model with t-values

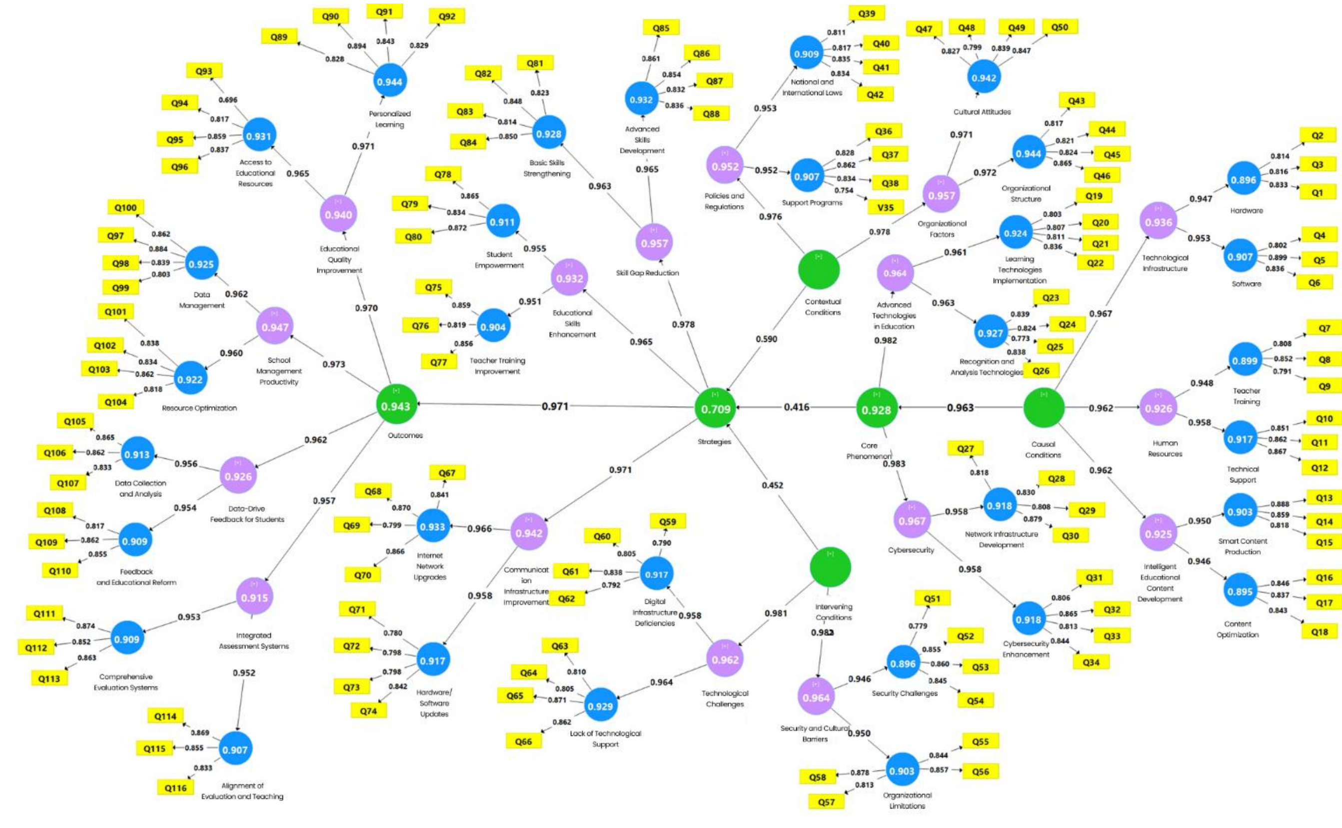

Figure 2. Model with Beta Values

Discussion and Conclusion

The present study aimed to develop and validate a contextually grounded model for the implementation of artificial intelligence in school management within Iraq. The findings revealed that AI integration in educational leadership is a multidimensional phenomenon influenced by causal, contextual, and intervening conditions, and mediated through strategic actions that ultimately lead to significant educational and administrative outcomes. Through a combination of qualitative grounded theory and quantitative structural modeling, six major components were identified: causal conditions (e.g., infrastructure, human resources, content development), core phenomenon (AI deployment in school management), contextual conditions (e.g., policy and organizational factors), intervening conditions (e.g., technological and cultural barriers), strategic actions (e.g., infrastructure enhancement, skill development), and outcomes (e.g., educational quality, managerial efficiency, and assessment integration).

Quantitative analysis strongly supported the relationships among these constructs. The causal conditions had a direct and powerful influence on AI implementation in school management ($\beta = 0.963$), explaining 92.8% of its variance. This highlights the critical role of technological infrastructure, trained human capital, and intelligent content development as prerequisites for AI-driven transformation. These findings align with existing literature emphasizing that the availability of robust hardware and software, along with digitally literate staff, is essential for successful AI integration in educational institutions (1, 2). For instance, research by Harte et al. confirms that infrastructure and training are foundational elements for digital transitions in both academic and administrative settings (22).

The study also found that the implementation of AI in school management significantly predicted the adoption of strategic interventions ($\beta = 0.416$), which in turn had a very strong effect on educational outcomes ($\beta = 0.971$). This supports the notion that AI functions as a facilitator for strategic change, enabling more responsive and data-driven decisions. Similar observations were made by Song, who emphasized the role of machine learning tools in improving institutional learning design and responsiveness (8). Moreover, contextual factors—such as supportive policies, regulatory clarity, and organizational readiness—were shown to directly influence the formation of strategic actions ($\beta = 0.560$), reaffirming the argument that AI adoption must be institutionally scaffolded through enabling governance structures (5, 14).

