AI-Driven Leadership in Higher Education: Evidence from a Mixed-Methods Study at the University of Sharjah

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Abstract: This study examines how artificial intelligence (AI) tools are incorporated into university leadership practice and whether the intensity of AI use is associated with leaders' perceived effectiveness. A convergent mixed-methods design was integrated into a quantitative survey of 69 administrative leaders, faculty in leadership roles, and professional staff at the University of Sharjah, with 60 qualitative narratives. Descriptives and ordinary least squares regression assessed associations, and inductive thematic analysis elaborated mechanisms and boundary conditions. Respondents reported moderate familiarity (M=3.30, SD=1.26) and moderate use of AI in leadership tasks (M=3.49, SD=1.41); 57.9% used AI at least weekly. Agreement that AI improves decision making was high (M=3.70, SD=1.09). The dominant barrier was lack of training (60.8%), followed by concerns about recommendation reliability (39.1%), data privacy (33.3%), and ethics (30.4%). AI use was positively associated with perceived leadership effectiveness ($R=.492$, $R^2=.242$, $p<.001$). Some narratives emphasized time savings and increased clarity of communication, while others described ethical expectations regarding privacy, bias, accessibility, and academic integrity. Realization of value relies on (capability; role-specific AI literacy), (governance; privacy, assurance, bias, integrity), and (technology; reliable, low-friction tools). Our findings offer unique institution-level evidence from the Gulf context around the use of AI in relation to perceived leadership effectiveness and distil a pragmatic agenda which higher education leaders may find useful.

Key-Words: artificial intelligence, leadership, higher education, mixed methods, governance, capability, Gulf universities, data ethics.

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1 Introduction

Artificial intelligence (AI) has moved from experimental pilots to core infrastructure in many universities, reshaping how leaders interpret evidence, allocate resources, and steward academic missions. Beyond instructional uses, leadership teams increasingly rely on AI-enabled analytics, workflow automation, and generative tools to support admissions forecasting, student success initiatives, research administration, and day-to-day operations [1], [2]. The promise is attractive: faster, more transparent decision cycles and improved service quality on a scale. Yet the same properties that make AI useful, speed, scale, and statistical inference, also raise concerns about reliability, explainability, privacy, equity, and academic integrity [3], [4], [5]. For university leaders, value realization is therefore not a purely technical problem; it is a socio-technical change that depends on human capability, governance, and culture.

Despite growing interest, two gaps persist in the literature. First, much scholarship focuses on teaching and learning or on technology adoption in the abstract, rather than on leadership practice and decision environments within higher education institutions (HEIs). Second, evidence from the Gulf/MENA region, where higher education systems are undergoing rapid digital transformation, remains comparatively under-represented in mainstream outlets. There is limited, institution-level, mixed-methods evidence that connects the intensity of AI use by leaders to leadership outcomes, and that simultaneously surfaces the governance and ethical conditions under which AI augments (rather than substitutes for) expert judgment [6], [7], [8].

To our knowledge, this study provides the first institution-level mixed-methods dataset from a Gulf higher-education institution that empirically links the intensity of AI use among leaders to perceived leadership effectiveness using validated constructs.

This study addresses those gaps through an institution-specific service at the University of Sharjah (UoS). We define AI-driven leadership as the purposeful use of AI tools and techniques to inform, automate, or extend core leadership functions planning, resource allocation, coordination, and performance oversight, while preserving accountability, academic values, and equity. AI contributes value when human expertise, data governance, and organizational routines are aligned to make AI outputs trustworthy, understandable, and actionable.

1.1 Research purpose and questions

The study has three aims: (a) to map leaders' familiarity with and usage of AI tools at UoS; (b) to identify perceived opportunities, barriers, and ethical implications accompanying adoption, and (c) to test whether perceived leadership effectiveness is associated with the intensity of AI use. Four questions guide the inquiry:

- What opportunities do AI-driven tools and techniques present for leadership at UoS?
- What challenges have UoS leaders encountered when integrating AI into decision-making and operations?
- How do leaders at UoS perceive the ethical implications of using AI in leadership?
- To what extent do perceived benefits of AI-driven leadership align with perceived outcomes at UoS?

Consistent with these questions, we examine the following testable proposition:

- H0 (null): AI-driven tools and techniques do not significantly influence the perceived effectiveness of leadership at UoS.
- H1 (alternative): AI-driven tools and techniques significantly influence the perceived effectiveness of leadership at UoS.

1.2 Conceptual lens and scope

Our way of thinking is from a socio-technical perspective: the result of leadership is an interplay between such things as (i) capability (e. G., artificial intelligence literacy, skills, change management), (ii) governance (e. G. data protection, assurance, bias mitigation and accountability) and (iii) technical tool reliability, usability and fit to task. For perceived leadership effectiveness (for example, efficiency of decision-making, strategic planning, and administrative results), we will first provide this study. Ethics also fill the background - privacy, impartiality, accessibility, and academic integrity are crucial to the credibility and acceptance of mission-driven institutions [4], [9].

1.3 Empirical setting and design

Compared to other institutions in the region, the University of Sharjah provides an appropriate environment given its national size, great diversity of disciplines and degrees offered, and because digitalization efforts are typical of today's Arab world. A convergent mixed-methods design was employed, using a structured survey of leaders and staff together with qualitative narratives for triangles. Permission forms for media products constitute an important investigatory task. This design enables both breadth (descriptives, regression linking AI use to perceived effectiveness) and depth (contextual mechanisms and boundary conditions). The article makes three kinds of contributions to scholarship and practice:

- Evidence on leadership practice: It provides institution-level, mixed-methods evidence from a Gulf HEI that links leaders' AI use to perceived leadership effectiveness, moving beyond technology-centric accounts.
- Governance-capability framing: It advances an actionable triad of capability, governance, and technology as co-determinants of AI value in leadership, clarifying conditions under which augmentation is most likely.
- Policy and implementation agenda: It distills a pragmatic agenda for HEI leaders: role-specific AI literacy, assurance, and procurement standards (performance, bias, auditability), data-governance and privacy safeguards, accessibility/equity commitments, and clear positions on academic integrity in the era of generative AI.

