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DATA QUALITY AND THE TRUST–INTERPRETABILITY PARADOX: TOWARD A MID-RANGE FRAMEWORK FOR AI ADOPTION IN EDUCATIONAL INFORMATION SYSTEMS

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ABSTRACT

Aim/Purpose	This study examines limitations in existing AI adoption models in education, which often treat data quality, interpretability, trust, and organizational factors as independent elements. This separation may lead to incomplete explanations of AI implementation outcomes in educational information systems.
Background	This study introduces and empirically examines the Data–Knowledge Alignment Theory for Educational Information Systems (DKAT-EIS). The framework draws on insights from Information Systems, Knowledge Management, and Explainable Artificial Intelligence to explore how data quality, knowledge interpretability, and trust relate to AI adoption in universities. DKAT-EIS is presented as a context-specific analytical framework that offers initial insights into these relationships in higher education.
Methodology	A quantitative survey was conducted with 1,150 respondents (students, faculty, and staff) at Jazan University in Saudi Arabia. Cross-sectional data were analyzed using Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA) to test the proposed relationships.

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Contribution	The study proposes and examines the DKAT-EIS framework to better understand how data and knowledge processes influence AI adoption in higher education. The findings highlight the role of data quality in supporting knowledge interpretability and indicate that the relationships between interpretability, trust, and adoption may be more complex than suggested in traditional technology adoption models. Given the single-institution and cross-sectional design, the findings should be interpreted as context-specific evidence that encourages further validation in other settings.
Findings	Data quality significantly predicts knowledge interpretability. However, interpretability does not significantly influence ethical trust, and trust does not directly predict AI adoption success. This pattern suggests a “trust–interpretability paradox.” In addition, organizational readiness does not significantly moderate the relationships in the model.
Recommendations for Practitioners	Educational institutions should prioritize data governance and data quality when implementing AI systems. Improving system transparency alone may not build trust; organizations should also address ethical, organizational, and cultural factors that strengthen user confidence.
Recommendations for Researchers	Future studies should examine additional factors, such as fairness perceptions, digital culture, and institutional context, that may explain the gap between interpretability and trust. Further testing of the DKAT-EIS framework across different universities and regions is recommended.
Impact on Society	The findings suggest that responsible AI adoption in higher education requires a balanced socio-technical approach that combines strong data foundations with attention to ethical and organizational factors that foster trust.
Future Research	Future research should include longitudinal studies, cross-institutional validation, and qualitative investigations to better understand how contextual factors influence AI adoption, trust, and interpretability.
Keywords	artificial intelligence adoption, data quality, ethical trust, knowledge interpretability, organizational readiness, structural equation modeling

INTRODUCTION

Higher education has undergone a profound transformation driven by the rapid diffusion of artificial intelligence (AI), big data, and advanced analytics, reshaping how institutions collect, analyze, and use data for decision-making. Contemporary universities generate vast volumes of data through learning management systems, student information platforms, assessment tools, digital libraries, and administrative workflows (Habib et al., 2021). Despite this abundance, a persistent gap remains between data availability and its meaningful use, as many institutions struggle to convert raw data into actionable knowledge (Räsänen et al., 2024). This disconnect constrains the effectiveness of educational information systems and limits the development of data-driven instruction, evidence-based management, and personalized learning experiences.

The growing adoption of AI-driven educational systems, such as predictive analytics, adaptive learning platforms, and automated decision-support tools, has intensified the need for accurate, interpretable, and high-quality data (Alhubaishy & Aljuhani, 2021; Lytras et al., 2024).

These systems depend on the alignment between data inputs and the knowledge outputs they generate to produce reliable insights that can guide academic and administrative decision-making (Ma-

hamad et al., 2025; Verma & Singhal, 2024). In Saudi Arabia, universities are implementing AI-enabled and data-driven systems to enhance student outcomes and institutional performance (Lytras et al., 2024). However, as noted by (Alenezi & Akour, 2023), many institutions experience a misalignment between the data collected and the knowledge produced by these systems. Such misalignment risks biased recommendations, inaccurate predictions, and outcomes that conflict with educational objectives, underscoring the need for a structured theoretical framework to guide effective AI adoption in higher education.

This study introduces the Data–Knowledge Alignment Theory for Educational Information Systems (DKAT-EIS) as a mid-range framework (Corley & Gioia, 2011) that integrates constructs from established models, including the IS Success Model, TAM/UTAUT, Knowledge Management Theory, and Explainable AI (XAI) principles, into a single explanatory structure, proposing that AI adoption success (AS) in education depends on the alignment between data inputs and interpretable knowledge outputs, offering a more comprehensive explanation of AS than any individual predecessor model.

Educational settings present challenges that differ fundamentally from those encountered in commercial AI applications. The interpretation, trust, and use of AI-generated insights are shaped by institutional culture, pedagogical norms, academic governance, and variations in faculty and staff digital literacy (Choi et al., 2023; Verboom et al., 2025; Verma & Singhal, 2024). Traditional technology adoption models provide only partial explanations of these dynamics. For example, the Technology Acceptance Model (TAM) explains behavioral intention through perceived usefulness and ease of use (Venkatesh & Davis, 2000). Yet, it neglects data quality, interpretability of AI outputs, and ethical trust in decision-making. Similarly, the DeLone and McLean IS Success Model (DeLone & McLean, 2003)(Vuckovic et al., 2023) emphasizes system and information quality but offers limited insight into how AI-generated knowledge is understood, trusted, and applied within complex educational environments (Dimitriadou & Lanitis, 2023; Khan et al., 2025). Although UTAUT incorporates social influence and facilitating conditions (Venkatesh et al., 2003)(Al-Emran & Griffy-Brown, 2023), it does not address the ethical and cognitive dimensions of AI-derived knowledge.

