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Generative AI in Higher Education Management: A Mixed-Methods Study of School Leaders' Awareness, Readiness, and Adoption Intentions

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Abstract. This study examined higher education school leaders' awareness, readiness, and adoption intentions regarding the use of generative AI in institutional management. An exploratory convergent mixed-methods design was used to integrate survey results and qualitative written responses from 24 school leaders representing 10 universities. The instrument measured awareness, readiness, and adoption intention through Likert-scale items and used open-ended prompts to explore perceived opportunities, concerns, and enabling conditions for responsible use. Descriptive statistics, reliability analysis, Spearman correlations, and reflexive thematic analysis were employed. The findings showed high awareness ($M = 3.82$, $SD = 0.52$) and high adoption intention ($M = 3.61$, $SD = 0.63$), but only moderate readiness ($M = 3.36$, $SD = 0.61$). Awareness was positively related to readiness ($r_s = .62$, $p = .001$) and adoption intention ($r_s = .59$, $p = .003$), while readiness showed the strongest relationship with adoption intention ($r_s = .68$, $p < .001$). Qualitative findings identified five themes: strategic efficiency under human oversight; governance and data protection as prerequisites; leadership-focused training; accuracy and reputational risk; and uneven access and resistance. The integrated findings indicate that leaders are not merely asking whether generative AI is useful; they are asking whether their institutions can use it responsibly. The study recommends leadership-centered professional development, explicit governance protocols, low-risk pilot projects, and human-centered accountability structures.

Keywords: generative AI; higher education; academic leadership; institutional governance; technology acceptance

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1. Introduction

Generative AI refers to artificial intelligence systems that can produce new content, such as text, images, code, summaries, or analytic suggestions, in response to prompt and data inputs. In higher education, such tools have become prominent because they are accessible to nontechnical users and can support tasks that involve writing, summarizing, translating, brainstorming, and organizing information. The emergence of large language models has therefore widened the institutional conversation beyond teaching and assessment. Universities now face questions about how generative AI should be used in management processes, how its outputs should be checked, how sensitive data should be protected, and how leadership teams should define responsible boundaries for experimentation (Floridi & Chiriatti, 2020; Kasneci et al., 2023; Miao & Holmes, 2023).

The literature on artificial intelligence in education has expanded rapidly. Reviews have documented AI applications in adaptive learning, assessment, learning analytics, student support, online learning, and institutional digital transformation (Chen et al., 2020; Crompton & Burke, 2023; Hwang et al., 2020; Luckin et al., 2016; Ouyang et al., 2022; Roll & Wylie, 2016; Zawacki-Richter et al., 2019; Zhai et al., 2021). The arrival of generative AI has intensified this trajectory because tools such as ChatGPT can be used without specialist programming knowledge, prompting institutional reactions that range from innovation to anxiety (Dempere et al., 2023; García-Peñalvo, 2023; Lo, 2023; Rudolph et al., 2023; Tlili et al., 2023). Recent studies have examined the effects of generative AI on assessment, faculty practice, academic integrity, educator perceptions, and student acceptance (Chan & Hu, 2023; Chiu, 2024; Lee et al., 2024; Shahzad et al., 2024; Strzelecki, 2024). These studies show that higher education communities recognize the technology's promise but remain concerned about hallucinated content, hidden bias, privacy, authorship, and overreliance.

However, the management dimension of generative AI remains less developed than the instructional dimension. Higher education school leaders may encounter generative AI in routine correspondence, policy drafting, accreditation preparation, strategic planning, records management, meeting documentation, grant support, quality assurance, and stakeholder communication. These tasks are not merely technical conveniences. They involve institutional accountability because inaccurate or poorly governed AI-assisted outputs can affect policy interpretation, compliance, personnel decisions, data protection, and public trust. This management context makes leadership awareness and readiness central to responsible adoption. A university may have access to generative AI tools, but adoption becomes fragile when leaders do not know how to evaluate outputs, define safe use cases, or translate policy into practice.

International and institutional guidance increasingly frames AI adoption as a governance issue. UNESCO (2021) and Miao and Holmes (2023) emphasize human oversight, transparency, equity, and capacity building. The Organization for Economic Co-operation and Development (2023), the European Commission (2022), and the U.S. Department of Education (2023) similarly stress that digital and AI adoption should be accompanied by ethical safeguards, educator

preparation, and accountability structures. In higher education, institutional policy analyses show that universities are developing guidance for teaching, research, administration, and student support, yet policy scope and maturity vary considerably (An et al., 2025; Chan, 2023; Dotan et al., 2024; Jin et al., 2025). This unevenness matters for school leaders because policy ambiguity often produces inconsistent practice across units.

Educational management research has long shown that institutional change depends on leadership interpretation, resource allocation, and the creation of enabling conditions (Hallinger, 2011; Rogers, 2003). Generative AI adoption is similar. Higher education school leaders not only decide whether a tool is useful; they also shape norms for acceptable practice, determine whether staff will receive training, coordinate governance with information technology units, and set expectations for human review. Their awareness, readiness, and adoption intentions are therefore meaningful indicators of whether generative AI will remain an informal individual practice or become a responsibly governed institutional capability.