The remainder of this article is organized as follows: Section 2 reviews the relevant literature on AI in higher-education leadership; Section 3 describes the mixed-methods design, sampling, and analytic approach; Section 4 presents the quantitative, qualitative, and integrated findings; and Section 5 discusses the implications for leadership practice, policy, and future research.

2. Literature review

2.1 The Evolution of AI in Higher Education

Artificial intelligence (AI) has progressed from narrow automation to a suite of capabilities, prediction, classification, generation, and optimization, that increasingly structure decision-making and service delivery in higher education institutions. Strategic accounts such as Competing in the Age of AI [2] and Prediction Machines [8] conceptualize this shift as architectural. When prediction becomes cheap, and models are embedded in workflows, organizations reconfigure processes and governance around data leverage. In universities, the change is clearly present in adaptive learning systems, intelligent tutoring, predictive enrollment and persistence analytics, and the early general use of generative systems for summarization, drafting, and translation. A synthesis of AI software development outside the academy lists leadership and management among its beneficiaries. Researchers at [10] stress AI's ability to take on perception-type jobs, interactive conversation, and decision aid, thus making it possible for command centers to staff logistics, academy security, or human resources, as well as trade schools' financial aid office studies staff development. All these opportunities to intervene. Their call for "open management" transparency, participation, and digital skill development emphasizes how these technologies can be made to serve evolving institutional goals.

2.2 Opportunities for Higher-Education Leadership

AI provides senior leaders with a broader evidence base, therefore, for strategic and tactical choices, ways to redeploy money and thus enhance their professional productivity, and indeed the potential for tailoring services to suit students and staff who are as diverse as ours. In [2] we describe how "AI factories " become the habitat for loops of learning that comprise three stages: each data, model, and outcome. Since the two objects natural in process are almost synonymous with endowment, such regular forward-looking data collecting forms may be desirable, where it opens us up to looking forward to a future already here. In [7], further argue that organizations realizing outsized returns integrate AI into core processes, governance, and culture rather than isolating efforts as pilots, a lesson that maps closely to the distributed decision environments typical of universities.

2.3 Challenges, Risks, and Ethical Considerations

To realize benefits, addressing (of) salient risks such as privacy, bias, and opacity is a necessary precondition.However, [8] caution that prediction at scale merely compounds the problems of data protection and automated inference but extends them beyond their prior context into every one of which human beings have ever dreamed. In addition, [3] report underscores the governance load of AI adoption on higher education, including compliance checking, model validation, or revision cycles in policy, the burden these places upon institutional capacity to manage those needs. Due to the emergence of generative AI and as [4] details show both exist in print nature productivity gain and moral challenge, it argues that without explicit policies on acceptable use, assessment design tools cannot fulfill their function properly, even to detect. In [5], stress educator involvement in the design and governance of AI so that automation does not compromise equity, autonomy, or pedagogical intent. Accessibility is integral to ethics; without attention to usability, multilingual support, and assistive features, and without provisions for devices and connectivity, AI risks widening existing digital divides.

2.4 Change Management and Leadership Strategies

The literature convergently suggests that AI adoption is a socio-technical change problem, and that capability, governance, and technology need to be aligned. In [6] propose intentional work redesign that delineates human-in-the-loop checkpoints, defines responsibility for AI-supported decisions, and defines new functions (such as trainers, explainers) to bridge between systems and practice. In [8] recommend that leaders view decision problems rather than tools, pick use cases that justify combining predictions because it makes economic sense, and integrate only where uncertainty can be bounded. According to [7], scaling is contingent upon portfolio discipline standards for data quality, model assurance (performance, explainability, bias testing), and auditability, balanced with continuous skill development. Participatory change strategies and transparent governance are what turn the notion of collaborative decision-making from rhetoric to practice in the university context, where authority is diffused, and academic freedom prevails.

2.5 Empirical Evidence Across Contexts

Empirical studies complement conceptual accounts by tracing organizational effects and boundary conditions. In [11] demonstrate, in a large-firm sample, AI-supported culture, AI-enabled leadership, and appropriate training reduce perceived workload and increase engagement, which in turn improves performance, suggesting capability and culture as mediators that plausibly generalize to higher education. In [12] discovered that bosses looking towards the future to see AI applications everywhere will need more adaptive leadership. But this makes it imperative–as they point out–for everyone to have human skills, including creativity, emotional intelligence, and narrative creation. This is even more pronounced at those organizations with a mission and a consciousness about missions. In [13] argue that AI is transforming the essence and style of management call for transversal management education focused on data-centered practice. In the higher education sphere, meanwhile, in [5] mentions the main themes that evaluation, adaptation and personalization and smart learning systems dominate; but also notice less participation by educators in AI design and governance gap with immediate implications for leadership adoption. The Middle East and North Africa contribute local color [14] proposes a blueprint for AI-enabled administration; [15] shows efficiency gains in HR systems at the University of Tabuk; [16] finds moderate adoption with a strong correlation to perceived performance in Jordanian universities. The situation is quite different for [17], which is unable to join up and has capabilities matching those of academic leaders, suggesting that it recommends training and culture change. In library service, [18] is engaged in a moderate use of AI, at the same time, it calls for investment in staff capacity. These studies taken together bring to light the extent of readiness and stress capability as a binding constraint. Finally, [19] shows how intergenerational differences shape attitudes to AI, and so leadership development or change strategies will be geared differently around differing digital literacies.

