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MANAGEMENT READINESS FOR ARTIFICIAL INTELLIGENCE ADOPTION IN EDUCATIONAL INSTITUTIONS

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Abstract

The integration of Artificial Intelligence (AI) in educational institutions represents a transformative shift in pedagogical approaches and administrative operations. However, the successful adoption of AI technologies is contingent upon the readiness of institutional management to embrace, implement, and sustain these innovations. This study employs the Analytic Hierarchy Process (AHP) methodology to assess management readiness for AI adoption across multiple dimensions including technological infrastructure, organizational culture, financial resources, human capital development, and strategic planning. Data were collected from 25 expert respondents comprising university administrators, IT directors, and academic leaders from various educational institutions. The AHP analysis, conducted using AHPPRO software, revealed that human capital development (weight = 0.312) emerged as the most critical factor, followed by technological infrastructure (0.268), organizational culture (0.221), strategic planning (0.142), and financial resources (0.057). The findings provide actionable insights for educational leaders seeking to enhance their institutional readiness for AI transformation, highlighting the paramount importance of investing in faculty and staff development alongside technological capabilities

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Introduction (12pts)

The advent of Artificial Intelligence (AI) has ushered in a new era of technological innovation across various sectors, with education emerging as one of the most promising domains for AI application. Educational institutions worldwide are increasingly recognizing the transformative potential of AI technologies in enhancing learning outcomes, personalizing educational experiences, streamlining administrative processes, and advancing research capabilities (Chen, Chen, & Lin, 2020; Holmes, Bialik, & Fadel, 2019). From intelligent tutoring systems and automated grading platforms to predictive analytics for student success and AI-powered research tools, the applications of AI in education are diverse and expanding rapidly (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). However, despite the evident potential and growing interest, the actual adoption and effective implementation of AI technologies in educational settings remain significantly limited, with many institutions struggling to move beyond pilot projects and isolated initiatives (Crompton & Burke, 2018).

The successful integration of AI in educational institutions is not merely a technological challenge but fundamentally an organizational and managerial endeavor that requires comprehensive readiness across multiple dimensions. Management readiness encompasses the institution's capacity to recognize the need for AI adoption, assess its current capabilities, develop strategic plans for implementation, allocate necessary resources, and lead organizational change effectively (Huang, Rust, & Maksimovic, 2019). This readiness extends beyond technical infrastructure to include organizational culture, leadership commitment, faculty and staff competencies, financial sustainability, and strategic alignment with institutional mission and goals (Bates et al., 2020). Research has consistently demonstrated that technology adoption failures in educational contexts often stem not from technological limitations but from inadequate organizational preparation, insufficient change management, and lack of stakeholder buy-in (Sugar, Haddad, & Metha, 2018). Therefore, assessing and enhancing management readiness represents a critical prerequisite for successful AI adoption in educational institutions.

Despite the growing body of literature on AI in education, several critical problems persist in understanding and facilitating management readiness for AI adoption. First, there exists a significant gap in empirical research that systematically examines the multidimensional nature of management readiness specifically for AI technologies in educational contexts (Popenici & Kerr, 2017). While numerous studies have explored general technology readiness or specific AI applications, few have comprehensively investigated the organizational, strategic, and human factors that constitute management readiness for AI adoption in higher education and K-12 settings (Chassignol, Khoroshavin, Klimova, & Bilyatdinova, 2018). Second, educational leaders often lack structured frameworks and validated assessment tools to evaluate their institution's readiness for AI implementation, leading to ad-hoc decision-making and resource allocation that may not address the most critical readiness factors (Alenezi, 2021). This absence of systematic assessment methodologies results in incomplete readiness evaluations that overlook crucial dimensions such as organizational culture change or faculty development needs.

Furthermore, the rapid pace of AI technological advancement creates a moving target for educational institutions, making it challenging to maintain sustained readiness and adapt to emerging capabilities and requirements (Luckin et al., 2016). Many institutions find themselves perpetually reactive rather than proactive in their AI readiness efforts, constantly playing catch-up with technological developments while struggling to build fundamental organizational capacities (Selwyn, 2019). Additionally, there is insufficient understanding of the relative importance of different readiness factors and their interdependencies, making it difficult for educational leaders to prioritize investments and interventions effectively (Akgun & Greenhow, 2021). Resource constraints, which are common in educational institutions, necessitate strategic allocation decisions, yet the lack of evidence-based prioritization frameworks often results in suboptimal resource distribution that fails to address the most critical readiness gaps (Bond et al., 2019).

To address these challenges and enhance management readiness for AI adoption in educational institutions, a comprehensive and systematic approach is required. First, educational leaders must conduct thorough readiness assessments that examine all relevant dimensions including technological infrastructure, organizational culture, human capital, financial resources, and strategic planning capabilities (Roll & Wylie, 2016). Such assessments should employ validated frameworks and methodologies that provide reliable and actionable insights into institutional strengths and gaps. Second, institutions need to develop evidence-based prioritization strategies that identify the most critical readiness factors and guide resource allocation decisions accordingly (Baker & Smith, 2019). This requires sophisticated analytical tools capable of handling multiple criteria and stakeholder perspectives while accounting for the complex interdependencies among readiness dimensions.

This study addresses these needs by employing the Analytic Hierarchy Process (AHP), a proven multi-criteria decision-making methodology, to systematically assess and prioritize management readiness factors for AI adoption in educational institutions. The AHP approach enables structured evaluation of complex decision problems by decomposing them into hierarchical components and utilizing pairwise comparisons to determine relative importance weights (Saaty, 1980). By applying AHP methodology to management readiness assessment, this research provides educational leaders with a rigorous framework for evaluating their institution's preparedness for AI adoption and identifying priority areas for intervention and investment. The findings contribute to both theoretical understanding of organizational readiness for emerging technologies and practical guidance for educational administrators navigating the complexities of AI integration in their institutions.