1.1 Research Problem

The problem addressed in this study is the mismatch between the fast diffusion of generative AI tools and the slower development of leadership readiness for their responsible use in higher education management. Prior studies have generated valuable evidence on students, instructors, policy documents, and broad educational applications (Bearman et al., 2023; Chan & Hu, 2023; Lee et al., 2024; Mah & Groß, 2024; Shahzad et al., 2024). Yet less is known about the readiness of school leaders who manage institutional workflows and translate policy into operational decisions. This gap matters because leaders may be expected to approve AI-related policies, guide faculty and staff, and model ethical use even when their own practice is still emerging.

The problem is not simply a lack of tools. Many generative AI tools are already accessible. The more serious issue is a leadership capacity gap involving knowledge, confidence, policy interpretation, data governance, and human oversight. When this gap is ignored, universities may either prohibit useful experimentation because risks feel unmanageable or allow uncoordinated use without safeguards. Both pathways weaken institutional learning. Evidence is therefore needed on how leaders understand generative AI, how ready they feel to learn and govern it, what adoption intentions they hold, and what qualitative concerns shape their willingness to proceed.

1.2 Research Objectives

This study aimed to examine higher education school leaders' awareness, readiness, and adoption intentions regarding generative AI in management-related work. Specifically, it sought to:

1. describe the profile of participating school leaders from the higher education sector;
2. determine their levels of awareness, readiness, and adoption intention toward generative AI in management-related work;
3. examine the relationships among awareness, readiness, and adoption intention;

4. identify the perceived opportunities, concerns, and enabling conditions associated with generative AI adoption; and
5. integrate the quantitative and qualitative findings to derive implications for leadership development, institutional governance, and responsible adoption.

1.3 Research Questions

The following research questions guided the inquiry:

1. What is the profile of the participating higher education school leaders?
2. What are their levels of awareness, readiness, and adoption intention toward generative AI in higher education management?
3. To what extent are awareness, readiness, and adoption intention related?
4. What opportunities, concerns, and enabling conditions do leaders identify in relation to generative AI adoption?
5. How do the qualitative findings explain, extend, or qualify the quantitative patterns?

2. Theoretical and Empirical Background

2.1 Generative AI as a Governance Concern in Higher Education

The study drew on four complementary bodies of literature: generative AI governance in higher education; AI literacy; organizational readiness; and technology acceptance. These perspectives were selected because the study did not treat adoption intention as a purely individual preference. In higher education management, leaders' intentions are shaped by what they know about generative AI, how prepared they and their institutions are, and whether they believe adoption can be made useful, safe, and accountable.

AI in education has a long history, but the public accessibility to generative AI has altered the pace and character of institutional response. Earlier AI-in-education studies examined intelligent tutoring, adaptive learning, analytics, automated feedback, and student support (Chen et al., 2020; Crompton & Burke, 2023; Ouyang et al., 2022; Popenici & Kerr, 2017; Selwyn, 2019; Williamson & Eynon, 2020; Zawacki-Richter et al., 2019). Generative AI shifts the issue because many users can now produce plausible text, summaries, code, and documents without deep technical expertise. This capability creates new opportunities for management work but also increases the risk that unverified output may enter official workflows.

Recent higher education studies indicate that generative AI can assist with brainstorming, writing support, translation, feedback generation, coding, administrative drafting, and information synthesis (Chiu, 2024; Dempere et al., 2023; Kasneci et al., 2023; Lee et al., 2024; Lim et al., 2023). At the same time, scholars emphasize risks related to accuracy, hallucinated references, algorithmic bias, privacy, and unequal access (Floridi & Chiriatti, 2020; Lo, 2023; Tlili et al., 2023). These risks have major consequences in management contexts because official documents and decisions are associated with institutional authority.

Policy studies show that higher education institutions have responded unevenly. An et al. (2025) found that guidelines in leading universities addressed teaching,

learning, research, and administration, but differed in specificity and enforcement. Jin et al. (2025) likewise showed that institutional adoption policies vary in how they allocate responsibilities and communicate acceptable use. Chan (2023) proposed an AI policy education framework with pedagogical, governance, and operational dimensions. Dotan et al. (2024) similarly argued that responsible adoption requires practical points to consider rather than abstract ethical statements alone. These studies support the present focus on leaders because leaders are the actors who often convert policy language into local management routines.

2.2 AI Literacy and Leadership Readiness

AI literacy refers to the knowledge and evaluative capacity needed to understand, use, and critically assess AI systems. Long and Magerko (2020) described AI literacy as a set of competencies that enable people to evaluate AI technologies, communicate about them, and use them effectively. Ng et al. (2021) conceptualized AI literacy as involving knowledge, use, evaluation, creation, and ethical understanding. In a leadership context, these competencies are not optional. Leaders need to understand not only what generative AI can produce, but also why generated outputs require verification and what kinds of institutional data should not be entered into unmanaged tools.