Recent studies show that AI is reshaping knowledge creation, dissemination, and professional roles: (Xing et al., 2026) highlight curriculum and pedagogical shifts in LIS education, with risks of role alienation and dehumanized learning, while (Call et al., 2026) identify the “AI-specific Matthew Effect,” where high performers leverage AI to increase value creation gaps. These insights extend traditional knowledge management theories (Nonaka et al., 1996) by revealing AI-specific cognitive, ethical, and social challenges in higher education, particularly regarding interpretability and trust.

DKAT-EIS addresses these gaps by positioning data-to-knowledge alignment as the central mechanism influencing AI adoption and effectiveness in higher education. The theory identifies four inter-related constructs. First, data quality (DQ) ensures that data are accurate, timely, and relevant. Second, knowledge interpretability (KI) emphasizes the clarity, usability, and comprehensibility of AI-generated insights. Third, ethical trust (ET) captures the extent to which faculty, administrators, and staff trust and rely on AI outputs in decision-making. Fourth, organizational readiness (OR) reflects institutional capacity, including infrastructure, skills, governance, and policies, to support AI adoption. Together, these constructs form a socio-technical framework that recognizes the dynamic interplay between technological capabilities, human cognition, and organizational context, highlighting that even highly advanced AI systems may fail if their outputs are not interpretable, trusted, or supported.

The research problem guiding this study is therefore clear: although higher education institutions implement AI-driven information systems, many fail to realize their full potential due to misalignment between data inputs, AI-generated knowledge, user interpretation, and organizational support. This misalignment undermines system adoption, erodes trust, complicates decision-making, and limits educational impact. Accordingly, the central research question is the following:

What are the effects of the alignment between educational data and AI-generated knowledge on educational information systems?

Sub-questions:

- *How does this alignment affect system adoption?*
- *How does this alignment affect user trust?*
- *How does this alignment affect system success?*

To address this question, the study pursues several objectives. First, it identifies the key data- and knowledge-related factors shaping AI adoption in higher education. Second, it examines how AI-generated insights are interpreted and integrated into administrative, instructional, and learning processes. Third, it investigates the role of ethical trust in user acceptance, particularly in contexts where AI-informed decisions carry academic and administrative consequences. Fourth, it explores how organizational readiness and governance structures moderate the effects of data and knowledge processes on system outcomes. Finally, the study develops and tests an integrated model grounded in data-to-knowledge alignment to explain adoption intention, trust, and system effectiveness.

This research examines this question empirically at Jazan University, a large public institution in Saudi Arabia, undergoing rapid digital transformation as part of the national Vision 2030 initiative. While the study is conducted in a single context, the core constructs (data quality, knowledge interpretability, ethical trust, and organizational readiness) reflect challenges common to higher education institutions globally.

DKAT-EIS represents a proposed theoretical extension as a mid-range theory that synthesizes established frameworks into a unified, holistic explanation of AI adoption in education. Although empirically examined at Jazan University (a representative case of rapid digital transformation aligned with Saudi Arabia's Vision 2030), the theory addresses universal challenges. The core constructs (DQ, KI, ET, and OR) are foundational to AI integration across educational contexts, positioning DKAT-EIS as a potentially portable diagnostic framework for researchers, policymakers, and institutional leaders worldwide.

LITERATURE REVIEW

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The integration of AI into educational information systems has transformed how universities collect, process, and use data for teaching, learning, and decision-making (Marengo et al., 2024). Although AI promises efficiency, predictive accuracy, and personalization, its effectiveness depends on the alignment of data quality, knowledge generation, ethical considerations, and organizational support.

Existing adoption models, such as TAM and UTAUT, explain perceptions of usefulness and ease of use (Venkatesh & Davis, 2000; Venkatesh et al., 2003) but largely overlook the roles of DQ, KI, and ET in AI-driven systems. Similarly, the DeLone and McLean IS Success Model emphasizes system and information quality while giving limited attention to interpretability and ethical implications of AI-based decision-making (DeLone & McLean, 2003). To address these gaps, this study proposes DKAT-EIS, which integrates DQ, KI, ET, OR, and AS into a unified framework

Data Quality (DQ)

DQ is a core determinant of information system success. DQ reflects data accuracy, completeness, consistency, and timeliness, ensuring reliable inputs for AI-driven predictions and recommendations (Liu et al., 2016; Sinha et al., 2025). Completeness guarantees that no important information is missing, consistency reduces contradictions within datasets, timeliness ensures that information is relevant when needed, and accuracy reflects real-world conditions without error. The Information Systems Success Model (ISSM), which asserts that high-quality information is a crucial factor in determining user satisfaction and system success, supports the theoretical applicability of DQ (DeLone &

McLean, 2003; Vuckovic et al., 2023). Because algorithms depend on clean, structured inputs to produce accurate predictions and recommendations, DQ is important in AI-driven contexts (Bangad et al., 2024; Elouataoui, 2024).