Literature Review

Artificial Intelligence in Educational Contexts

The application of Artificial Intelligence in educational settings has evolved significantly over the past two decades, transitioning from simple computer-based instruction to sophisticated adaptive learning systems and intelligent educational agents. Zawacki-Richter et al. (2019) conducted a systematic review of AI applications in higher education and identified four primary domains: profiling and prediction, assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems. Their analysis of 146 publications revealed that while AI research in education has grown exponentially, implementation remains concentrated in specific areas such as student performance prediction and automated assessment, with significant gaps in applications addressing teaching support and institutional management. Similarly, Holmes et al. (2019) provided a comprehensive framework for understanding AI's role in education, distinguishing between AI applications that support administrative functions, enhance teaching practices, and facilitate student learning, while emphasizing the need for ethical frameworks and pedagogical foundations to guide AI implementation.

However, contrasting perspectives emerge regarding the actual impact and readiness for AI adoption in educational institutions. While optimistic accounts emphasize AI's potential to revolutionize personalized learning and educational access (Chen et al., 2020), critical scholars like Selwyn (2019) argue that much of the discourse around AI in education is characterized by technological determinism and commercial interests that overshadow pedagogical considerations and potential risks. This debate extends to questions of whether current educational institutions possess the necessary infrastructure, culture, and human capital to effectively implement AI technologies. Baker and Smith (2019) found that despite significant investments in educational technology, many institutions lack the fundamental data infrastructure and analytical capabilities required for advanced AI applications, suggesting that technological readiness alone is insufficient without corresponding organizational and human readiness. The gap between AI's theoretical potential and its practical implementation in educational settings underscores the critical importance of comprehensive management readiness assessment.

Organizational Readiness for Technology Adoption

Organizational readiness theory provides essential frameworks for understanding how institutions prepare for and implement technological innovations. Weiner (2009) conceptualized organizational readiness for change as a multilevel construct encompassing change commitment and change efficacy, arguing that successful implementation requires both collective motivation to pursue change and shared belief in the organization's capacity to execute it successfully. This framework has been extensively applied to technology adoption in various contexts, with studies demonstrating that higher organizational readiness correlates with more successful implementation outcomes, greater user adoption, and sustained technology utilization (Shea et al., 2014). In educational settings, Holt, Armenakis, Feild, and Harris (2007) identified five critical dimensions of readiness: discrepancy (the perceived need for change), appropriateness (the fit between change and organizational needs), efficacy (capability to implement change), principal support (leadership commitment), and valence (perceived benefits), all of which apply directly to AI adoption readiness.

The debate in organizational readiness literature centers on whether readiness should be viewed as a state to be achieved before implementation or as a dynamic process that evolves during implementation. Traditional models, such as Parasuraman's (2000) Technology Readiness Index, conceptualize readiness as a relatively stable individual trait reflecting propensity to embrace technology, measured through optimism, innovativeness, discomfort, and insecurity dimensions. However, recent scholarship challenges this static view, arguing that readiness is contextual, multifaceted, and continuously evolving (Helfrich et al., 2009). For AI adoption specifically, Bates et al. (2020) found that institutions exhibit different readiness profiles across technological, organizational, and individual levels, with misalignments between these levels creating significant barriers to successful implementation. This finding suggests that comprehensive readiness assessment must account for multiple dimensions and their interactions, highlighting a critical gap in existing assessment approaches that often focus on single dimensions such as technological infrastructure or individual attitudes.

Critical Success Factors for AI Implementation

Research on technology implementation in educational institutions has identified numerous critical success factors that influence adoption outcomes. Alenezi (2021) conducted a comprehensive analysis of digital transformation in higher education and found that strategic leadership, organizational culture, technological infrastructure, and human capital development emerged as the most significant predictors of successful implementation. Specifically, institutions with clearly articulated digital strategies aligned with their educational mission, supportive organizational cultures that encourage innovation and risk-taking, robust IT infrastructure including data systems and connectivity, and comprehensive faculty development programs demonstrated higher success rates in technology adoption. Similarly, Crompton and Burke (2018) emphasized the importance of change management practices, arguing that technological initiatives fail when organizations neglect to address resistance, provide adequate training, and ensure stakeholder engagement throughout the implementation process.

However, debate exists regarding the relative importance of different success factors and whether universal principles apply across diverse educational contexts. While some researchers advocate for technology-focused approaches emphasizing infrastructure and technical capabilities (Huang et al., 2019), others argue that human and organizational factors are more critical determinants of success (Popenici & Kerr, 2017). For instance, Chassignol et al. (2018) found that faculty attitudes and pedagogical beliefs about AI significantly influenced adoption patterns, often overshadowing the impact of technological capabilities. This suggests that investments in human capital development may yield higher returns than infrastructure improvements in certain contexts. Furthermore, the applicability of success factors identified in general technology adoption research to AI-specific implementation remains uncertain, as AI technologies present unique challenges including algorithmic transparency, ethical considerations, and data privacy requirements that may necessitate additional readiness factors (Luckin et al., 2016). This gap in understanding AI-specific success factors and their relative importance motivates the need for systematic prioritization research.

Multi-Criteria Decision Making in Educational Technology

Multi-criteria decision-making (MCDM) methodologies have gained increasing application in educational technology research as tools for addressing complex decisions involving multiple stakeholders and competing objectives. The Analytic Hierarchy Process (AHP), developed by Saaty (1980), represents one of the most widely adopted MCDM approaches due to its ability to structure complex problems hierarchically, incorporate both quantitative and qualitative criteria, and synthesize expert judgments systematically. In educational contexts, AHP has been successfully applied to various decision problems including technology selection (Yuen & Majid, 2007), learning management system evaluation (Ozkan-Ozen & Kazancoglu, 2022), and e-learning platform assessment (Abdullah & Zailani, 2019). These applications demonstrate AHP's versatility in handling educational decision-making challenges characterized by multiple evaluation criteria, stakeholder perspectives, and uncertainty.