Readiness is broader than awareness. It refers to personal and institutional preparedness to learn, evaluate, support, and govern generative AI use. Readiness includes confidence, training access, digital infrastructure, policy guidance, support mechanisms, and organizational openness. Mah and Groß (2024) showed that AI-related self-efficacy and professional development needs shape faculty orientations toward AI. The same logic applies to school leaders, but the stakes differ because leaders supervise workflows and approve documents that may carry institutional consequences.

Privacy and data governance are particularly important. Research on learning analytics has already shown that data-intensive educational technologies raise questions about consent, control, transparency, and responsible data use (Ifenthaler & Schumacher, 2016; Slade & Prinsloo, 2013). AI ethics scholarship extends these concerns by emphasizing accountability, fairness, transparency, non-maleficence, and auditability (Floridi & Cows, 2019; Holmes et al., 2022; Jobin et al., 2019; Nguyen et al., 2023; Raji et al., 2020; Shneiderman, 2020). For higher education management, these principles become concrete when leaders decide whether generative AI may be used for reports, minutes, planning documents, or sensitive communications.

2.3 Technology Acceptance and Adoption Intention

Technology acceptance research offers complementary lens. The Technology Acceptance Model explains user acceptance through perceived usefulness and perceived ease of use (Davis, 1989). The Unified Theory of Acceptance and Use of Technology extend this logic by emphasizing performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Later extensions also emphasize behavioral intention and contextual conditions (Venkatesh et al., 2012). The theory of planned behavior similarly treats intention

as a proximal indicator of planned action, shaped by attitudes, norms, and perceived control (Ajzen, 1991).

Technology acceptance research in education supports this interpretation. Scherer et al. (2019) showed that acceptance models remain useful for explaining educators' adoption of digital technologies, especially when contextual support is considered. Recent generative AI studies reach comparable conclusions. Shahzad et al. (2024) found that awareness and trust are linked to ChatGPT adoption processes. Lai et al. (2023) extended technology acceptance to ChatGPT use in learning contexts. Strzelecki (2024) likewise used technology acceptance to explain students' willingness to use ChatGPT in higher education. These studies justify examining adoption intention, but they also show why intention must be interpreted alongside readiness and governance conditions.

In leadership contexts, adoption intention should be treated as conditional rather than automatic. Leaders may intend to use generative AI for routine drafting or summarization, but hesitate to use it for confidential, evaluative, legal, or high-stakes decisions. Thus, adoption intention in this study does not mean willingness to automate leadership judgment. It means willingness to learn, encourage responsible exploration, and support selected uses under human oversight.

2.4 Conceptual Framework and Hypotheses

The conceptual framework assumes that awareness provides the cognitive base for readiness and adoption intention. Leaders who understand generative AI are better positioned to evaluate its potential uses, identify risks, and recognize the need for safeguards. Readiness represents the enabling conditions that make adoption appear feasible and responsible. Adoption intention is the proximal outcome, reflecting whether leaders are willing to learn, support, and pursue selected uses in management work. Because the study included a small exploration sample, the quantitative framework focused on relationships rather than causal prediction.

The qualitative strand was included to explain why leaders might be aware and willing but not fully ready. Open-ended responses were expected to clarify the management contexts, perceived opportunities, and governance conditions behind the scale scores. In this sense, qualitative findings were not supplementary padding. They were integral to interpreting the readiness gap.

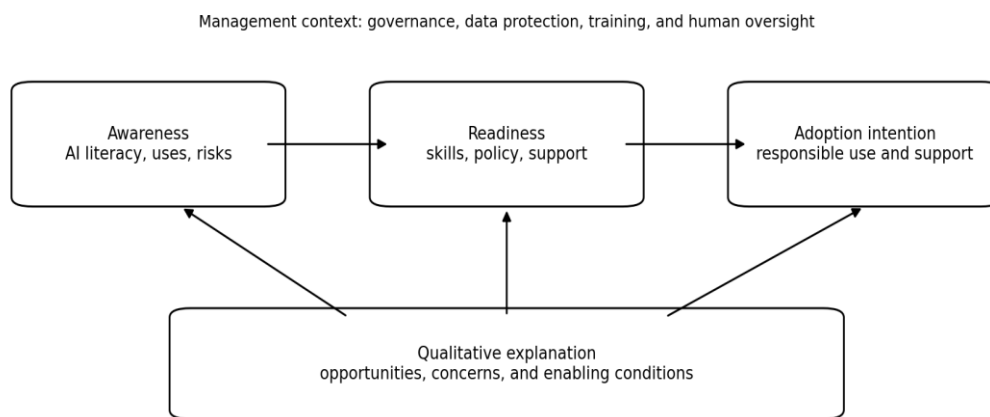


Figure 1: Conceptual framework of awareness, readiness, adoption intention, and qualitative explanation

The following hypotheses guided the quantitative component of the study:

H1: Awareness is positively related to readiness.

H2: Awareness is positively related to adoption intention.

H3: Readiness is positively related to adoption intention.