Poor DQ has a negative impact on user trust and the KI of AI-generated insights, according to empirical research. For instance, learning analytics systems are only useful when student data is accurate and comprehensive, according to McCarthy et al. (2025). Similarly, Fu et al. (2024) emphasized that in higher education information systems, user satisfaction and adoption are predicted by information timeliness and reliability. Accordingly, DQ is conceptualized as an antecedent of KI in DKAT-EIS.

In light of this theoretical and empirical basis, the study suggests:

H1: Higher data quality positively influences knowledge/insight interpretability in AI-based educational information systems.

Despite the established importance of DQ across information systems research, existing models treat it as an isolated technical attribute rather than an antecedent to interpretability in AI contexts. This gap motivates H1 in DKAT-EIS, which positions DQ as foundational to KI—a relationship that prior frameworks have not theorized or tested in educational AI settings.

Knowledge/Insight Interpretability (KI)

KI refers to the extent to which AI-generated outputs are understandable and actionable for users. KI is crucial in educational settings because it establishes whether administrators and teachers can convert algorithmic predictions into well-informed choices (Chitti et al., 2020; Nnadi et al., 2024; Y. Wang, 2021). Knowledge management theory, specifically Nonaka and Takeuchi's SECI model, which highlights the transformation of implicit and explicit knowledge into actionable forms, provides the theoretical foundation for this construct (Nonaka et al., 1996).

Research on Explainable AI (XAI) emphasizes the significance of KI even more. AI outputs that lack transparency may be accurate yet practically unusable (Hassija et al., 2024; Kalasampath et al., 2025; Mahto, 2024). Poor KI in educational information systems can lead to misunderstandings, misuse of forecasts, and a decline in trust, all of which can lower adoption (X. Li et al., 2022; Mathew et al., 2025). Xing et al. (2026) extend this concern by identifying “role alienation” as a risk when AI systems lack interpretability, leading users to become mere “system operators” rather than informed decision-makers, thereby eroding reflective learning and professional judgment. On the other hand, interpretable AI outputs close the gap between data and useful knowledge by boosting user confidence and enabling informed decision-making. Thus, this research proposes the following hypothesis that links interpretability to user confidence and informed action:

H2: Greater knowledge/insight interpretability positively affects ethical trust in AI-based educational information systems.

While XAI research assumes that interpretability fosters trust, this relationship has been tested in educational contexts. The existing literature documents the consequences of poor KI but does not explain whether interpretability alone is sufficient to build ethical trust among diverse educational stakeholders. This theoretical gap underpins H2 in DKAT-EIS, which explicitly models the KI→ET pathway for empirical testing.

Ethical Trust (ET)

ET reflects users' perceptions of the fairness, transparency, and reliability of AI systems. In educational environments, factors such as algorithmic bias, data privacy, and adherence to ethical standards influence trust, in addition to system performance (X. Li et al., 2022; Mathew et al., 2025). While low trust can lead to the rejection of otherwise technically sound systems, high ET promotes adoption and efficient use.

Theoretically, socio-technical systems theory and TAM/UTAUT frameworks serve as the foundation for ET. According to TAM, behavioral intention is driven by perceptions of usefulness and ease of use (Venkatesh & Davis, 2000). However, in AI contexts, trust becomes an additional crucial driver, especially when algorithmic decisions impact academic outcomes. Technology adoption depends on the interaction among organizational, technical, and human factors, according to socio-technical theory (Yu et al., 2023). Call et al. (2026) extend this understanding by introducing the “AI-specific Matthew Effect,” arguing that trust and adoption may be influenced by how users perceive AI’s impact on their professional autonomy and value creation. Their framework suggests that users who view AI as enhancing their bargaining power and professional identity are more likely to develop ethical trust than those who perceive AI as a threat to their role. This connection is supported by empirical evidence. For example, research by Abdelazim et al. (2025) showed that trust and intention to adopt AI-based systems in educational institutions are significantly influenced by perceived fairness and transparency in AI algorithms. Accordingly, this study hypothesizes:

H3: Higher ethical trust positively influences the adoption and success of AI-based educational information systems.

Although TAM/UTAUT and socio-technical theory acknowledge the importance of trust, they conceptualize it broadly without specifying how AI-specific factors, such as fairness perceptions, algorithmic transparency, or professional autonomy, shape trust in educational settings. Recent work by Call et al. (2026) and Abdelazim et al. (2025) begins to address this, yet the direct link between ethical trust and adoption success remains underexplored. DKAT-EIS addresses this gap through H3, which tests whether ET independently predicts AS in AI-driven educational systems.

Organizational Readiness (OR)

OR refers to an institution’s capacity to support AI adoption through infrastructure, governance, training, and data management (Tornatzky & Fleischer, 1990). The relationships between DQ, KI, ET, and adoption outcomes are moderated by this crucial contextual factor.

Socio-technical systems theory (Baxter & Sommerville, 2011), which highlights that organizational support and alignment between human and technical components are necessary for technological success, provides theoretical justification (A. Q. Li et al., 2020). Without adequate training, infrastructure, or governance, even high-quality and interpretable AI outputs may fail to be adopted. This view is supported by empirical research: Allam et al. (2025), Hwang and Seo (2025), and Veseli et al. (2025) discovered that OR amplifies the impact of information quality on system adoption in higher education. Thus, grounded in socio-technical systems theory and empirical evidence on organizational enablement, this research proposes the following moderating hypotheses:

H4: Organizational readiness positively moderates the relationship between data quality and knowledge interpretability.