Despite its widespread use, debates persist regarding AHP's applicability to educational technology decisions and its methodological limitations. Critics argue that pairwise comparison judgments may be inconsistent, subjective, and influenced by the order of presentation (Dyer, 1990), while proponents contend that AHP's consistency checking mechanisms and mathematical foundation address these concerns adequately (Saaty, 2013). In the context of AI adoption readiness assessment, AHP offers distinct advantages including the ability to decompose complex readiness constructs into manageable components, quantify expert opinions about relative importance, and identify priority areas for intervention based on systematic analysis rather than intuition (Akgun & Greenhow, 2021). However, limited research has applied AHP specifically to AI adoption readiness in educational institutions, representing a significant methodological gap. Existing AHP studies in educational technology have primarily focused on product selection or evaluation rather than organizational readiness assessment, and none have comprehensively examined the multidimensional nature of management readiness for AI adoption. This research addresses this gap by applying AHP methodology to systematically assess and prioritize management readiness factors for AI implementation in educational settings.

Research Gaps and Study Rationale

The literature review reveals several critical gaps that this study addresses. First, while substantial research exists on general technology readiness and specific AI applications in education, there is limited empirical investigation of management readiness specifically for AI adoption in educational institutions, particularly using systematic assessment methodologies. Second, although various readiness factors have been identified in disparate studies, there is insufficient understanding of their relative importance and prioritization for resource allocation decisions. Third, the application of rigorous MCDM approaches like AHP to AI adoption readiness remains unexplored, despite the methodology's demonstrated utility in other educational technology contexts. Finally, practical tools and frameworks that educational leaders can employ to assess and enhance their institution's AI readiness are notably absent from the literature. By employing AHP to systematically evaluate management readiness dimensions, this study fills these gaps and provides both theoretical contributions to organizational readiness theory and practical guidance for educational administrators pursuing AI transformation initiatives.

Methodology

This study employs a quantitative research design utilizing the Analytic Hierarchy Process (AHP) methodology to assess and prioritize management readiness factors for Artificial Intelligence adoption in educational institutions. AHP is selected as the primary analytical framework due to its proven effectiveness in handling multi-criteria decision problems, its capacity to structure complex hierarchical relationships among factors, and its ability to synthesize expert judgments into quantifiable priority weights (Saaty, 1980). The research follows a systematic AHP implementation process encompassing problem structuring, pairwise comparison data collection, priority derivation, and consistency verification to ensure methodological rigor and reliability of findings.

The Analytic Hierarchy Process (AHP) Method

The Analytic Hierarchy Process, developed by Thomas L. Saaty in 1980, is a structured technique for organizing and analyzing complex decisions based on mathematics and psychology. AHP provides a comprehensive framework for representing the elements of any problem hierarchically and for deriving ratio scales for priorities from paired comparisons of the elements (Saaty, 2008). The fundamental principle underlying AHP is that human judgment about relative importance can be systematically measured and synthesized through pairwise comparisons using a defined scale, typically ranging from 1 (equal importance) to 9 (extreme importance), enabling the transformation of qualitative expert opinions into quantitative priority weights.

The AHP methodology offers several distinct advantages for management readiness assessment in educational contexts. First, it allows for the decomposition of complex, multidimensional readiness constructs into manageable hierarchical components, making the assessment process more systematic and comprehensive. Second, AHP enables the integration of both objective data and subjective expert judgments, which is particularly valuable when assessing organizational readiness factors that may not be readily quantifiable. Third, the method incorporates consistency checking mechanisms that ensure the logical coherence of expert judgments, thereby enhancing the reliability and credibility of the results. Fourth, AHP provides clear, interpretable priority rankings that facilitate actionable decision-making and resource allocation strategies (Saaty, 2013). These characteristics make AHP particularly suitable for assessing management readiness for AI adoption, where multiple interrelated factors must be evaluated and prioritized to guide institutional planning and investment decisions.

Hierarchical Structure Development

Based on comprehensive literature review and expert consultation, the management readiness hierarchy for AI adoption was structured into three levels: Goal (Level 1), Main Criteria (Level 2), and Sub-criteria (Level 3). The goal level represents the overall objective of assessing management readiness for AI adoption in educational institutions. The main criteria level comprises five critical dimensions identified from the literature: (1) Technological Infrastructure Readiness, (2) Organizational Culture and Change Readiness, (3) Human Capital and Competency Development, (4) Financial Resources and Sustainability, and (5) Strategic Planning and Governance.

Each main criterion is further decomposed into sub-criteria representing specific readiness factors. Technological Infrastructure includes: data systems and storage capacity, network connectivity and bandwidth, computing resources and cloud infrastructure, and cybersecurity and data protection systems. Organizational Culture encompasses: innovation orientation and risk tolerance, collaboration and knowledge sharing practices, leadership commitment to AI adoption, and resistance to change management. Human Capital comprises: faculty and staff AI literacy and competencies, professional development programs and training, recruitment and retention of AI talent, and interdisciplinary collaboration capabilities. Financial Resources include: budget allocation for AI initiatives, cost-benefit analysis capabilities, funding diversification strategies, and long-term financial sustainability planning. Strategic Planning consists of: AI adoption vision and mission alignment, stakeholder engagement and communication, policy and governance frameworks, and performance metrics and evaluation systems. This hierarchical structure provides a comprehensive framework for systematically assessing all critical dimensions of management readiness.

Steps in the AHP Methodology

Step 1: Problem Definition and Hierarchy Construction. The first step involves clearly defining the decision problem and constructing the hierarchical structure that represents all relevant factors and their relationships. In this study, the problem was defined as assessing and prioritizing management readiness factors for AI adoption in educational institutions. The hierarchy was constructed through an iterative process involving literature review, expert consultation, and pilot testing to ensure comprehensiveness and relevance of all included criteria and sub-criteria.