3. Methodology

3.1 Research Design

The study used an exploratory convergent mixed-methods design. Mixed-methods research combines quantitative and qualitative forms of inquiry to produce a more complete understanding of a research problem than either strand can provide alone (Johnson et al., 2007). A convergent design collects and interprets quantitative and qualitative evidence in relation to the same research problem, while integration occurs through comparison, explanation, and joint interpretation (Creswell & Plano Clark, 2018; Fetters et al., 2013).

The quantitative strand consisted of Likert-scale items measuring awareness, readiness, and adoption intention. The qualitative strand consisted of open-ended written responses about opportunities, concerns, and enabling conditions. This design was appropriate because the sample was small and the topic is emerging. The purpose was not to produce sector-wide estimates or a predictive model. Rather, the purpose was to combine scale-based patterns with richer qualitative explanations of how leaders make sense of generative AI in management work.

3.2 Participants and Sampling Criteria

The participants were 24 school leaders from 10 universities in the higher education sector. The sample included leaders whose responsibilities involved institutional planning, academic management, administrative coordination, quality assurance, program supervision, or policy implementation. Participants represented senior executive, college-level, unit-level academic, and administrative leadership roles.

A purposive maximum-variation sampling approach was used rather than a probability sampling design. The selection criteria were as follows: participants had to hold a leadership or management role in a university; have responsibility for academic, administrative, or institutional decision-making; be able to comment on technology use in management work; and voluntarily complete both the closed-ended and open-ended components. The 10 universities were included to avoid drawing responses from a single institutional setting and to capture variation in policy maturity, leadership level, and technology exposure.

The sample size should be understood in relation to the exploratory mixed-methods purpose. Twenty-four participants is modest for quantitative generalization but defensible for an exploratory study that emphasizes qualitative explanation and cautious correlational analysis. Qualitative sample adequacy depends on information power, response depth, analytic focus, and the degree to which recurring patterns become identifiable (Guest et al., 2020; Vasileiou et al., 2018). Accordingly, the study reports descriptive and relational patterns conservatively and does not claim population representativeness.

3.3 Instrumentation

Data was collected using a structured questionnaire composed of four parts. Part A gathered profile information, including leadership level, years of leadership experience, prior structured generative AI training, frequency of work-related generative AI use, and institutional AI policy status. Part B measured awareness using five Likert-type items. Part C measured readiness using six items. Part D measured adoption intention using five items. All closed-ended items used a five-point scale ranging from 1 (strongly disagree) to 5 (strongly agree). Part E consisted of open-ended prompts on perceived opportunities, concerns, and support needs.

Items were contextualized to higher education management rather than classroom-only use. For example, general statements about technology usefulness were modified to refer to administrative drafting, policy review, quality assurance, meeting documentation, and decision-support tasks. Awareness items were derived from AI literacy scholarship (Long & Magerko, 2020; Ng et al., 2021). Readiness items reflected personal preparedness, infrastructure, training, policy support, and critical evaluation. Adoption intention items were informed by technology acceptance and behavioral intention literature (Ajzen, 1991; Davis, 1989; Scherer et al., 2019; Venkatesh et al., 2003).

The initial item pool was reviewed by three experts with backgrounds in educational leadership, research methods, and educational technology. Their feedback was used to clarify wording, reduce overlap, and ensure that items reflected management-related uses of generative AI. A small pre-administration review was also conducted to check readability and completion time. The open-ended prompts were retained because they allowed respondents to explain conditions that fixed-response items might not capture.

3.4 Data Collection Procedure

Participants received an invitation explaining the purpose of the study, the voluntary nature of participation, and the confidentiality measures applied to the data. The questionnaire was administered in English. Respondents were asked to answer based on their current leadership experience and their understanding of generative AI tools used or discussed in higher education. Responses were screened for completeness before analysis. No institutional or personal names were reported in the manuscript.

3.5 Data Analysis

Quantitative data were analyzed using descriptive statistics, reliability analysis, and Spearman rank-order correlations. Means and standard deviations summarized scale scores, while frequencies and percentages described profile variables. Cronbach's alpha was calculated to estimate internal consistency, although the values were interpreted cautiously because of the small sample size. Interpretation ranges for composite means followed equal-width intervals on the five-point scale: 1.00-1.80 = very low, 1.81-2.60 = low, 2.61-3.40 = moderate, 3.41-4.20 = high, and 4.21-5.00 = very high.

Spearman correlations were used because the sample was small and the Likert-scale composites were treated cautiously as ordinal-derived indicators. The assumptions considered before analysis included paired observations, monotonic relationships, and the absence of extreme outliers. Scatterplot inspection and rank-order review indicated that the relationships were suitable for Spearman analysis. Regression and analysis of variance were not used because the sample size did not support stable multivariable modeling or subgroup inference.

Qualitative data were analyzed through reflexive thematic analysis informed by Braun and Clarke (2006, 2021). The process involved familiarization with all responses, initial coding of meaning units, clustering of codes into candidate themes, comparison of themes against the full dataset, and refinement of theme names. The coding emphasized semantic meaning and practical implications for management work. The qualitative results were then integrated with the quantitative findings through a joint display, allowing the study to identify how open-ended explanations supported, extended, or qualified the numerical patterns.