H5: Organizational readiness positively moderates the relationship between ethical trust and adoption and success.

Socio-technical theory positions organizational factors as critical enablers of technology success, yet existing research rarely specifies how OR moderates specific relationships between technical, cognitive, and ethical constructs. While recent studies (Allam et al., 2025; Veseli et al., 2025) confirm OR’s importance, they do not examine whether readiness amplifies the DQ→KI link or strengthens the ET→AS pathway. DKAT-EIS addresses this through H4 and H5, which test these moderating effects directly.

Adoption and Success (AS)

The ultimate outcomes of AI-based educational information systems include adoption and success, as reflected in behavioral intention, actual use, user satisfaction, and performance gains. These outcome measures draw on foundational models such as the ISSM (DeLone & McLean, 2003) and

UTAUT (Venkatesh et al., 2003), which remain cited in contemporary research. Recent studies continue to validate and extend these frameworks in AI contexts: Al-Emran and Griffy-Brown (2023) demonstrated the applicability of UTAUT to understanding technology adoption for sustainable development, while Abdelazim et al. (2025) found that IS Success Model dimensions significantly predict AI adoption decisions among educational leaders. To facilitate successful implementation, AS in AI-driven educational systems is influenced by ET, KI, and OR, in addition to perceived utility and ease of use. Systems with clear AI outputs and robust organizational support have been shown to improve educational outcomes, increase user satisfaction, and be used more frequently (Lin et al., 2023). The suggested pathways from the DKAT-EIS model are summarized in this study, which suggests:

H6: Higher levels of knowledge/insight, interpretability, and ethical trust positively influence the adoption and success of AI-based educational information systems.

Foundational adoption models (TAM, UTAUT, IS Success Model) provide robust frameworks for understanding technology acceptance, but they were developed before AI systems became prevalent in education. Contemporary extensions (Abdelazim et al., 2025; Al-Emran & Griffy-Brown, 2023) confirm these models' continued relevance while revealing the need for AI-specific adaptations. DKAT-EIS responds through H6, which tests whether KI and ET (constructs underrepresented in traditional models) directly influence AS in AI contexts.

Theoretical Integration and Research Gap

The literature on AI adoption in educational information systems reveals several interrelated gaps. First, existing models such as TAM and UTAUT (Venkatesh & Davis, 2000; Venkatesh et al., 2003) and the ISSM (DeLone & McLean, 2003) treat technical, cognitive, and ethical factors in isolation, neglecting the role of data quality and knowledge interpretability as integrated precursors to adoption. Second, although XAI research suggests that interpretability fosters trust (Hassija et al., 2024; Mathew et al., 2025), this assumption remains untested in educational settings, where professional identity and pedagogical norms may shape trust formation (Viberg et al., 2025; Xing et al., 2026). Third, the influence of ethical trust on adoption success is underdeveloped, particularly regarding its interaction with organizational factors, despite evidence that fairness and transparency affect adoption (Abdelazim et al., 2025; Call et al., 2026). Finally, while socio-technical theory highlights organizational readiness as critical (Baxter & Sommerville, 2011), prior research provides limited clarity on whether it functions as a moderator of key relationships, such as data quality to knowledge interpretability or trust to adoption, or as a direct antecedent itself (Allam et al., 2025; Veseli et al., 2025).

CONCEPTUAL MODEL AND THEORETICAL FRAMEWORK

This section presents the DKAT-EIS conceptual model and the theoretical framework underpinning the study. Conceptual models are essential for clarifying relationships among constructs, particularly when introducing a novel theoretical framework (Kulkarni et al., 2006). DKAT-EIS explains how AI-based educational information systems generate value by integrating five core constructs: DQ, KI, ET, OR, and AS.

The model posits that high-quality data enables the generation of interpretable AI insights, thereby enhancing users' understanding and supporting informed decision-making. As KI increases, ET in the system's fairness, transparency, and responsible data use is strengthened, thereby promoting adoption and successful use. OR further conditions these relationships by providing the infrastructure, governance, and training necessary to translate trust and understanding into sustained system use and performance outcomes. Together, these relationships position DKAT-EIS as a coherent socio-technical framework that explains AI adoption and effectiveness in educational contexts. The constructs, hypotheses, and theoretical foundations are summarized in Table 1.

Table 1. Summary of constructs, theoretical foundations, and hypotheses

Construct	Definition	Theoretical foundation	Hypothesis	Gap addressed
DQ	Accuracy, completeness, consistency, and timeliness of data	IS Success Model (DeLone & McLean, 2003; Vuckovic et al., 2023)	H1: DQ → KI	TAM/UTAUT neglects data quality as an antecedent to interpretability
KI	Ease of understanding and using AI outputs	XAI (Mathew et al., 2025); Knowledge Management (Nonaka et al., 1996)	H2: KI → ET	Interpretability-trust link assumed but untested in education
ET	Perceived fairness, transparency, and reliability	TAM/UTAUT (Venkatesh et al., 2003); Trust in IS (Abdelazim et al., 2025; Viberg et al., 2025)	H3: ET → AS	The role of ethical trust in adoption is underspecified
OR	Infrastructure, governance, training, policies	Socio-technical Theory (Baxter & Sommerville, 2011); Innovation Readiness (Tornatzky & Fleischer, 1990)	H4: OR moderates DQ→KI H5: OR moderates ET→AS	Moderating mechanisms of readiness ambiguous
AS	Behavioral intention, usage, satisfaction, performance	TAM (Venkatesh & Davis, 2000); UTAUT (Venkatesh et al., 2003); IS Success Model (DeLone & McLean, 2003)	H6: KI and ET → AS	Need for AI-specific extension of adoption models

DKAT-EIS achieves both conceptual rigor and practical relevance by defining its constructs, specifying testable relationships, and grounding the model in established theoretical frameworks. DKAT-EIS provides a systematic approach for explaining how educational data are transformed into actionable knowledge that is interpretable, ethically trusted, and adopted. This conceptual clarity underpins empirical testing by guiding the development of measurement instruments, hypothesis formulation, and the selection of appropriate analytical techniques, such as structural equation modeling (SEM). As a result, DKAT-EIS is both robust and verifiable, providing a solid foundation for examining AI-based educational information systems.