Step 2: Pairwise Comparison Data Collection. Once the hierarchy is established, pairwise comparison matrices are constructed for each level of the hierarchy. Experts compare each pair of criteria with respect to their relative importance using Saaty's nine-point scale, where 1 indicates equal importance and 9 indicates extreme importance of one criterion over another. For each level in the hierarchy, if there are n criteria, n(n-1)/2 pairwise comparisons are required. In this study, expert respondents completed structured questionnaires containing all necessary pairwise comparisons for main criteria and sub-criteria within each dimension.

Step 3: Priority Calculation and Synthesis. The third step involves calculating priority weights from the pairwise comparison matrices using eigenvector method or other mathematical techniques. For each comparison matrix, the principal eigenvector is computed and normalized to obtain local priority weights for the criteria at that level. These local priorities are then synthesized through multiplication along the hierarchy to obtain global priority weights that represent the overall importance of each criterion and sub-criterion with respect to the ultimate goal. The mathematical rigor of this process ensures that the derived priorities accurately reflect the collective expert judgments.

Step 4: Consistency Verification. A critical feature of AHP is the consistency checking mechanism that ensures the logical coherence of expert judgments. For each pairwise comparison matrix, a Consistency Ratio (CR) is calculated by comparing the matrix's Consistency Index (CI) with Random Index (RI) values derived from random matrices of the same order. The formula for CR is: $CR = CI/RI$, where $CI = (\lambda max - n)/(n-1)$, λmax is the maximum eigenvalue of the comparison matrix, and n is the matrix dimension. A CR value below 0.10 (10%) is generally considered acceptable, indicating that the judgments are sufficiently consistent. Matrices with $CR > 0.10$ are returned to experts for revision to improve consistency.

Step 5: Aggregation of Expert Judgments. When multiple experts participate in the AHP assessment, their individual judgment matrices must be aggregated to produce a collective priority ranking. Two primary approaches exist for aggregation: Aggregation of Individual Judgments (AIJ), where individual pairwise comparison matrices are aggregated using geometric mean before priority calculation, and Aggregation of Individual Priorities (AIP), where priorities are first calculated for each individual and then averaged. This study employs the AIJ approach using geometric mean aggregation, which has been shown to preserve the reciprocal property of pairwise comparisons and maintain mathematical consistency (Saaty, 2013).

Step 6: Sensitivity Analysis. The final step involves conducting sensitivity analysis to examine how changes in criterion weights affect the final priority rankings. This analysis helps identify robust findings that remain stable across different weighting scenarios and highlights factors whose rankings are sensitive to weight variations. Sensitivity analysis enhances the reliability and interpretability of AHP results by revealing the stability of conclusions and identifying critical factors whose weights have substantial impact on final priorities.

Expert Selection Criteria

The validity and reliability of AHP results depend significantly on the expertise and credibility of respondents providing pairwise comparison judgments. Therefore, rigorous expert selection criteria were established to ensure participation of knowledgeable and experienced individuals capable of making informed assessments about management readiness for AI adoption. Experts were selected based on the following criteria: (1) holding senior management or leadership positions in educational institutions (e.g., university presidents, provosts, deans, department chairs, or directors), (2) having at least 5 years of experience in educational administration or technology leadership, (3) demonstrated involvement in technology adoption initiatives or digital transformation projects within their institutions, (4) possessing knowledge of Artificial Intelligence technologies and their potential applications in education, and (5) representing diverse institutional contexts including public and private universities, community colleges, and K-12 educational organizations to ensure breadth of perspectives.

A total of 25 expert respondents participated in this study, comprising 8 university administrators (presidents, provosts, vice chancellors), 7 academic deans and department chairs with technology oversight responsibilities, 6 Chief Information Officers or IT directors from educational institutions, and 4 educational technology researchers with expertise in AI applications in education. This expert panel represents a balanced composition of strategic decision-makers, operational leaders, technical specialists, and academic researchers, providing diverse perspectives on management readiness factors.

All experts received detailed orientation about the study objectives, AHP methodology, and pairwise comparison process before completing the assessment questionnaires.

Data Collection Procedure

Data collection was conducted through structured questionnaires administered both online and in person over a three-month period. Each questionnaire contained detailed instructions about the AHP pairwise comparison process, definitions of all criteria and sub-criteria, and Saaty's nine-point fundamental scale with explanations. The questionnaire was organized into sections corresponding to the hierarchical structure, with the first section addressing pairwise comparisons among the five main criteria, followed by sections for pairwise comparisons among sub-criteria within each main criterion dimension.

To enhance data quality and expert understanding, a pilot test was conducted with three experts who provided feedback on questionnaire clarity, completion time, and any ambiguities in criteria definitions. Based on pilot feedback, minor revisions were made to improve clarity and reduce respondent burden. The final questionnaire included examples of pairwise comparisons to illustrate the process, and experts were encouraged to contact researchers with any questions during completion. All experts completed the questionnaire independently without consultation, and their responses were checked for consistency before being included in the analysis. Responses with unacceptable consistency ratios (CR > 0.10) were discussed with respective experts, who were given the opportunity to review and revise their judgments.

Data Analysis Using AHPPRO Software

Data analysis was performed using AHPPRO software, a specialized computer program designed specifically for Analytic Hierarchy Process calculations and analysis. AHPPRO provides comprehensive functionality for AHP applications including pairwise comparison matrix input, priority calculation using eigenvector method, consistency checking, expert judgment aggregation, and sensitivity analysis. The software automates the complex mathematical computations required for AHP while ensuring accuracy and allowing researchers to focus on interpretation rather than calculation.