3.6 Ethical Considerations

The study treated participation as voluntary, informed, and confidential. Respondents were informed that no institution or individual would be identified by name. The manuscript reports only aggregated profiles, scale results, and anonymized qualitative excerpts. Participant quotations were labeled using generic participant codes. Because the topic involves institutional technology use and potential governance concerns, the analysis avoided naming specific universities, offices, or persons.

4. Results and Findings

4.1 Profile of Participants

Table 1 presents the profile of the participating school leaders. The sample consisted of 24 leaders from 10 universities. Participants varied by leadership level, experience, training background, and institutional policy status. This variation is important because generative AI adoption in management is likely to be shaped not only by individual familiarity, but also by leadership role, institutional support, and exposure to training.

Table 1: Profile of participating school leaders

Characteristic	Category	n	%
Gender	Female	13	54.2
	Male	11	45.8
Leadership level	Senior executive	3	12.5
	College-level leader	6	25.0
	Unit-level academic leader	12	50.0
	Administrative coordinator/director	3	12.5
Years of leadership experience	1-5 years	5	20.8
	6-10 years	9	37.5
	11-15 years	7	29.2
	16 years and above	3	12.5
Prior structured generative AI training	None	8	33.3
	Webinar or brief orientation	7	29.2
	Workshop	6	25.0
Frequency of work-related generative AI use	Multiple workshops or certification	3	12.5
	Never or rarely	9	37.5
	Monthly	5	20.8
	Weekly	7	29.2
	Daily	3	12.5
Institutional AI policy status	No formal guidance	9	37.5
	Drafting or consultation stage	8	33.3
	Approved policy or interim guidance	7	29.2

Note. Percentages are based on N = 24. Participants represented 10 universities. Mean age was 45.8 years (SD = 6.1), and mean leadership experience was 9.2 years (SD = 4.2).

Table 1 shows that the participants represented varied leadership levels and experience bands. Half were unit-level academic leaders, while the remaining participants were senior executives, college-level leaders, or administrative coordinators and directors. The profile also shows uneven preparation for generative AI. Eight participants reported no structured training, and nine reported never or rarely using generative AI for work-related purposes. At the same time, seven participants reported weekly or daily use, and seven indicated that their institutions had approved or interim AI guidance. This variation provided a useful basis for interpreting the awareness-readiness gap.

4.2 Levels of Awareness, Readiness, and Adoption Intention

Table 2 presents the descriptive statistics, and reliability estimates for the main constructs.

Table 2: Descriptive statistics and reliability of the main constructs

Construct	Items	alpha	M	SD	Interpretation
Awareness	5	.85	3.82	0.52	High
Readiness	6	.91	3.36	0.61	Moderate
Adoption intention	5	.90	3.61	0.63	High

Note. Interpretation ranges: 1.00-1.80 = very low; 1.81-2.60 = low; 2.61-3.40 = moderate; 3.41-4.20 = high; 4.21-5.00 = very high. Alpha values should be interpreted cautiously because of the small sample size.

Awareness obtained the highest mean ($M = 3.82$), indicating that participants generally understood what generative AI is, could identify likely management uses, and recognized the need for verification and ethical caution. Adoption intention was also high ($M = 3.61$), showing that leaders were willing to learn more and support selected uses. Readiness was lower ($M = 3.36$), which placed it at the upper end of the moderate range. This pattern indicates that willingness was not matched by full confidence in policy, infrastructure, training, or institutional support.

The interpretation should not be overstated. A moderate readiness score does not mean that leaders were unprepared in all respects. Rather, it shows uneven preparation. Personal willingness to learn was stronger than confidence in institutional conditions. This finding became clearer in the qualitative strand, where leaders repeatedly linked their willingness to adopt generative AI with policy clarity, privacy safeguards, training, and safe experimentation.

4.3 Relationships Among Awareness, Readiness, and Adoption Intention

The correlation results in Table 3 supported all three hypotheses.

Table 3: Spearman correlations among awareness, readiness, and adoption intention

Variable	1	2	3
1. Awareness	-		
2. Readiness	.62**	-	
3. Adoption intention	.59**	.68***	-

Note. ** $p < .01$. *** $p < .001$. Spearman correlations were used due to the exploratory design and small sample size.

Awareness was positively related to readiness ($r_s = .62, p = .001$), supporting H1. Awareness was also positively related to adoption intention ($r_s = .59, p = .003$), supporting H2. Readiness had the strongest relationship with adoption intention ($r_s = .68, p < .001$), supporting H3. These results indicate that leaders' willingness to adopt generative AI was linked not only to knowing about technology but also to feeling prepared to use and govern it. The strongest coefficient was between readiness and adoption intention. This is a key result because it places governance and enabling conditions at the center of adoption. In practical terms, leaders may recognize generative AI's potential, but their intention to adopt it becomes

stronger when they believe that policies, infrastructure, training, and review procedures can support responsible implementation.