The following methodology section outlines the operationalization of constructs, sampling procedures, and analytical methods used to test these theoretical relationships.

METHODOLOGY

RESEARCH DESIGN

This study employed a quantitative, cross-sectional survey design to test the DKAT-EIS model empirically. Quantitative methods allow systematic examination of relationships among constructs (DQ, KI, ET, OR, and AS) using statistically verifiable indicators. Survey-based research enabled organized data collection from a broad population, ensuring representative and generalizable results (Creswell, 2002). The cross-sectional design captured participants' responses at a specific point in time (Ifinedo, 2012; Venkatesh & Bala, 2008) and facilitated the analysis of both direct and moderated relationships, which are critical to evaluating DKAT-EIS.

The study was conducted at Jazan University, a large public institution in Saudi Arabia that exemplifies the digital transformation goals of the national Vision 2030 agenda. With approximately 2,490 academic staff, 1,706 administrative staff, and over 36,000 students across 14 colleges, the university’s scale and organizational complexity provide a rich context for examining AI adoption challenges in higher education.

TARGET POPULATION AND SAMPLING STRATEGY

The target population comprised faculty, staff, and students at Jazan University who regularly interact with AI-based educational systems. Including all three groups ensured comprehensive perspectives on DQ, KI, ET, and AS (Zawacki-Richter et al., 2025). A stratified random sampling technique was applied, treating each college, department, and administrative unit as a separate stratum. This approach reduced sampling bias while accounting for heterogeneity in system use (Hair & Alamer, 2022). Sample sizes were calculated for 95% confidence and 5% margin of error using standard formulas (Ahmad & Halim, 2017; G. D. Israel, 1992). Table 2 presents the minimum sample of 1,028 respondents: 334 academic staff, 314 administrative staff, and 380 students.

$$n = (N \times p \times (1-p)) / [(N-1) \times (e^2/Z^2) + p \times (1-p)]$$

where:

- n = required sample size
- N = population size for each subgroup
- p = proportion of the population (conservatively set at 0.5 for maximum variability)
- e = margin of error (0.05)
- Z = Z-value for 95% confidence level (1.96)

Table 2. Sample sizes for Jazan University respondents

Population subgroup	Total population	Confidence level	Margin of error	Sample size
Academic Staff	2,490	95%	5%	334
Administrative Staff	1,706	95%	5%	314
Students	36,000+	95%	5%	380

The initial data collection yielded 1,215 responses. After cleaning, 1,150 complete responses remained, exceeding the minimum requirement by 122 cases. Table 3 presents the final achieved sample after data collection. The final sample of 1,150 exceeds the minimum requirement by 122 cases (11.9% oversampling), with the largest increase occurring among student respondents. Oversampling improves statistical power, reduces the margin of error to ±2.8%, and strengthens SEM analysis (Hair, 2014). Table 3 details the demographic distribution.

Table 3. Participant demographics overview (n = 1,150)

Demographic variable	Category	Frequency	Valid percent (%)	Cumulative percent (%)
Status at university	Academic Staff	336	29.22	29.22
	Administrative Staff	334	29.04	58.26
	Students	480	41.74	100.00
Age	18-24 years	395	34.35	34.35
	25-34 years	203	17.65	52.00
	35-44 years	372	32.35	84.35
	45-54 years	122	10.61	94.96
	55 years or older	58	5.04	100.00
Gender	Male	523	45.48	45.48
	Female	627	54.52	100.00

Demographic variable	Category	Frequency	Valid percent (%)	Cumulative percent (%)
Educational level	Bachelor's Degree	693	60.26	60.26
	Master's Degree	108	9.39	69.65
	Doctoral Degree	226	19.65	89.30
	Other	123	10.70	100.00
College/Faculty	Business	251	21.83	21.83
	College of Arts and Humanities/ Education	135	11.74	33.57
	College of Nursing and Health Sciences	88	7.65	41.22
	College of Engineering and Computer Sciences	149	12.96	54.17
	College of Science	156	13.57	67.74
	College of Sharia and Law	108	9.39	77.13
	Applied College	102	8.87	86.00
	University College in Ad-Darb	77	6.70	92.70
	College of Industrial Applications – Baish	68	5.91	98.61
	College of Medicine	16	1.39	100.00

SURVEY INSTRUMENT

A structured questionnaire designed to assess each DKAT-EIS model construct served as the main tool for gathering data. To guarantee construct validity and reliability, validated scales from earlier research were modified. Items covering accuracy, completeness, consistency, and timeliness were modified for DQ from R. Y. Wang and Strong (1996) and Pipino et al. (2002). Items modified from XAI research (Doshi-Velez & Kim, 2017; Pipino et al., 2002) were used to measure KI, evaluating the applicability, usability, and clarity of AI outputs. The ET items, which focused on opinions of fairness, transparency, and dependability, were taken from McKnight et al. (2011) and Lee and See (2004). Using frameworks for innovation readiness and socio-technical theory, OR items addressed infrastructure, governance, training, and policy support (Lyytinen & Damsgaard, 2011; Tornatzky & Fleischer, 1990). Lastly, AS items that captured behavioral intention, system usage, user satisfaction, and perceived performance improvements were modified from TAM, UTAUT, and the IS Success Model (DeLone & McLean, 2003; Venkatesh et al., 2003).