The analysis procedure in AHPPRO followed these steps: First, the hierarchical structure was defined in the software by specifying the goal, main criteria, and sub-criteria with their relationships. Second, individual expert pairwise comparison matrices were entered into the system for each level of the hierarchy. Third, AHPPRO calculated consistency ratios for each individual judgment matrix and flagged any matrices with CR > 0.10 for review and potential revision. Fourth, after confirming acceptable consistency across all individual matrices, geometric mean aggregation was performed to combine expert judgments into group consensus matrices. Fifth, AHPPRO computed local priority weights for each criterion using the eigenvector method, calculated from the principal eigenvector of the aggregated comparison matrices.

Sixth, global priority weights were calculated by synthesizing local priorities through multiplication along the hierarchy paths from each sub-criterion to the goal. These global priorities represent the overall importance of each factor with respect to management readiness for AI adoption. Seventh, sensitivity analysis was conducted using AHPPRO's built-in functionality to examine how variations in main criterion weights affect sub-criterion rankings and identify robust versus sensitive priority relationships. Finally, AHPPRO generated comprehensive output reports including priority vectors, consistency indices, ranking tables, and graphical visualizations of the results, all of which were used to interpret findings and derive implications for educational institutions pursuing AI adoption initiatives.

Findings

Consistency Analysis

Before presenting the priority weights, it is essential to verify the consistency of expert judgments. The consistency analysis revealed that all aggregated pairwise comparison matrices met the acceptable consistency threshold. The Consistency Ratio (CR) for the main criteria comparison matrix was 0.047, well below the 0.10 threshold, indicating high consistency in expert judgments. Similarly, the CR values for sub-criteria comparison matrices ranged from 0.032 to 0.089, all within acceptable limits. These consistency indices demonstrate that expert respondents provided logically coherent judgments throughout the assessment process, lending credibility to the derived priority weights and rankings.

Priority Weights of Main Criteria

Table 1 presents the priority weights and rankings for the five main criteria of management readiness for AI adoption in educational institutions. The AHP analysis revealed that Human Capital and Competency Development emerged as the most critical dimension with the highest priority weight of 0.312 (31.2%), significantly outweighing all other criteria. This finding indicates that experts consider people-related factors, including faculty and staff capabilities, training, and talent management, as the most essential prerequisite for successful AI adoption.

Technological Infrastructure Readiness ranked second with a priority weight of 0.268 (26.8%), highlighting the continued importance of robust technical foundations including data systems, network infrastructure, computing resources, and cybersecurity capabilities. Organizational Culture and Change Readiness occupied the third position with a weight of 0.221 (22.1%), emphasizing the significance of institutional culture, leadership support, and change management in facilitating AI adoption. Strategic Planning and Governance ranked fourth with a weight of 0.142 (14.2%), reflecting the necessity of clear vision, stakeholder engagement, and governance frameworks. Surprisingly, Financial Resources and Sustainability received the lowest priority weight of 0.057 (5.7%), suggesting that while financial resources are necessary, they are considered less critical than human, technological, cultural, and strategic factors in determining AI adoption readiness.

Main Criteria	Priority Weight	Rank
Human Capital and Competency Development	0.312	1
Technological Infrastructure Readiness	0.268	2
Organizational Culture and Change Readiness	0.221	3
Strategic Planning and Governance	0.142	4
Financial Resources and Sustainability	0.057	5

Table 1: Priority Weights and Rankings of Main Criteria

Note: Consistency Ratio (CR) = 0.047

Priority Weights of Sub-Criteria

Table 2 presents the detailed analysis of sub-criteria within each main dimension, including local priority weights (relative importance within their respective main criterion), global priority weights (overall importance with respect to the ultimate goal), and rankings. This comprehensive breakdown provides granular insights into specific readiness factors that educational institutions should prioritize.

Sub-Criteria	Main Criterion	Local Weight	Global Weight
Faculty and Staff AI Literacy	Human Capital	0.385	0.120
Professional Development Programs	Human Capital	0.342	0.107

Sub-Criteria	Main Criterion	Local Weight	Global Weight
AI Talent Recruitment and Retention	Human Capital	0.158	0.049
Interdisciplinary Collaboration	Human Capital	0.115	0.036
Data Systems and Storage	Tech Infrastructure	0.356	0.095
Cybersecurity and Data Protection	Tech Infrastructure	0.298	0.080
Computing Resources and Cloud	Tech Infrastructure	0.219	0.059
Network Connectivity and Bandwidth	Tech Infrastructure	0.127	0.034
Leadership Commitment	Organizational Culture	0.412	0.091
Innovation Orientation	Organizational Culture	0.287	0.063
Collaboration and Knowledge Sharing	Organizational Culture	0.189	0.042
Change Resistance Management	Organizational Culture	0.112	0.025
Vision and Mission Alignment	Strategic Planning	0.368	0.052
Policy and Governance Frameworks	Strategic Planning	0.294	0.042
Stakeholder Engagement	Strategic Planning	0.212	0.030
Performance Metrics and Evaluation	Strategic Planning	0.126	0.018
Budget Allocation for AI	Financial Resources	0.445	0.025
Long-term Sustainability Planning	Financial Resources	0.298	0.017
Cost-Benefit Analysis Capabilities	Financial Resources	0.157	0.009
Funding Diversification	Financial Resources	0.100	0.006

Table 2: Priority Weights of Sub-Criteria

Within the Human Capital dimension, Faculty and Staff AI Literacy emerged as the most critical sub-factor with a local weight of 0.385 and global weight of 0.120, representing the single most important specific readiness factor overall. Professional Development Programs ranked second within this dimension (local weight = 0.342, global weight = 0.107), emphasizing the importance of systematic training initiatives. AI Talent Recruitment and Retention received a local weight of 0.158 (global = 0.049), while Interdisciplinary Collaboration had the lowest priority within human capital factors at 0.115 (global = 0.036).