4.4 Qualitative Themes on Opportunities, Concerns, and Enabling Conditions

The qualitative responses produced five major themes. The themes were not mutually exclusive because many respondents described both opportunities and concerns in the same response. Table 4 summarizes the themes and provides illustrative excerpts. The excerpts were edited only to remove identifying details and improve readability without changing meaning.

Table 4: Qualitative themes and illustrative excerpts

Theme	Analytic focus	n (%)	Illustrative excerpts
Strategic efficiency under human oversight	Low-risk management support such as drafting, summarizing, and organizing evidence	16 (66.7)	"It can help us prepare first drafts of reports and minutes, but the final decision must remain with us" (P04).
Governance and data protection as prerequisites	Rules for confidential data, disclosure, verification, and accountability	15 (62.5)	"I will not encourage wider use unless we have rules on confidential data" (P11).
Leadership-focused training and guided experimentation	Role-specific workshops, guided pilots, and sandbox activities	15 (62.5)	"Administrators need training designed for administrators, not only for teachers" (P17).
Accuracy, bias, overreliance, and reputational risk	Concern about polished but inaccurate outputs, invented sources, and official-document risk	13 (54.2)	"The danger is that the output sounds correct even when it is not" (P02).
Uneven access, budget, and staff resistance	Resource constraints, workload, unequal support, and change-management concerns	9 (37.5)	"Some units can experiment, but others lack staff time and support" (P20).

Note. Percentages are based on N = 24. Themes are not mutually exclusive. Excerpts are anonymized and lightly edited for readability.

The first theme, strategic efficiency under human oversight, showed that leaders saw practical value in generative AI for management tasks. Participants mentioned drafting memoranda, summarizing meeting notes, organizing accreditation evidence, preparing initial policy language, and converting long documents into brief decision summaries. However, they did not frame these uses as full automation. Their comments emphasized that generative AI should be a first-draft or support tool, with humans retaining responsibility for review,

judgment, and approval. The second theme, governance and data protection as prerequisites, explained why readiness was lower than awareness. Leaders repeatedly asked for rules on confidential data, acceptable use, disclosure, review procedures, and accountability. They were especially cautious about student records, personnel matters, institutional planning documents, and official reports. This theme shows that leaders' willingness to adopt generative AI was conditional on governance clarity.

The third theme, leadership-focused training and guided experimentation, indicated that leaders wanted applied professional development rather than broad awareness sessions. Participants asked for examples that directly reflect leadership work, such as AI-assisted drafting of reports, review of policy language, preparation of quality assurance documents, and summarization of non-confidential meetings. They also preferred guided pilots and sandbox environments, which would allow leaders to learn the technology without immediately applying it to high-risk institutional records.

The fourth theme, accuracy, bias, overreliance, and reputational risk, reflected concern about the polished quality of AI outputs. Participants worried that generative AI could produce persuasive but inaccurate summaries, invent sources, misrepresent policy, or reproduce biased assumptions. This concern was not purely technical. Leaders connected accuracy problems to reputational risk because official documents, even when AI-assisted, are still treated as institutional outputs. The fifth theme, uneven access and resistance, highlighted budget, workload, and change-management issues that may affect implementation across units.

4.5 Integrated Interpretation of the Mixed-Methods Findings

Table 5 integrates the quantitative and qualitative findings. The joint display shows that the qualitative data did more than repeat the numerical patterns. It explains why leaders could be aware and willing while still not fully ready.

Table 5: Integrating quantitative and qualitative findings

Quantitative pattern	Qualitative explanation	Integrated interpretation
Awareness was high (M = 3.82).	Leaders could identify management uses such as drafting, summarizing, planning, and quality assurance support.	Generative AI is visible to leaders and is already understood as relevant to management work.
Readiness was moderate (M = 3.36).	Participants emphasized missing policy, privacy rules, training, and safe trial environments.	Readiness depends on governance and institutional support, not awareness alone.
Adoption intention was high (M = 3.61).	Leaders were willing to explore low risk uses under human review.	Adoption intention is cautious and conditional rather than uncritical.
Readiness had the strongest relationship with adoption intention (rs = .68).	Leaders linked willingness to clear accountability, reliable review procedures, and protected data practices.	Readiness functions as a bridge between awareness and responsible adoption.

Note. The joint display integrates descriptive, correlational, and thematic findings

The central integrated insight is that leaders were not primarily asking whether generative AI is useful. They were asking whether their institutions can use it responsibly. Readiness therefore emerged as the practical hinge between knowledge and adoption. This integrated result is important for institutional management. It indicates that leaders' adoption intentions should be interpreted as cautious and conditional, not as simple enthusiasm. Generative AI was viewed as promising for low-risk management support, but respondents wanted clear accountability, verified outputs, protected data, and role-specific training before broader implementation.