To ensure sensitivity to minute variations in perception, all constructs were measured using multi-item Likert scales (1 = strongly disagree, 5 = strongly agree). Because these variables can affect how participants view and engage with AI-based educational systems, demographic information, including role, department, years of experience, and prior exposure to AI systems, was collected. By adjusting for these variables, bias resulting from individual or organizational differences is lessened, and the impact of the primary constructs (DQ, KI, ET, and OR) on system AS is isolated. Subgroup analyses were made possible while preserving methodological rigor, minimizing measurement bias, and guaranteeing comparability among administrators, faculty, and students (Hair & Alamer, 2022; Kline, 2023).

Table 4 presents the full set of survey items for all DKAT-EIS constructs, providing a clear mapping between operational measures and their theoretical underpinnings. To ensure sufficient coverage of the theoretical dimensions of each construct in the DKAT-EIS model while preserving survey manageability, each construct was measured with four survey items. According to research in SEM and psychometrics, three to five carefully crafted items per construct offer adequate construct validity and reliability without burdening respondents (Bollen, 1989; Hair & Alamer, 2022; Kline, 2023). By capturing several aspects of a construct, lowering measurement error, and facilitating reliable statistical estimation in SEM, four items achieve a balance.

Table 4. Survey constructs, theoretical foundations, and items for DKAT-EIS

Construct	Definition	Theoretical foundation	Survey items (4 per construct)
DQ	Accuracy, completeness, consistency, and timeliness of data in AI-based educational systems	IS Success Model (DeLone & McLean, 2003); Data Quality Framework (Pipino et al., 2002; R. Y. Wang & Strong, 1996)	<ol style="list-style-type: none"> 1. The data provided by AI-based educational systems is accurate and error-free. 2. The AI system delivers complete information necessary for academic decision-making. 3. The data from AI-based systems is consistent across reports and platforms. 4. The information generated by AI-based systems is delivered in a timely manner for practical use.
KI	Ease of understanding and applying AI-generated outputs for educational and administrative purposes	Explainable AI (Doshi-Velez & Kim, 2017; Lipton, 2018); Knowledge Management (Nonaka et al., 1996)	<ol style="list-style-type: none"> 1. The outputs of AI-based systems are clear and easy to understand. 2. I can easily interpret the recommendations provided by AI-based tools. 3. AI-generated insights help me make informed decisions efficiently. 4. The system provides clear explanations that help me understand the reasoning behind its outputs.
ET	Perceived fairness, transparency, and reliability of AI systems	TAM/UTAUT (Venkatesh & Davis, 2000; Venkatesh et al., 2003); Trust in IS (Lee & See, 2004; McKnight et al., 2011)	<ol style="list-style-type: none"> 1. I believe the AI-based system provides fair and unbiased recommendations. 2. The system operates transparently, allowing me to understand how decisions are generated. 3. I trust the AI-based system to support important academic or administrative decisions. 4. The outputs of the AI system are reliable and consistent over time.
OR	Institutional infrastructure, governance, training, and policies supporting AI system use	Socio-technical Theory (Baxter & Sommerville, 2011); Innovation Readiness (Lyytinen & Damsgaard, 2011; Tornatzky & Fleischer, 1990)	<ol style="list-style-type: none"> 1. The university provides adequate infrastructure to support the use of AI-based systems. 2. Training and guidance for using AI-based systems are sufficient and easily accessible. 3. Policies and procedures are in place to ensure effective use of AI-based systems. 4. The university leadership actively encourages the use of AI tools for educational and administrative improvement.

Construct	Definition	Theoretical foundation	Survey items (4 per construct)
AS	Behavioral intention, usage, satisfaction, and perceived performance outcomes	TAM, UTAUT (Venkatesh & Davis, 2000; Venkatesh et al., 2003); IS Success Model (DeLone & McLean, 2003)	<ol style="list-style-type: none"> 1. I frequently use AI-based systems in my teaching, administrative, or learning activities. 2. I intend to continue using AI-based systems in the future. 3. I am satisfied with the performance and usefulness of the AI-based systems. 4. The use of AI-based systems has improved my academic and professional efficiency and decision-making quality.

PILOT TESTING

The survey was pilot tested with 20–30 participants from a population analog. The pilot assessed clarity, technical comprehension, and consistent interpretation, and provided preliminary reliability data via Cronbach’s alpha and exploratory factor analysis. Feedback guided refinements to improve validity and reliability (DeVellis & Thorpe, 2021).

DATA COLLECTION PROCEDURE

Surveys were distributed electronically from September 12 to November 16, 2025, to faculty, administrative staff, and students. Using a single instrument across all groups ensured consistent measurement and allowed comparative analysis.