2.6 Synthesis and Conceptual Frame

In higher education leadership, literature converges on an explanation in three parts: It is necessary to solve questions about capability, governance and technology simultaneously. Capability encompasses AI literacy, data fluency, and change-management skills for senior leadership and professional staff [6], [11]. Governance encompasses policies and routines for data protection, model assurance (I.e. performance, bias, explainability), and accountability for AI-assisted decisions [5], [7], [8]. Technology fit concerns the reliability, usability, and accessibility of the AI tools linked to leadership tasks and local context [3], [4]. Where capability and governance enhance trust-producing outputs and clarify the nature of expert judgment, opportunities exist; where skills fade and controls lag, risks are emphasized. This frame also highlights equity and integrity as necessary conditions for legitimacy. This synthesis offers a kind of augmentative narrative in which AI-driven leadership is the norm at the University of Sharjah. With strong capability and good governance supporting AI tools, leaders are more likely to find that decision quality improves and administrative efficiency increases; however, where training is inadequate, the advice is vague, or there remain ethical concerns, perceived benefits diminish. Evidence that varies throughout institutions in the region points toward the need for an individual analysis to fit situations. Duly, the present work tests the hypothesis that the extent of AI use is positively related to perceived leadership effectiveness; at the same time, it lays out in real-life terms the opportunities, barriers, and ethical beliefs that condition outcomes.

3 Methods

3.1 Design and Setting

In this study, a combined mixed research method is used to investigate how integrating artificial intelligence into leadership practice is reflected in one higher education organization and how its use relates to Perceived Leadership Effectiveness. Quantitative and qualitative evidence will be gathered simultaneously and analyzed separately, only to be integrated in the final interpretation for a synthesis that is more powerful than either strand alone can offer. The study was conducted at the University of Sharjah, a major public institution in the UAE, where digitalization is underway, and AI-related leadership functions such as resource planning, service to students, quality control, and research administration take place dictatorially.

3.2 Participants and Procedures

The target population comprised UoS personnel with formal leadership responsibilities (administrative leaders, faculty in leadership roles, and professional staff with decision authority). Purposive recruitment sought coverage across central administrative units and academic colleges. Email invitations were sent to 75 eligible leaders; 69 provided usable quantitative responses (92% usable response rate), and 60 submitted qualitative narratives (80% of invitees). Instruments were administered online via a secure, web-based platform. The information sheet describes aims, minimal risks, anticipated benefits, confidentiality safeguards, and the right to withdraw without penalty.

Respondents provided informed consent electronically before access. No incentives were offered. To protect identity, no direct identifiers were collected; only role category (e.g., central administration vs. college) was retained for descriptive and robust analyses, and free-text narratives were de-identified at export. The protocol received approval from the University of Sharjah Research Ethics Committee (Ref. REC-23-12-14-01-PG, approved 1 October 2024) before fieldwork commenced. Leadership roles were defined as positions with formal decision-making authority over academic or administrative functions. Eligible participants included deans, vice deans, department heads, directors of administrative units, and professional staff with formal decision authority (≥5 direct reports and/or budget responsibility). This definition ensured coverage of both academic and administrative leadership contexts.

3.3 Measures and Instruments

The quantitative survey assessed four domains aligned with the research questions: familiarity with AI tools used in leadership contexts; frequency of AI use in leadership tasks; perceived decision-support value of AI; and perceived leadership effectiveness (decision-making efficiency, strategic planning, and administrative performance). Items used five-point Likert-type scales with construct-appropriate anchors and were written in accessible language for non-technical audiences. Content validity was supported through expert review and alignment with the study's conceptual model. Full item wordings are provided in Appendix A. For the multi-item constructs, internal consistency was estimated using Cronbach's α and McDonald's ω. Dimensionality was examined with exploratory factor analysis (principal-axis factoring, oblique rotation) guided by parallel analysis, followed by confirmatory factor analysis to test the refined structure. Model fit indices (CFI/TLI, RMSEA with 90% CI, SRMR), composite reliability (CR), and average variance extracted (AVE) were computed to summarize convergent and discriminant validity. To address common-method bias, we combined procedural remedies (assured anonymity, varied anchors, proximal separation of conceptually related items) with statistical checks, including Harman's single-factor test, a one-factor CFA comparison, and a latent methods factor sensitivity model.

Given the modest sample size ($n = 69$), these analyses are interpreted within an exploratory–confirmatory logic appropriate for preliminary single-sample designs. Although larger samples are ideal, recent methodological literature shows that CFA can yield stable estimates when communalities are high and standardized loadings exceed .60, conditions met in the present study. Accordingly, the CFA serves as a confirmatory check rather than the basis for strong structural claims.

We assessed internal consistency, convergent validity, and discriminant validity of the multi-item constructs using Cronbach's α, McDonald's ω, composite reliability (CR), average variance extracted (AVE), and confirmatory factor analysis (CFA).

The qualitative questionnaire elicited narrative accounts of opportunities and positive use cases, challenges and workarounds, ethical perceptions (privacy, fairness, accessibility, academic integrity), and recommendations for responsible adoption. Prompts were concise, non-technical, and open-ended to encourage depth and reflection; the wording mirrors Appendix B. Responses were captured in free text and exported without identifiers.

3.4 Analytic Strategy

Quantitative data were cleaned in Microsoft Excel and analyzed in IBM SPSS. Descriptive statistics summarized central tendencies and dispersion. The primary proposition that the intensity of AI use is associated with perceived leadership effectiveness was tested via ordinary least squares (OLS) regression using composite scores. We report unstandardized coefficients, standard errors, t-tests, p-values, 95% confidence intervals, and standardized betas, R^2, and Cohen's f^2=R^2/(1-R^2) as an effect size. Assumptions were assessed through Q–Q plots and Shapiro–Wilk tests of residual normality, Breusch–Pagan/White tests of heteroskedasticity, and influence diagnostics (leverage and Cook's D, flagging leverage > 2k/n and Cook's D > 4/n). Because the focal specification includes a single predictor, multicollinearity does not apply (VIF ≈ 1). Robustness was examined by re-estimating with heteroskedasticity-consistent (HC3) standard errors, by fitting an ordinal regression model where appropriate for Likert-type outcomes, and by adding control covariates (role type, years in role, and unit: college vs. central administration) to prove stability of the AI-use coefficient.