5. Discussion

The study contributes to literature by shifting attention from generative AI as a classroom tool to generative AI as a higher education management concern. The findings showed that school leaders were generally aware of the technology and willing to explore it, but their readiness was moderated by governance, training, privacy, and accountability concerns. This extends prior research on AI in higher education by focusing on leaders who must translate institutional policy into operational practice.

The high awareness finding is consistent with the rapid diffusion of generative AI discourse across higher education. Studies have shown that faculty, students, and institutions are increasingly aware of generative AI tools and their implications (Chan & Hu, 2023; Crompton & Burke, 2023; Dempere et al., 2023; Lee et al., 2024; Shahzad et al., 2024). However, this study adds a leadership-specific insight: awareness among school leaders is connected to administrative use cases such as policy drafting, report preparation, accreditation support, and communication. These tasks are less frequently discussed than assessment and academic integrity, yet they are central to institutional management.

The moderate readiness result aligns with policy-oriented studies showing that institutional responses to generative AI remain uneven. An et al. (2025) and Jin et al. (2025) found that universities are developing guidelines, but the clarity and scope of policies differ considerably. Chan (2023) argued that AI policy must integrate teaching, governance, ethics, privacy, and institutional support. The present findings support this argument by showing that leaders' readiness depends on policy clarity and implementation support. Leaders may understand generative AI, but they hesitate when the institution has not yet defined acceptable data practices, review standards, or accountability arrangements.

The correlation results also fit technology acceptance theory. The Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology both suggest that adoption intention depends on perceived usefulness, ease of use, and facilitating conditions (Davis, 1989; Venkatesh et al., 2003, 2012). The present study found that readiness had the strongest relationship with adoption intention, which indicates that facilitating conditions are especially important in leadership contexts. This finding is compatible with Scherer et al.'s (2019) meta-analytic conclusion that contextual support matters in educational technology adoption. It also relates to Shahzad et al. (2024), who found that awareness

influences adoption processes, and to Lai et al. (2023), who extended technology acceptance to ChatGPT adoption.

The qualitative themes clarify why readiness matters. Leaders did not reject generative AI as a management tool. Instead, they wanted bounded experimentation, clear policy, and human oversight. This pattern is consistent with human-centered AI principles, which emphasize that AI systems should augment rather than replace human responsibility (Shneiderman, 2020). It also aligns with broader AI ethics scholarship emphasizing accountability, fairness, transparency, and auditability (Floridi & Cows, 2019; Holmes et al., 2022; Jobin et al., 2019; Nguyen et al., 2023; Raji et al., 2020). In higher education management, these principles become concrete when leaders decide which data can be entered into a tool, which outputs require verification, and who remains accountable for official documents.

The findings also respond to concerns about hallucinated output and overreliance. Generative AI tools can produce fluent text that appears authoritative even when it contains errors or fabricated information (Floridi & Chiriatti, 2020; Kasneci et al., 2023; Lo, 2023). For management work, the risk is not limited to academic integrity. It may involve inaccurate policy summaries, misleading accreditation documents, flawed strategic analyses, or official communication that misrepresents institutional decisions. This makes humans review core leadership responsibility rather than a minor editing step.

Training emerged as a major practical issue. Prior research has shown that educators' AI self-efficacy and professional development needs vary substantially (Mah & Groß, 2024). The present study extends this issue to higher education leadership. Participants did not ask only for general literacy. They asked for role-specific training that would demonstrate how generative AI can be used in planning, documentation, quality assurance, and communication without compromising confidentiality or accountability. This matters because leadership adoption is likely to influence staff norms. Leaders who understand both affordances and risks are better positioned to model responsible use.

Finally, the study adds nuance to the concept of institutional readiness. Readiness is not simply infrastructure availability. It involves alignment across policy, training, privacy, leadership judgment, and organizational culture. The qualitative findings indicate that leaders may adopt generative AI more confidently when the institution provides a safe experimentation pathway. Such a pathway would begin with low-risk administrative tasks and gradually expand only after reviewing protocols, training, and governance structures are in place. This phased approach is consistent with diffusion theory, which emphasizes trialability, observability, and compatibility as important features of innovation adoption (Rogers, 2003).

6. Conclusion

This study examined higher education school leaders' awareness, readiness, and adoption intentions regarding generative AI in management work. The findings

indicate that leaders are already aware of generative AI and willing to explore its use, but their readiness remains constrained by governance, data privacy, training, accountability, and uneven access. The central takeaway for university leaders and senior administrators is that generative AI adoption cannot be advanced responsibly through enthusiasm or tool access alone. It requires human-centered governance that defines acceptable use, protects sensitive information, assigns accountability, and builds leadership capability.

The qualitative findings deepen this conclusion by showing that leaders value generative AI for drafting, summarizing, planning, and quality assurance support, yet remain cautious about hallucinated outputs, overreliance, staff resistance, and reputational risk. Readiness emerged as the bridge between awareness and adoption intention, suggesting that institutions should prioritize professional development and policy structures before expecting broad implementation. Although based on a small exploratory sample, the study offers a useful management-focused perspective on a global issue: generative AI adoption in higher education is most viable when innovation is matched with literacy, safeguards, and accountable human judgment.