Intervening conditions, particularly technological and cultural barriers, also played a considerable role ($\beta = 0.452$), indicating that resistance to AI, low trust in automation, and cybersecurity concerns could significantly hinder effective strategy formulation. This is consistent with findings from Viberg et al., who documented cross-national differences in teachers' trust in AI due to disparities in digital culture and organizational support (24). The Iraqi context, where digital literacy varies widely and infrastructure remains uneven across provinces, further validates this observation. Indeed, educational leaders must navigate not only the technical but also the social and ethical dimensions of AI deployment (9, 10).

The model's high R^2 values and strong Q^2 indicators across all dimensions confirm its predictive and explanatory power. In particular, the constructs of strategy and outcome demonstrated very high levels of explained variance ($R^2 = 0.709$ and 0.943, respectively), showing that when AI implementation is supported by appropriate leadership strategies, the impact on educational outcomes is substantial. This reinforces earlier arguments that AI is most effective when aligned with human-centered leadership practices and when viewed as an augmentative—not substitutive—tool (4, 15). Studies in similar educational settings suggest that while AI can reduce workload and improve decision accuracy, it must be embedded within broader institutional reforms that prioritize ethical reasoning and collaborative governance (9, 29).

The findings also suggest that educational outcomes are enhanced not merely by the presence of AI tools, but by the strategic use of these tools to improve resource optimization, personalized learning, and integrated assessment systems. For example, participants emphasized the value of AI in generating data-informed feedback for students, which echoes prior research on learning analytics and adaptive technologies in classrooms (12, 20). Similarly, the connection between strategy and outcome in the model confirms prior empirical work on AI's role in improving quality assurance and administrative responsiveness in schools (3, 7).

Furthermore, qualitative findings offered rich insights into the perceived value and limitations of AI in school management. Participants consistently stressed the need for ethical clarity, transparency, and training support, especially in the context of decision-making involving student records, disciplinary actions, and resource distribution. These concerns mirror those raised by Roberts in his exploration of AI policy in schools, where he emphasized the importance of framing AI adoption within ethical and legal frameworks (5). Similarly, Rezaei noted that educators often express concern over algorithmic bias and the opacity of AI systems, which may undermine trust and autonomy if not properly addressed (16).

From a theoretical standpoint, the model reinforces the layered nature of AI integration in education, as suggested by Song's three-phase learning design model and Saritepeci's framework on reflective thinking in AI-based design learning (8, 18). It bridges the cognitive, organizational, and technological dimensions, offering a more comprehensive framework than those previously limited to instructional technology or digital tools. The incorporation of contextual and intervening factors in the model reflects a systems thinking approach, aligning with Wang and Li's position that AI must be considered within the broader institutional ecosystem (27).

Additionally, the model addresses the importance of digital culture and AI literacy as prerequisites for sustainable integration. This is supported by research from Walter and Sezavar, who argue that without targeted professional development and digital awareness programs, even well-designed AI interventions can fail to take root in schools (7, 11). In the Iraqi context, where AI knowledge among educators is still emerging, professional capacity-building should be prioritized as a strategic entry point.

Finally, while AI has been shown to improve the efficiency of school management, the study cautions against viewing it as a one-size-fits-all solution. The effectiveness of AI depends largely on the alignment between technical solutions and local educational realities. The high communality and AVE scores in this study confirm that the proposed components of the model are internally consistent and theoretically cohesive, yet their successful implementation requires ongoing contextual adaptation and stakeholder involvement (19, 28).

Despite its strengths, this study has certain limitations. First, while the model was tested with a relatively large sample of school administrators and teachers in Iraq, the findings may not be fully generalizable to other national contexts with different educational infrastructures and digital readiness. Second, the reliance on self-reported data introduces the possibility of social desirability bias, especially in respondents' attitudes toward AI. Third, while the study employed a mixed-methods design, the qualitative component could have been enhanced by including observational data or document analysis to deepen triangulation. Additionally, given the rapidly evolving nature of AI technologies, some technical or pedagogical developments may have emerged after the data collection phase, which could affect the model's long-term applicability.

Future research should explore the longitudinal impact of AI integration in school leadership by tracking institutional performance indicators over time. Comparative studies between urban and rural schools or between public and private sectors would also be valuable to assess how infrastructural disparities affect AI adoption. Moreover, future investigations could expand the scope to include student perspectives and parental attitudes toward AI-supported school environments. Methodologically, incorporating ethnographic or participatory action research approaches would enrich the contextual depth of findings and foster greater stakeholder engagement in model refinement. Lastly, integrating emerging AI tools like large language models and predictive behavioral analytics could offer deeper insights into how real-time decision systems influence school dynamics.

To operationalize the proposed AI model in Iraqi schools, it is essential to begin with comprehensive needs assessments at the provincial and school levels. Capacity-building programs must be launched to train school leaders and teachers not only in technical skills but also in data interpretation and ethical governance. Pilot programs should be rolled out in digitally mature schools to iteratively test and adapt the model before broader implementation. Government policy must support infrastructural investment, equitable access, and regulatory clarity. Finally, AI integration should be guided by participatory leadership practices that empower educators and build trust through transparency, professional dialogue, and culturally responsive innovation.

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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

All ethical principles were adheried in conducting and writing this article.

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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