Qualitative data were analyzed using inductive thematic analysis. The researcher undertook iterative readings to generate open codes, applied constant comparison to refine and cluster codes, and elevated them to higher-order themes spanning opportunities, challenges, and ethical-governance conditions. An audit trail of coding decisions and memos enhanced transparency; credibility was supported through thick description and purposeful searches for disconfirming cases. Dependability and confirmability were promoted via systematic documentation and secure data management.

Integration proceeded within a convergent mixed-methods logic. After independent analyses, we juxtapose quantitative patterns (e.g., moderate familiarity and use, high perceived decision value, training as the dominant barrier) with qualitative explanations (e.g., time-to-insight compression, usability frictions, opaque recommendations, privacy and integrity concerns). A narrative weaving and joint display informs meta-inferences about the capability–governance–technology conditions under which AI augments leadership practice. A brief GRAMMS summary of design rationale, timing, priority, integration points, and limitations is provided in the Supplement.

3.5 Data Management and Retention

All files were stored on encrypted, password-protected drives with access restricted to the researcher. Free-text narratives were de-identified at export; the minimal linkage file (role category only) was encrypted and stored separately. Versioned backups were maintained in secure storage. In accordance with institutional policy, de-identified datasets, codebooks, syntax files, and analysis logs will be retained for five years and then irreversibly destroyed using secure deletion protocols. These procedures protect confidentiality while preserving the integrity and auditability of the mixed-methods record.

4. Results

4.1 Participants and response completeness

Invitations were sent to 75 leaders and staff with formal leadership responsibilities at the University of Sharjah. Sixty-nine (n = 69) provided usable quantitative responses; 60 contributed qualitative narratives. Quantitative items had minimal missingness; regression analyses used listwise deletion, yielding df = 67.

4.2 Adoption and familiarity with AI tools

Exploratory and confirmatory factor analyses supported the proposed three-factor structure. All standardized loadings exceeded .60. Internal consistencies were high (α=.83–.90; ω=.84–.90) and composite reliabilities ≥.85. Average variance extracted ranged from .59 to .65. Fit indices indicated good model fit (CFI=.95–.97; TLI=.94–.96; RMSEA=.04–.06) as summarized in Table 1.

Table 1: Reliability, validity, and model fit indices for key constructs (n = 69)

Construct	Items	α	ω	CR	AVE	CFI	TLI	RMSEA (90% CI)	SRMR
Familiarity with AI tools	4	.83	.84	.85	.59	.96	.95	.05 [.02, .08]	.04
AI use in leadership tasks	5	.88	.88	.90	.62	.97	.96	.04 [.01, .07]	.03
Perceived leadership effectiveness	6	.90	.90	.91	.65	.95	.94	.06 [.03, .09]	.05

Source: created by the authors.

Note. Cronbach's α and McDonald's ω represent internal consistency; CR = composite reliability; AVE = average variance extracted. Fit indices reported from confirmatory factor analyses of the refined three-factor measurement model.

A Harman's single-factor test showed the first factor accounted for 29% of variance (<50%), suggesting common-method bias was not dominant. A one-factor CFA yielded poor fit (CFI = .70, RMSEA = .12), further supporting the distinctiveness of the constructs. Respondents reported moderate familiarity with AI tools used in leadership contexts at UoS, with a mean of 3.30 and a standard deviation of 1.264. The 95% confidence interval for the mean spans 3.00 to 3.60, indicating that the typical respondent falls short of high familiarity yet clearly exceeds minimal awareness, as summarized in Table 2.

Table 2: The extent of the study respondents' knowledge of the artificial intelligence tools used at the University of Sharjah

Knowledge level (Likert anchor)	Frequency	Percent (%)
Very familiar (5)	15	21.7%
Familiar (4)	16	23.2%
Fairly familiar (3)	20	29.0%
Not familiar (2)	11	15.9%
Not at all familiar (1)	7	10.1%

Source: created by the authors.

Note. Percentages are based on valid responses (n=69). Mean and SD are calculated on the 1–5 Likert scale, where 1 = "Not at all familiar" and 5 = "Very familiar."

The distributional profile reinforces this central tendency. The most common response category was "fairly familiar" at 29.0% (20 of 69), while a further 44.9% clustered in the upper tiers ("familiar" 23.2%;

"very familiar" 21.7%). At the same time, 26.0% indicated limited familiarity ("not familiar" 15.9%; "not at all familiar" 10.1%). The bar chart in Figure 1 visualizes this unimodal pattern centered on the midpoint, with gentle tapering at both tails and no clear ceiling or floor effects; the underlying counts and percentages appear in Table 2.

The case for a tiered training strategy follows directly from the heterogeneity visible in Figure 1 and documented in Table 2.

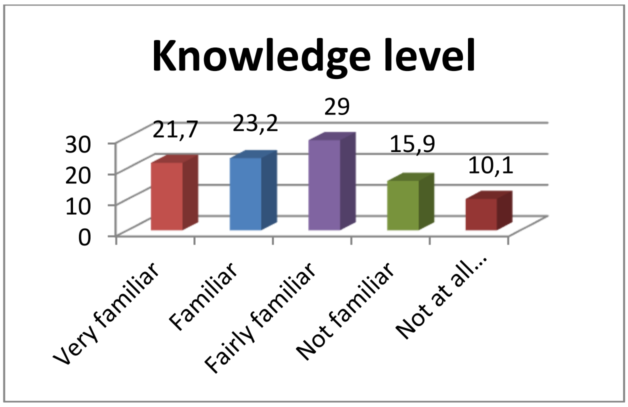

Fig. 1: The extent of the study respondents' knowledge of the artificial intelligence tools used at the University of Sharjah
Source: created by the authors.