For Technological Infrastructure, Data Systems and Storage capacity ranked highest with a local weight of 0.356 (global = 0.095), followed closely by Cybersecurity and Data Protection at 0.298 (global = 0.080). Computing Resources and Cloud Infrastructure received a local weight of 0.219 (global = 0.059), while Network Connectivity and Bandwidth, despite being fundamental, ranked lowest at 0.127 (global = 0.034), likely reflecting widespread availability of basic connectivity in most institutions.

Within Organizational Culture, Leadership Commitment dominated with the highest local weight of 0.412 (global = 0.091), underscoring the critical role of executive support in cultural transformation. Innovation Orientation ranked second at 0.287 (global = 0.063), while Collaboration and Knowledge Sharing received 0.189 (global = 0.042). Change Resistance Management, while important, ranked lowest at 0.112 (global = 0.025).

For Strategic Planning factors, Vision and Mission Alignment received the highest priority with a local weight of 0.368 (global = 0.052), followed by Policy and Governance Frameworks at 0.294 (global = 0.042). Stakeholder Engagement ranked third at 0.212 (global = 0.030), while Performance Metrics and Evaluation received the lowest weight at 0.126 (global = 0.018).

Finally, within Financial Resources, Budget Allocation for AI Initiatives received the highest local weight of 0.445 (global = 0.025), followed by Long-term Sustainability Planning at 0.298 (global = 0.017). Cost-Benefit Analysis Capabilities and Funding Diversification received lower priorities at 0.157 (global = 0.009) and 0.100 (global = 0.006) respectively.

Overall Priority Ranking

When examining global priority weights across all sub-criteria, the top five readiness factors are: (1) Faculty and Staff AI Literacy (0.120), (2) Professional Development Programs (0.107), (3) Data Systems and Storage (0.095), (4) Leadership Commitment (0.091), and (5) Cybersecurity and Data Protection (0.080). This ranking reveal that three of the top five factors relate to human capital development, with two technological infrastructure factors rounding out the critical priorities. Notably, all financial resource sub-criteria ranked in the bottom tier of global priorities, with the highest financial factor (Budget Allocation) receiving only a 0.025 global weight, ranked 13th among 20 sub-criteria.

Sensitivity Analysis Results

Sensitivity analysis was conducted to examine the robustness of the priority rankings under different weighting scenarios. The analysis revealed that the top ranking of Human Capital and Competency Development remained stable even when its weight was reduced by 20%, indicating robust prioritization. Similarly, the relative positions of Technological Infrastructure and Organizational Culture remained consistent across various weight perturbations. The rankings of Strategic Planning and Financial Resources were more sensitive to weight changes, suggesting less consensus regarding their relative importance. At the sub-criteria level, Faculty and Staff AI Literacy maintained its top ranking across all realistic weighting scenarios, while the rankings of mid-tier factors showed greater variability, indicating areas where expert opinions diverged more substantially.

Discussion

Interpretation of Main Findings

The findings of this study reveal a clear prioritization of human capital factors over technological, financial, and strategic considerations in management readiness for AI adoption in educational institutions. The emergence of Human Capital and Competency Development as the most critical dimension, with a priority weight of 0.312, challenges the common assumption that technological infrastructure represents the primary barrier to AI adoption. This finding aligns with the arguments of Popenici and Kerr (2017) and Chassignol et al. (2018), who emphasized that human factors, particularly faculty attitudes and competencies, play a more decisive role in technology adoption success than purely technical capabilities. The dominance of Faculty and Staff AI Literacy as the single most important sub-factor (global weight = 0.120) suggests that institutional readiness ultimately depends on whether educators and administrators possess the knowledge, skills, and confidence to effectively utilize AI technologies in their professional practice.

The second-place ranking of Technological Infrastructure (weight = 0.268) confirms that technical capabilities remain essential but not sufficient for AI adoption readiness. This finding resonates with Baker and Smith's (2019) observation that many institutions invest heavily in technology while lacking the human capacity to leverage it effectively. The relatively high priority assigned to Data Systems and Storage (global weight = 0.095) and Cybersecurity and Data Protection (global weight = 0.080) within the technological dimension reflects growing awareness of data governance challenges in AI implementation. Educational institutions increasingly recognize that AI systems require robust data infrastructure and security mechanisms to function effectively while protecting student privacy and institutional information (Akgun & Greenhow, 2021). The finding that Network Connectivity received the lowest technological priority likely reflects the maturation of basic internet infrastructure in most educational settings, shifting concerns toward more advanced capabilities.

Perhaps most surprising is the relatively low priority assigned to Financial Resources and Sustainability (weight = 0.057), which ranked last among the five main dimensions. This finding contradicts common discourse about resource constraints as the primary barrier to educational technology adoption. Several interpretations are plausible. First, experts may recognize that financial resources, while necessary, are less determinative of success than how those resources are deployed and whether human and organizational capacities exist to utilize them effectively. Second, the increasing availability of cloud-based AI services and open-source tools may have reduced the perceived financial barriers to AI adoption compared to earlier generations of technology. Third, experts may view financial constraints as more tractable than cultural or human capital challenges, given that institutions have established mechanisms for fundraising and budget reallocation but fewer proven strategies for transforming organizational culture or rapidly developing AI literacy among faculty.

Comparison with Existing Literature

The findings both align with and extend existing literature on organizational readiness for technology adoption. The prioritization of human capital factors strongly supports Weiner's (2009) organizational readiness theory, which emphasizes that change efficacy and collective competence represent fundamental prerequisites for successful implementation. Similarly, the high ranking of Leadership Commitment (global weight = 0.091) within the Organizational Culture dimension validates Holt et al.'s (2007) identification of principal support as a critical readiness dimension. However, this study extends previous research by providing empirical quantification of relative importance across multiple readiness dimensions specifically for AI adoption, addressing gaps identified by Alenezi (2021) regarding the lack of systematic prioritization frameworks.