Multi-stakeholder sampling reflects the ecosystem-wide adoption of AI in higher education. Relying on a single group would have missed critical perspectives: students’ experiences, faculty interpretations, and staff management of data and infrastructure (Verboom et al., 2025; Zawacki-Richter et al., 2025). Aligning with Alhubaishy and Aljuhani (2021) guidelines, distribution leveraged official channels; email and LMS for students, email lists with departmental support for faculty and staff. In accordance with Dillman et al. (2014), follow-up reminders ensured strong subgroup representation, yielding 1,150 complete responses.

DATA ANALYSIS

Data was analyzed using Stata 18. Descriptive statistics summarized construct scores and participant profiles. CFA verified that items reflected underlying latent variables. SEM tested direct effects (DQ → KI → ET → AS) and the moderating effect of OR (Hair & Alamer, 2022; Kline, 2023). Model fit indices (CFI, TLI, RMSEA, SRMR) were computed, and Cronbach’s alpha, composite reliability (CR), and Average Variance Extracted (AVE) assessed construct validity and reliability.

ETHICAL CONSIDERATIONS

Participants provided informed consent, were informed of voluntary participation, and could withdraw at any time. Responses were anonymous, and data were securely stored with limited access (M. Israel & Hay, 2006). The study protocol was approved by the local ethics committee and adhered to national and university guidelines (Resnik, 2018), ensuring participant rights, privacy, and the credibility of findings.

RESULTS

This section presents the study's findings from comprehensive analyses using Confirmatory Factor Analysis (CFA), SEM, and moderation testing. The analysis examines the measurement quality of the DKAT-EIS model and evaluates the hypothesized structural relationships among DQ, KI, ET, OR, and AS. The results are interpreted in light of the theoretical model and supported by insights from prior literature.

MEASUREMENT MODEL ASSESSMENT

The first analysis stage assessed the adequacy of the measurement model. As shown in Table 5, the model fits the data exceptionally well, with all indices exceeding conventional thresholds. The chi-square value ($\chi^2 = 163.493$, $df = 164$, $p = 0.496$) is non-significant, while the CFI and TLI both equal 1.000, surpassing the recommended 0.90 threshold. RMSEA = 0.000 and SRMR = 0.018 further confirm excellent fit.

Table 5. Measurement model fit statistics

Fit statistic	Value	Recommended	Interpretation
χ^2 (Chi-square)	163.493	-	-
Degrees of freedom(df)	164	-	-
p-value	0.496	>0.05	Excellent
CFI	1.000	>0.90	Excellent
TLI	1.000	>0.90	Excellent
RMSEA	0.000	<0.08	Excellent
SRMR	0.018	<0.08	Excellent
AIC	28,230.938	-	-
BIC	28,564.074	-	-

RELIABILITY AND CONVERGENT VALIDITY

The results demonstrate strong reliability and convergent validity (Table 6). All standardized factor loadings exceed 0.70 (0.798–0.860), showing that items represent their constructs. Cronbach's alpha values are above 0.89, indicating excellent internal consistency (Christmann & Van Aelst, 2006), while CR values exceed 0.90, confirming measure stability (Hair et al., 2020). AVE values range from 0.679 to 0.722, surpassing the 0.50 threshold and showing that each construct explains substantial variance in its indicators.

Table 6. Standardized factor loadings and reliability

Construct	Item	Loading	S.E.	z-value	p-value	α	CR	AVE
DQ	dq1	0.848	0.011	78.50	<0.001	0.901	0.904	0.696
	dq2	0.831	0.011	72.60	<0.001			
	dq3	0.831	0.011	72.55	<0.001			
	dq4	0.826	0.012	70.90	<0.001			
KI	ki1	0.835	0.011	76.53	<0.001	0.912	0.915	0.722
	ki2	0.849	0.010	82.40	<0.001			
	ki3	0.855	0.010	84.83	<0.001			
	ki4	0.860	0.010	87.08	<0.001			
ET	et1	0.843	0.011	77.21	<0.001	0.903	0.905	0.701
	et2	0.847	0.011	78.68	<0.001			
	et3	0.824	0.012	70.54	<0.001			
	et4	0.834	0.011	74.06	<0.001			

Construct	Item	Loading	S.E.	z-value	p-value	α	CR	AVE
OR	or1	0.823	0.012	69.93	<0.001	0.903	0.907	0.700
	or2	0.833	0.011	73.60	<0.001			
	or3	0.846	0.011	78.10	<0.001			
	or4	0.843	0.011	77.07	<0.001			
Adoption Success	as1	0.810	0.013	64.41	<0.001	0.894	0.897	0.679
	as2	0.798	0.013	61.20	<0.001			
	as3	0.852	0.011	78.31	<0.001			
	as4	0.835	0.012	72.59	<0.001			

Note: All loadings significant at $p < 0.001$; α = Cronbach's alpha, CR = Composite Reliability, AVE = Average Variance Extracted

DISCRIMINANT VALIDITY

Discriminant validity was assessed using the Fornell–Larcker criterion. As shown in Table 7, the square root of each construct’s AVE exceeds its correlations with other constructs, confirming that DKAT-EIS constructs capture distinct conceptual domains. Correlations among constructs are generally low, with some near zero or slightly negative. While this does not violate discriminant validity, it suggests that the conceptual relationships in this dataset are weaker than expected (Dash & Paul, 2021), providing an early explanation for why some hypothesized structural relationships were unsupported.