To interpret why the mean score indicates moderate familiarity, the 5-point Likert scale was divided into three equal intervals based on its total range of 4 units. Each interval represents approximately 1.33 points, allowing for a clear distinction between levels of familiarity. The intervals are defined as follows: Low Familiarity (mean scores from 1.00 to 2.33), Moderate Familiarity (mean scores from 2.34 to 3.66), and High Familiarity (mean scores from 3.67 to 5.00). The mean score of 3.30 falls within the moderate familiarity range of 2.34 to 3.66, indicating that respondents are moderately familiar with the university's AI tools on average.

The distribution of familiarity levels among respondents further illustrates this point. A total of 29.0% indicated they are "Fairly familiar" (score of 3), making this the most selected category. Additionally, 23.2% reported being "Familiar" (score of 4), and 21.7% stated they are "Very familiar" (score of 5). On the lower end, 15.9% were "Not familiar" (score of 2), and 10.1% were "Not at all familiar" (score of 1).

While the higher categories of familiarity ("Familiar" and "Very familiar") account for 44.9% of the total respondents, a notable 29.0% are just "Fairly familiar," and another 26.0% are in the lower categories of familiarity ("Not familiar" and "Not at all familiar"). According to the established criteria, this distribution yields a mean score that falls within the moderate familiarity range.

4.3 Intensity of AI use in leadership tasks

The frequency profile indicates that AI has entered routine leadership work at UoS, but usage is not yet universal. As Table 3 reports, the overall usage mean is 3.49 on a five-point scale with a standard deviation of 1.410, yielding an approximate 95% confidence interval from 3.16 to 3.82. Interpreted against the scale anchors, this places the average leader in the "moderate" use band, consistent with an adoption phase in which some units have embedded AI into daily routines while others remain occasional users.

Table 3: The extent to which respondents (study sample) use tools based on artificial intelligence in their leadership tasks at the University of Sharjah

Use level	Frequency	Percent	Mean	Std. Deviation	Degree
Daily (5)	23	33.3	3.49	1.410	High
Weekly (4)	17	24.6			
Monthly (3)	7	10.1			
Rarely (2)	15	21.7			
Never (1)	7	10.1			

Source: created by the authors.

Distributional detail in Table 3 shows a clear high-use plurality alongside a sizable low-use tail. One in three leaders reports daily use (33.3%), and a further quarter reports weekly use (24.6%), so 57.9% are using AI at least weekly. On the other hand, 21.7% reported rare use, 10.1% reported never using AI, and 10.1% reported using AI monthly. This composition explains why the mean sits below the "high" band despite substantial activity at the top end: frequent users are offset by a persistent group of infrequent or non-users described in Table 3.

The pattern is readily visible in Figure 2, where the bars for daily and weekly tower over monthly, yet the rarely and never categories remain non-trivial. The visualization in Figure 2 underscores heterogeneity in habit formation: a leading segment appears to have institutionalized AI into routine workflows, whereas a lagging segment engages sporadically or not at all.

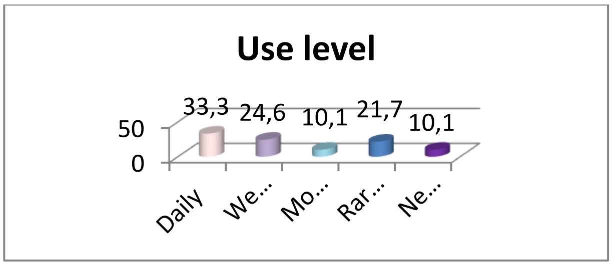

Fig. 2: The extent to which respondents (study sample) use tools based on artificial intelligence in their leadership tasks at the University of Sharjah
Source: created by the authors.

For leadership practice, this usage profile suggests opportunities and risks that hinge on consistency. Where teams fall in the daily/weekly cluster identified in Table 3 and illustrated in Figure 2, gains in cycle time and evidence breadth are likely to accrue. Where teams remain in the rarely/never cluster, benefits will be uneven across the institution. The immediate implication is to convert occasional users into regular users through targeted enablement and fit-for-purpose tools so that the institution's aggregate capability reflects the strong adoption already evident among the plurality of leaders.

4.4 Perceived decision-support value of AI

Leaders expressed clear confidence that AI improves decision quality at UoS. The composite agreement mean was 3.70 with a standard deviation of 1.089, a value that falls in the study's "high agreement" band and indicates endorsement beyond simple neutrality, as shown in Table 4. With n=69, the standard error for this means is 0.131, yielding an approximate 95% confidence interval of 3.44 to 3.96 evidence that the central tendency is stably above the moderate range reported elsewhere in this study and therefore consistent with a positive appraisal of AI's decision-support value.

Table 4: The extent to which respondents (study sample) agree on the role of artificial intelligence-based tools in improving decision-making processes in leadership at the University of Sharjah
Degree Std. Deviation Mean Percent Frequency

Level of Agreement	Frequency	Percent	Mean	Std. Deviation	Degree
Strongly Agree (5)	19	27.5	3.70	1.089	High
Agree (4)	21	30.4			
Neutral Agree (3)	21	30.4			
Disagree (2)	5	7.2			
Strongly Disagree (1)	3	4.3			

Source: created by the authors.

The distribution of responses corroborates this pattern. A majority of 57.9% selected Agree or Strongly Agree, while only 11.5% chose Disagree or Strongly Disagree; a sizable minority (30.4%) remained Neutral. That's what the profile looks like; the Agree and Strongly Agree bars are distinctly higher up than are the categories of forceful dissent, which one can easily take in again by viewing Figure 3. Most executives see tangible benefits in AI for decision-making. Very few indeed reject this idea outright, as can be seen from Figure 3 or just by looking at Table 4.