7. Implications

The findings have implications for leadership development, institutional governance, and educational management practice. First, leadership development should include AI literacy that is specific to management tasks. Leaders need to know how generative AI can support work such as meeting summarization, policy drafting, accreditation preparation, communication planning, and environmental scanning. However, training should also include verification, bias recognition, data classification, and responsible prompting.

Second, institutional governance documents should be explicit. An AI governance document should identify acceptable and prohibited uses, define levels of data sensitivity, specify whether and how AI assistance must be disclosed, establish human review requirements, and designate accountability for official outputs. It should also clarify procurement, cybersecurity, privacy, and record-keeping responsibilities. These details help reduce inconsistent practices across units.

Third, institutions should recognize that middle-level leaders are critical to implementation. Deans, department chairs, program heads, directors, and coordinators often convert policy into day-to-day workflows. If they lack readiness, institutional policy may remain aspirational. If they are trained and supported, they can identify realistic use cases, supervise low-risk experimentation, and guide staff toward responsible practice.

8. Limitations and Future Research

The study has limitations. The sample consisted of 24 leaders from 10 universities, so the quantitative findings should not be generalized as sector-wide estimates. The data were self-reported and cross-sectional, meaning the findings describe perceptions and intentions rather than observed long-term adoption behavior. The qualitative data came from open-ended written responses rather than

interviews or focus group discussions. Although the written responses provided useful insight, future research should include interviews, focus groups, policy-document analysis, and observation of actual AI-supported workflows.

Future studies should use larger samples to test predictive models, compare leadership levels, and examine whether institutional policy status moderates' adoption intention. Longitudinal work is also needed to examine how readiness changes as universities develop AI policies and training programs. Comparative studies across institutional types and national contexts would further clarify which readiness conditions are local and which are common across higher education systems.

9. Recommendations

Based on the findings, higher education institutions should begin with a phased governance pathway. In the first three months, institutions could conduct a leadership AI literacy audit, identify low-risk administrative use cases, and issue interim guidance on confidentiality and human review. Within six months, institutions should develop or update AI governance policies, designate responsible offices, and provide role-specific workshops for leaders. Within one academic year, institutions could implement monitored pilot projects in low-risk areas such as meeting summaries, draft communications, and non-confidential planning documents.

Institutions should also provide incentives for leadership training. These may include recognition in professional development plans, release time for workshops, micro-credentials, or inclusion of AI governance competence in leadership development programs. To address budget and resource barriers, universities could pool training resources across campuses, develop shared prompt libraries for low-risk tasks, and negotiate institutionally approved AI tools that provide stronger privacy, access control, and security protection than unmanaged personal accounts.

Sector-level and regulatory bodies should support institutions by issuing model AI governance templates, data privacy checklists, and professional development standards for higher education leaders. Such guidance should emphasize that generative AI may assist management work, but it should not replace human judgment in decisions involving students, personnel, finance, compliance, or institutional accountability.

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Conflict of Interest

The author declares no conflict of interest.

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Appendix A: Survey Instrument

The questionnaire was administered in English. Closed-ended items used the following response options: 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree.

Profile Variables

1. University code
2. Leadership position or designation
3. Leadership level
4. Gender
5. Age
6. Highest educational attainment
7. Years of leadership experience
8. Prior structured generative AI training
9. Frequency of work-related generative AI use
10. Institutional AI policy status

Likert-Scale Items

Table A1: Scale items used in the questionnaire

Scale	Code	Item
Awareness	A1	I am familiar with the concept of generative AI.
Awareness	A2	I can identify common generative AI tools relevant to higher education work.
Awareness	A3	I understand how generative AI may be used in administrative and management tasks.
Awareness	A4	I am aware of ethical and privacy issues related to generative AI use.
Awareness	A5	I am aware that generative AI outputs require human review and verification.
Readiness	R1	I am ready to learn how generative AI can be used in higher education management.
Readiness	R2	My institution has sufficient digital infrastructure to support responsible generative AI use.
Readiness	R3	Leaders in my institution are open to guided experimentation with generative AI tools.
Readiness	R4	My institution has or is developing policies that can guide responsible AI use.
Readiness	R5	I feel confident that I can evaluate generative AI outputs critically.
Readiness	R6	My institution is prepared to provide training and support for generative AI adoption.
Adoption intention	AI1	I intend to learn more about generative AI within the next six months.
Adoption intention	AI2	I am willing to use generative AI for selected administrative and decision-support tasks.

Adoption intention	AI3	I am willing to encourage responsible exploration of generative AI in my unit.
Adoption intention	AI4	I would support institutional training initiatives on generative AI.
Adoption intention	AI5	I would support the development of policies and pilot projects for generative AI adoption.

Note. Closed-ended items were rated from 1 = strongly disagree to 5 = strongly agree.

Open-Ended Questions

1. What opportunities do you see in the use of generative AI in higher education management?
2. What concerns do you have about leaders using generative AI in administrative work?
3. What support, policy, or training conditions would make you more willing to adopt generative AI for management tasks?