The findings partially diverge from some technology-focused perspectives in the literature. While Huang et al. (2019) emphasized technological infrastructure as the primary enabler of AI capabilities, this study's experts assigned greater importance to whether institutions possess the human expertise to design, implement, and evaluate AI applications appropriately. This divergence may reflect different stakeholder perspectives, with technical specialists naturally emphasizing infrastructure requirements while educational administrators focus on organizational and human challenges they confront daily. The synthesis of these perspectives through AHP methodology provides a more holistic understanding that acknowledges the necessity of both technical and human elements while clarifying their relative priorities for resource allocation decisions.

The emphasis on Professional Development Programs (global weight = 0.107) aligns strongly with recent calls for systematic AI literacy initiatives in education. Ng, Leung, Chu, and Qiao (2021) conceptualized AI literacy as encompassing technical understanding, ethical awareness, and critical evaluation capabilities, all of which require sustained professional development rather than one-time training. The high priority assigned to this factor suggests that experts recognize the inadequacy of current faculty development approaches and the need for comprehensive, ongoing programs that build both technical competencies and pedagogical applications of AI. This finding supports Southworth et al.'s (2023) advocacy for transforming higher education through systematic AI literacy development across the curriculum.

Theoretical Implications

This study contributes to organizational readiness theory by demonstrating that readiness hierarchies vary based on the specific technology being adopted. While general technology readiness frameworks like Parasuraman's (2000) Technology Readiness Index emphasize individual psychological traits, AI adoption readiness appears to prioritize collective organizational capabilities, particularly human capital development and cultural transformation. This suggests that different technologies may require distinct readiness profiles, with emerging technologies like AI placing greater demands on human expertise and organizational adaptation than more mature technologies. Future theoretical development should account for technology-specific characteristics when conceptualizing readiness constructs.

Additionally, the findings challenge the implicit assumption in much educational technology literature that financial constraints represent the primary barrier to innovation. The low priority assigned to Financial Resources suggests a more nuanced understanding of adoption barriers, where resource availability interacts with organizational capacity to deploy resources effectively. This implies that theories of educational change should move beyond resource-centric explanations toward more comprehensive models that account for the complex interplay of human, cultural, strategic, and technical factors. The application of AHP methodology demonstrates the value of multi-criteria decision-making approaches in unpacking these complex relationships and providing empirically grounded prioritization frameworks.

Practical Implications for Educational Institutions

The research findings offer several actionable implications for educational leaders pursuing AI transformation. First and foremost, institutions should prioritize investments in comprehensive faculty and staff development programs that build AI literacy and application competencies. Rather than allocating disproportionate resources to technological infrastructure while neglecting human capacity development, a more balanced approach that recognizes human capital as the critical enabler of technology utilization is warranted. This might involve establishing dedicated AI literacy programs, creating communities of practice for AI exploration, providing release time for faculty to develop AI-enhanced courses, and recruiting specialists who can support colleagues in adopting AI tools effectively.

Second, the high priority assigned to Leadership Commitment suggests that successful AI adoption requires visible, sustained engagement from senior administrators. Educational leaders should actively champion AI initiatives, articulate clear visions for AI's role in advancing institutional missions, allocate dedicated leadership attention to AI strategy, and model their own engagement with AI tools. The establishment of senior-level positions such as Chief AI Officer or Assistant Provost for AI and Innovation could signal institutional commitment while providing coordination for dispersed AI initiatives. Leadership development programs should include AI literacy components to ensure that decision-makers understand both the possibilities and limitations of these technologies.

Third, institutions should develop systematic approaches to building the identified priority capabilities rather than pursuing ad-hoc initiatives. This includes conducting formal readiness assessments using the framework developed in this study, identifying specific gaps in priority areas, developing targeted interventions to address those gaps, and establishing metrics to track progress over time. The AHP methodology employed in this research could be adapted as an institutional self-assessment tool, allowing educational organizations to benchmark their readiness against expert consensus while accounting for their unique contextual factors. Such assessments should be conducted periodically to monitor readiness evolution and adjust strategies as institutional capabilities develop.

Fourth, given the importance of Data Systems and Cybersecurity within technological infrastructure, institutions should ensure that AI adoption strategies include robust data governance frameworks. This encompasses developing policies for ethical AI use, establishing clear data privacy and security protocols, creating oversight mechanisms for AI applications that affect students or personnel decisions, and building technical capabilities for monitoring AI system performance and bias. The integration of AI into educational operations creates new data flows and decision points that require careful governance to protect stakeholder interests and maintain institutional integrity.

Limitations of the Study

Several limitations should be acknowledged when interpreting these findings. First, the study's reliance on expert judgment, while appropriate for AHP methodology, introduces potential biases based on respondents' experiences, institutional contexts, and exposure to AI technologies. The 25 expert respondents, though carefully selected for their knowledge and experience, may not fully represent the diversity of educational institutions globally, particularly those in resource-constrained settings or different cultural contexts. Future research should expand the expert panel to include broader geographic representation and institutional diversity.

Second, the hierarchical structure employed in this study, while comprehensive, necessarily simplifies the complex reality of organizational readiness. The five main criteria and twenty sub-criteria represent a manageable framework for analysis but may not capture all relevant factors or the dynamic interactions among them. Alternative hierarchical structures emphasizing different dimensions or decompositions might yield somewhat different priority rankings. Additionally, the study treats readiness factors as relatively independent, whereas in practice they exhibit complex interdependencies that AHP methodology does not fully capture. System dynamics or network analysis approaches might complement AHP by examining these interrelationships.

Third, this study provides a snapshot of expert opinions at a particular point in time, but readiness priorities may evolve as AI technologies mature, become more accessible, and demonstrate success or failure in early adoption contexts. The rapid pace of AI development means that current constraints may be resolved while new challenges emerge, potentially shifting priority rankings. Longitudinal research tracking how readiness priorities change over time would provide valuable insights into the dynamic nature of technology adoption readiness. Similarly, the COVID-19 pandemic's acceleration of digital transformation in education may have influenced expert perspectives in ways that might not persist in post-pandemic contexts.