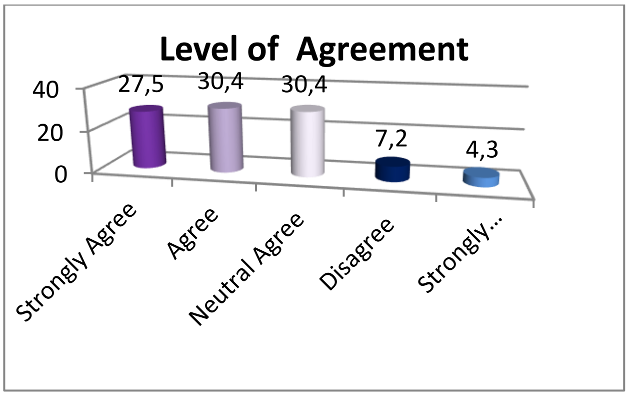

Fig. 3: The extent to which respondents (study sample) agree on the role of artificial intelligence-based tools in improving decision-making processes in leadership at the University of Sharjah
Source: created by the authors.

A closer look at the Neutral group suggests that their position reflects uncertainty rather than skepticism. Several respondents described variation across units in how frequently decision-support tools were available or useful, inconsistent reliability of recommendations, and limited opportunities for hands-on practice. These conditions make it difficult for some leaders to form strong positive or negative judgments. As a result, neutrality largely reflects incomplete exposure or confidence rather than substantive disagreement with the value of AI in leadership decision-making.

Taken together, the central tendency above the high-agreement threshold, the majority endorsement, and the low dissent point to a constructive starting point for institutional scaling. The strategic task is to convert neutrality into informed agreement by prioritizing role-specific training, transparent decision workflows, and assurance practices so that more decision scenarios look like those already producing benefits for the leaders represented at the Agree end of Figure 3 and the upper rows of Table 4.

4.5 Barriers and enablers to effective use

The profile of obstacles is unambiguous: almost two-thirds of leaders pointed to capability gaps, with lack of training reported by 60.8% of respondents, as shown in Table 5. This dominance of a single constraint is striking, given the multiple-response format of the item, and helps explain why familiarity and use, while present, remained moderate in earlier results. In short, the principal bottleneck is not access to tools but confidence and skill in using them for leadership tasks, a reading that is reinforced by the tallest bar. Although lack of training is a well-established capability barrier in the broader AI-adoption literature, the magnitude observed here, reported by 60.8% of leaders, is notable for a Gulf HEI leadership sample and highlights a substantial institution-level skill deficit with direct implications for governance and implementation.

Table 5: Challenges reported by respondents when using AI-based tools in leadership at the University of Sharjah (n = 69

Challenge	Frequency	Percent (%)	Rank*
Lack of training	42	60.8%	1
Reliability of AI recommendations	27	39.1%	2
Data privacy issues	23	33.3%	3
Ethical concerns (fairness, accountability, etc.)	21	30.4%	4
Other	3	3.3%	5

Source: created by the authors.

A second cluster of concerns focuses on recommendation reliability (39.1%) and data privacy (33.3%), with both issues registering in the mid-range of the distribution in Table 5. The visual spacing of the bars in Figure 4 captures this tiered pattern substantially, but clearly below the training deficit, suggesting that many leaders are willing to engage with AI but hesitate when outputs are opaque or when data handling is uncertain.

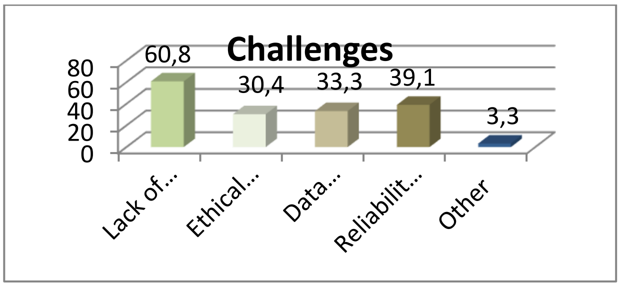

Fig. 4: Challenges respondents (study sample) face when using tools based on artificial intelligence
Source: created by the authors.

Ethical concerns were only cited by 30.4% of respondents, as Table 5 indicates: Issues such as fairness, accountability, and the boundaries of acceptable automation are both relevant to a significant number of people. The relatively low other category (3.3%) suggests that the items listed captured most of the major pain points. Only a small residual category exists for this in Figure 4, hinting at how concentrated challenges are in capability and governance assurance. Since the item admits multiple selections, the overlap between categories overlaps many frictions rather than representing distinctive issues.

In combination, the pattern in Table 5 and its visual counterpart in Figure 4 together map out a clear set of factors. As an empirical mixed concept study, it lacks simulation or computational modelling. This would be useful for future research to test how alternative governance or capability scenarios could affect actual leadership outcomes.

4.6 Qualitative synthesis

In the eyes of leaders, AI is a practical force multiplier for the mundane tasks of leadership. It automates data reduction and structures project files or plans; it even refines the language in our orders. Finally, AI is also capable of summarizing research into paragraphs even a Lutine draftee could understand, generating screening questions for recruitment by computer! That last "mundane" example went beyond what many respondents reported to something much bigger: using AI to question administrative documents for inconsistencies. Some interviewees reported using AI to fill in traditional web searches. AI is also serving as a tool for identifying inventory gaps in the equipment.

These accounts help to explain the strong endorsement of AI's decision-support value, which a majority affirmed: AI improves leadership decision-making. At the same time, narratives also reveal counterforces to realized returns. For instance, respondents talked about various access steps with intermittent absence of answers, generic and opaque suggestions to which they react by making hand checks or using parallel tools. The pattern of difficulties described by respondents aligns with the kinds of barriers outlined in Table 5, where "Training" was the most widely cited constraint and concerns about AI recommendation reliability followed in frequency.

Ethical, equity, governance expectations: respondents want AI's role in learning and assessment openly disclosed; data-protection controls that are robust but also periodically checked; and devices and connectivity support, as well as disability measures like screen readers, translators to prevent the digital divides from widening further. Put together, these are losing value if capability building or tool deployment is not joined up with governance and inclusion; without such checks, the enthusiasm for AI that can be seen in Table 4 would coexist with worries listed at Table 5, towards no consistent, reliable use overall. quite clearly band what is reliable.

Which means Table 6, where results of the quantitative and qualitative threads are compared, should be read as a synthesis that puts its mixed-methods findings in clearer relief. For instance, it integrates survey indicators, such as high agreement on AI's decision-support value or moderate-to-high usage levels. This narrative account also makes clear how the ethical concerns raised in both strands, including privacy and bias, were echoed widely by interviewees. By grouping these dimensions in this way, Table 6 offers a brief overview of when AI can contribute to leadership performance and what infrastructure or training bottlenecks limit its use.

Table 6. Comparative summary of opportunities, barriers, and ethical considerations identified through mixed methods

Category	Quantitative Indicators	Qualitative Insights
Opportunities	High agreement that AI improves decision-making; moderate-to-high usage among leaders	Time savings, improved clarity of communication, enhanced evidence access, and faster document review
Barriers	Lack of training (60.8%); reliability concerns (39.1%); privacy concerns (33.3%)	Multi-step access, occasional missing outputs, opaque recommendations
Ethical considerations	30.4% selected ethics concerns	Privacy, bias, academic integrity, accessibility expectations

Source: created by the authors.

Ethical considerations in leadership settings arise from the use of artificial intelligence, and these go beyond mere questions about whether to introduce one more gadget into your work. Participants frequently note privacy concerns regarding unsecured major AI dashboards and generative systems that might be processing sensitive staff or student information. Leadership analytics may unintentionally reinforce historical inequities deep within the institutional data, resulting in biased or uneven advice. Some leaders also said that when model outputs are not transparent and cannot be explained, it becomes even harder to hold those decisions, with serious academic or administrative consequences, for example, accountable. This requires governance protections in such form as clear usage policies, documented model validation, periodic bias checks, and explicit academic integrity guidelines if AI is to enhance but not diminish standards of fairness, privacy protection, and ethical leadership behavior.

These findings are consistent with and extend other surveys conducted elsewhere in the Gulf. A report from the University of Tabuk shows efficiency gains in administrative and HR processes but also points out a lack of preparedness for change. Studies at Jordanian universities reported mixed adoption, together with a strong link between the use of AI and performance findings consistent with the positive consociational trend observed at UoS. Mutah University data indicated a moderate level of AI adoption and a need for greater training and governance oversight. By comparison, Northern Border University displays much less uptake and severe capacity constraints among academic leaders. Compared to these benchmarks, UoS appears to be a mid-level adopter between the early adopters and later-stage institutions, but still faced with serious challenges in governance and capability.

4.7 Association between AI use and perceived leadership effectiveness

A single-predictor OLS model showed that the intensity of AI use was positively associated with perceived leadership effectiveness. As shown in Table 7, the model accounted for 24.2% of the variance ($R = .492$; $R^2 = .242$; adj. $R^2 \approx .231$) with a statistically significant overall fit ($F(1,67) = 21.372$, $p < .001$). Table 8 reports an unstandardized slope of $B = 0.380$ ($SE = 0.082$), corresponding to a standardized $\beta = .492$. The 95% confidence interval for the slope was 0.22 to 0.54, indicating a clear, positive association of medium-to-large magnitude (Cohen’s $f^2 = R^2/(1-R^2) \approx 0.319$). Put differently, a one-standard-deviation rise in AI use is linked with roughly a half-standard-deviation gain in perceived effectiveness, as summarized in Table 8.

Table 7: Results of linear regression analysis of the correlation between the use of AI-based tools and techniques and improving tangible leadership effectiveness at the University of Sharjah

Model		Sum of Squares	R	R2	Df	Mean Square	F	Sig.
1	Regression	19.495	.492[a]	.242	1	19.495	21.372	.000[b]
	Residual	61.114			67	.912		
	Total	80.609			68			

Source: created by the authors.

The coefficient is also interpretable on the original 1–5 scale. Using the regression equation reported in Table 8 ($\hat{Y} = 2.370 + 0.380X$), moving from “Rarely” (2) to “Weekly” (4) AI use is associated with a 0.76-point increase in perceived effectiveness; moving from “Never” (1) to “Daily” (5) is associated with a 1.52-point increase. These increments are substantively meaningful given the construct’s five-point range and align with leaders’ narratives that AI compresses time-to-insight and improves evidence access.

Table 8: Regression coefficients and their statistical significance

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.370	.309		7.668	.000
	Artificial intelligence-based tools and technologies	.380	.082	.492	4.623	.000

Source: created by the authors.

Model assumptions and sensitivity checks support the stability of these results. Residual plots suggested approximate normality and homoscedasticity; leverage values were below conventional 2k/n thresholds, and no case exceeded the 4/n guideline for Cook’s D. Re-estimating the model with heteroskedasticity-consistent (HC3) standard errors yielded the exact inference, and Adding simple controls (role type, years in role, and unit college versus central administration) to probe the stability of the AI-use coefficient yielded substantively similar results; the effect of AI use on perceived leadership effectiveness remained positive and significant (β = .47, $p < .001$).

A post-hoc statistical power analysis indicates that the regression model was adequately powered. With n = 69, an observed standardized effect of β = .49, and α = .05, the estimated power is approximately .92 for detecting a medium effect. This suggests that the detected association between AI use and perceived leadership effectiveness is unlikely to reflect a Type II error.