Finally, while AHP provides a rigorous framework for prioritization, the methodology relies on pairwise comparisons that can be cognitively demanding for respondents, potentially affecting judgment quality. Although consistency checking mechanisms help identify and address logical inconsistencies, they cannot eliminate subjective biases or ensure that all experts interpreted criteria definitions identically. Supplementing AHP analysis with qualitative interviews or focus groups could provide richer contextual understanding of why experts prioritized certain factors and how they conceptualized different readiness dimensions.

Conclusion

This study employed the Analytic Hierarchy Process methodology to systematically assess and prioritize management readiness factors for Artificial Intelligence adoption in educational institutions, addressing critical gaps in both theoretical understanding and practical guidance. The analysis of expert judgments from 25 educational leaders, administrators, and technology specialists revealed that Human Capital and Competency Development represents the most critical dimension of AI adoption readiness, with a priority weight of 0.312, significantly outweighing technological infrastructure, organizational culture, strategic planning, and financial resources. Within the human capital dimension, Faculty and Staff AI Literacy emerged as the single most important specific factor (global weight = 0.120), followed by

Professional Development Programs (0.107), underscoring the paramount importance of building human expertise and capabilities as the foundation for successful AI integration.

The research findings challenge prevalent assumptions about technology adoption barriers in educational contexts. While Technological Infrastructure received substantial priority (0.268), ranking second among main dimensions, it did not dominate readiness considerations as some technology-centric perspectives might suggest. More striking was the relatively low priority assigned to Financial Resources and Sustainability (0.057), which ranked last despite frequent discussions of budget constraints as primary obstacles to educational innovation. This prioritization suggests that expert stakeholders recognize that financial resources, while necessary, are less determinative of adoption success than whether institutions possess the human capabilities, organizational cultures, and strategic frameworks to utilize those resources effectively. The robustness of these priorities, confirmed through sensitivity analysis, indicates substantial expert consensus on the fundamental importance of human and organizational factors over purely technical or financial considerations.

From a theoretical perspective, this study contributes to organizational readiness literature by providing empirical quantification of relative factor importance specifically for AI adoption in educational settings. The findings extend Weiner's (2009) organizational readiness theory by demonstrating that collective competence and change efficacy manifest primarily through human capital development and organizational culture transformation rather than through resource accumulation or strategic planning sophistication alone. Additionally, the successful application of AHP methodology to readiness assessment demonstrates the value of multi-criteria decision-making approaches for unpacking complex organizational phenomena and providing actionable prioritization frameworks. Future theoretical development should continue to explore how readiness hierarchies vary across different technologies and organizational contexts, potentially revealing technology-specific or sector-specific patterns that could inform more nuanced readiness models.

The practical implications for educational institutions are substantial and actionable. First, institutional leaders should reorient their AI adoption strategies to prioritize comprehensive faculty and staff development initiatives that build both technical competencies and pedagogical applications of AI technologies. This requires moving beyond occasional workshops toward sustained programs of professional learning, communities of practice, dedicated support personnel, and systematic integration of AI literacy into faculty development frameworks. Second, senior leadership must provide visible, sustained commitment to AI initiatives through clear vision articulation, strategic resource allocation, governance structure establishment, and personal modeling of engagement with AI tools. The establishment of dedicated leadership roles for AI coordination and the integration of AI strategy into institutional planning processes signal the organizational importance of this transformation.

Third, institutions should employ systematic readiness assessment approaches, potentially adapting the AHP framework developed in this study, to identify specific capability gaps and track progress over time. Such assessments enable evidence-based resource allocation decisions that address the most critical readiness factors rather than pursuing diffuse or imbalanced initiatives. Fourth, the prioritization of data systems and cybersecurity within technological infrastructure highlights the necessity of robust data governance frameworks that ensure ethical AI implementation while protecting privacy and security. Educational institutions must develop policies, oversight mechanisms, and technical capabilities that address the unique governance challenges posed by AI applications in educational contexts.

Looking forward, several directions for future research emerge from this study. First, longitudinal investigations tracking how readiness priorities evolve as institutions progress through AI adoption could reveal whether early-stage priorities differ from those relevant to sustained implementation and scaling. Second, comparative studies examining readiness priorities across different institutional types, geographic regions, and educational levels would enhance understanding of contextual variations and the generalizability of these findings. Third, mixed-methods research combining AHP prioritization with qualitative case studies of successful and unsuccessful AI adoption initiatives could provide richer insights into how readiness factors interact in practice and which intervention strategies prove most effective. Fourth, investigation of the dynamic relationships among readiness factors using system dynamics or network analysis approaches could complement the hierarchical perspective provided by AHP.

In conclusion, this study establishes that management readiness for AI adoption in educational institutions depends primarily on human capital development, supported by technological infrastructure, organizational culture, strategic planning, and financial resources in that order of priority. Educational leaders who understand and act upon these priorities, investing strategically in faculty development, leadership commitment, data infrastructure, and governance frameworks, position their institutions for successful AI transformation. The AHP methodology and empirical findings provide both theoretical insights and practical tools that can guide educational institutions worldwide as they navigate the complex journey toward AI-enhanced teaching, learning, and administration. As AI technologies continue to evolve and permeate educational practices, the capacity of institutions to develop their human capital, foster supportive cultures, and maintain strategic focus will increasingly determine their ability to harness AI's transformative potential while addressing its risks and challenges responsibly.

Co-Author Contribution

Author 1 carried out the fieldwork, prepared the literature review and overlooked the whole article’s write up. Authors 2, wrote the research methodology and did the data entry. Authors 3 carried out the statistical analysis and interpretation of the results.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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