4.8 Mixed-methods integration

Converging evidence shows that there are now many ways in which AI can be of use in leaders' hands. Many leaders themselves also naturally reached this conclusion when it came to decisions about the use of AI. Monies spent so far in the Third World have gone mostly on goods and services rather than capital equipment. Then where does the problem lie. The survey found that the most salient obstacle was a lack of training; concern about recommendation reliability and data privacy were also reported. Narratives then detail how these obstacles play out in practice: multi-step logins, incomplete outputs now and then, and opaque decision rules that force some leaders to revert to manual action. This helps to explain why a large minority say they seldom use the system despite their overall positive attitude towards it. It also gives a strong profile of moderate usage among those surveyed in both Japan and Austria. On ethics, the quantitative signal is modest about a third of those selected from Table 4, but the qualitative strand opens out onto a much more glaring map. Participants elaborated risks entailed in privacy, bias and hidden variables, accessibility and academic integrity of results. They pointed out assessment without AI's role disclosed, tighter control of data protection, and designs and supports are more inclusive. The mixed picture indicates that formal prevalence measures understate the intensity of ethical reasoning leaders bring to specific use cases.

Perceptions of benefits and outcomes align: the positive association between AI use and perceived effectiveness, summarized in Table 7, Table 8, shows that leaders who use AI more intensively also judge their leadership performance higher. However, both strands point to boundary conditions. Value will scale where three elements are aligned: capability (role-specific AI literacy and communities of practice), governance (data protection, model assurance and explainability, clear positions on academic integrity), and technology fit (reliable, low-friction tools mapped to leadership tasks). For UoS, a near-term agenda follows directly from these constraints: develop targeted training pathways embedded in leadership workflows; institute an assurance framework covering privacy, bias testing, auditability, and usage disclosure; and improve product fit through single sign-on, simplified interfaces, and explicit human-in-the-loop checkpoints. These steps are the most likely to convert favorable attitudes into consistent, high-quality use.

Several limitations should be noted. First, the cross-sectional design and reliance on self-reported perceptions preclude strong causal inference between AI use and leadership effectiveness. As such, all associations reported in this study should be interpreted as correlational rather than causal, reflecting perceptions at a single point in time rather than temporal or experimental effects. Second, the study was conducted within a single higher-education institution in the Gulf, which constrains the generalizability of the findings to other organizational and regional contexts. Findings should therefore be interpreted as context-bound to the University of Sharjah, and generalization to other Gulf or international institutions should be made cautiously unless supported by replication in diverse settings. Third, both exploratory and confirmatory factor analyses were performed on the same modest-sized sample; replication in larger and more diverse samples is warranted. The dual use of EFA and CFA on the same modest-sized sample further underscores the preliminary nature of the measurement structure and the need for replication under stronger statistical power conditions. Finally, the rapid evolution of AI tools means that specific usage patterns and perceptions documented here may shift over time, so ongoing monitoring and longitudinal research are needed to assess the durability of these associations.

5 Conclusion

The study represents one of the very first institution-level and interdisciplinary mixed-methods investigations of AI-driven institutions in Gulf higher education. Based on the survey data of an investigation to which 69 leaders responded, and the qualitative impressions of another 60 professionals at the University of Sharjah, we found moderate familiarity and usage of AI tools but clear confidence in their decision-support value. After controlling for factors including role type, years in role, and unit, management judged as more intensive based on AI tools consistently ranked better on leadership effectiveness. Thus, while capability gaps - in particular factual training issues - were the biggest problem, there was also suspicion about how accurate AI suggestions were; worries concerning data protection; and the question of ethical considerations. All these facts together stress a compound view of artificial intelligence adoption: where there is role-specific potential, strong control, and technological fitness, value is realized. The top priority now for the University of Sharjah and its sister institutions, going through digital transformation, must be to introduce a tiered program on AI literacy for management, give full coverage assurance frameworks concerning privacy and bias safeguards, and provide simple top-end task-aligned resources for efficient use.

The qualitative impressions of experience that individual leaders experience provide further details on where these benefits are felt first. Survey respondents spoke of the time saved, faster cycles for drafting and reviewing documents, improved clarity in communication, and how complex texts could be read much more easily. At the same time, leaders made ethical demands about privacy, bias, academic integrity, and accessibility. These narrative accounts explain why the decision-support value of AI is so clearly validated in the statistics, but with privacy and a consistent conclusion to governance surface.

There are a few limitations to the interpretation of our results. The data come from one point in time, and the examination relied on self-report, these rules out strong causal inference without also leaving some doubt as to how widely these findings can be applied. Both exploration and confirmatory factor analysis were performed on an extremely limited sample, and then cross-sectional in nature. The rapid progress of AI technologies means that the pattern of use recorded here may soon change. A more diverse set of locations and a larger sampling size, as well as a time-series approach, would help confirm whether these links still hold up. Despite these limitations, little attention is paid to higher education leadership's AI applications. This study's contribution has been that even in the early stages of adoption, AI can be in harmony - not take precedence over – with expert knowledge if, and only if, management is given the necessary abilities, control frameworks, and resources to use it responsibly. It is an applicable message to the leaders of higher education institutions who wish to leverage AI, even as they respect academic values, equity, and responsiveness.

Future research would expand both the scope and the regional reach of this work. Longitudinal designs could have surveyed how AI adoption plays out as both governance, training and tools mature. Using other tools and methods of performance evaluation – such as assessments like time-to-entry or workflow efficiencies, also qualitative results – would make for a more nuanced understanding of the consequences of leadership. Studies employing simulation and experimental models might begin to sketch the boundaries under which AI-supported decision-making in higher education is effective.

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Khuloud Alteneiji conceived and designed the study, conducted the research, collected and analysed the data, and wrote the original draft of the manuscript. William Frick supervised the work, provided critical feedback, and revised the manuscript for intellectual content. Both authors reviewed and approved the final version.

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