Table 7. Discriminant validity (Fornell-Larcker criterion)

Construct	$\sqrt{\text{AVE}}$	1. DQ	2. KI	3. ET	4. OR	5. AS
1. DQ	0.834	0.834				
2. KI	0.850	0.062	0.850			
3. ET	0.837	-0.005	0.010	0.837		
4. OR	0.837	0.001	-0.003	0.024	0.837	
5. AS	0.824	-0.014	-0.025	-0.028	-0.045	0.824

Note: Diagonal elements (bold) represent square roots of AVE. Discriminant validity is established when diagonal elements exceed off-diagonal correlations (Fornell & Larcker, 1981).

DESCRIPTIVE STATISTICS AND CORRELATION PATTERNS

Descriptive statistics in Table 8 indicate moderate mean values for all five constructs, reflecting a generally neutral stance among respondents. Consistent standard deviations suggest similar within-group variability (Marshall & Jonker, 2010). Figure 1 displays the distribution of scores for each construct.

Correlation analysis reinforces previous findings: associations among constructs are weak, ranging from -0.045 to 0.062 . This indicates that changes in one construct have little correspondence with others in this sample, providing context for the limited support observed in the structural model.

Table 8. Descriptive statistics and correlations

Construct	Mean	SD	Min	Max	1	2	3	4	5
1. DQ	3.017	0.519	1.25	5.00	1.000				
2. KI	2.972	0.565	1.25	5.00	0.062	1.000			
3. ET	3.017	0.527	1.25	4.75	-0.005	0.010	1.000		

4. OR	3.011	0.547	1.25	5.00	0.001	-0.003	0.024	1.000	
5. AS	2.989	0.519	1.50	4.50	-0.014	-0.025	-0.028	-0.045	1.000

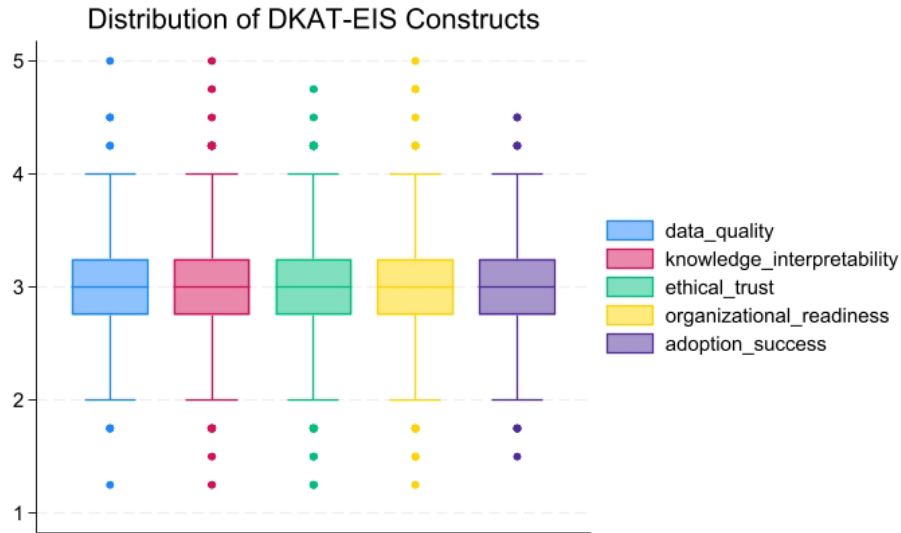


Figure 1. Distribution of DKAT-EIS construct scores across respondents

STRUCTURAL MODEL AND HYPOTHESIS TESTING

The structural model results (Table 9) show that only one of the six hypothesized relationships is statistically supported. Specifically, the link between DQ and KI (H1) is positive and significant ($\beta = 0.073, p = 0.032$). Figure 2 displays the positive relationship between DQ and KI ($\beta = 0.073$).

Table 9. Structural model and hypothesis testing results

Hypothesis	Relationship	Expected	SEM β	p-value	Regression β	p-value	Supported?
H1	DQ \rightarrow KI	+	0.073	0.032	0.068	0.035	Yes
H2	KI \rightarrow ET	+	0.011	0.720	0.009	0.734	No
H3	ET \rightarrow AS	+	-0.027	0.377	-0.027	0.356	No
H4	DQ \times OR \rightarrow KI	+	-	-	0.080	0.170	No
H5	ET \times OR \rightarrow AS	+	-	-	-0.050	0.351	No
H6	KI \rightarrow AS	+	-0.024	0.423	-0.023	0.396	No
-	OR \rightarrow AS	+	-0.044	0.150	-	-	No

*Note: SEM β = Standardized coefficients from Structural Equation Modeling; $p < 0.05$



Figure 2. Relationship between data quality and knowledge interpretability

As shown in Table 9, only Hypothesis 1 was supported ($DQ \rightarrow KI$: $\beta = 0.073$, $p = 0.032$). Hypotheses 2 ($KI \rightarrow ET$: $\beta = 0.011$, $p = 0.720$), 3 ($ET \rightarrow AS$: $\beta = -0.027$, $p = 0.377$), and 6 ($KI \rightarrow AS$: $\beta = -0.024$, $p = 0.423$) were not statistically significant. Neither moderation hypothesis ($H4: DQ \times OR \rightarrow KI$, $p = 0.170$; $H5: ET \times OR \rightarrow AS$, $p = 0.351$) was supported. Figure 3 displays the standardized path coefficients for all hypothesized relationships.

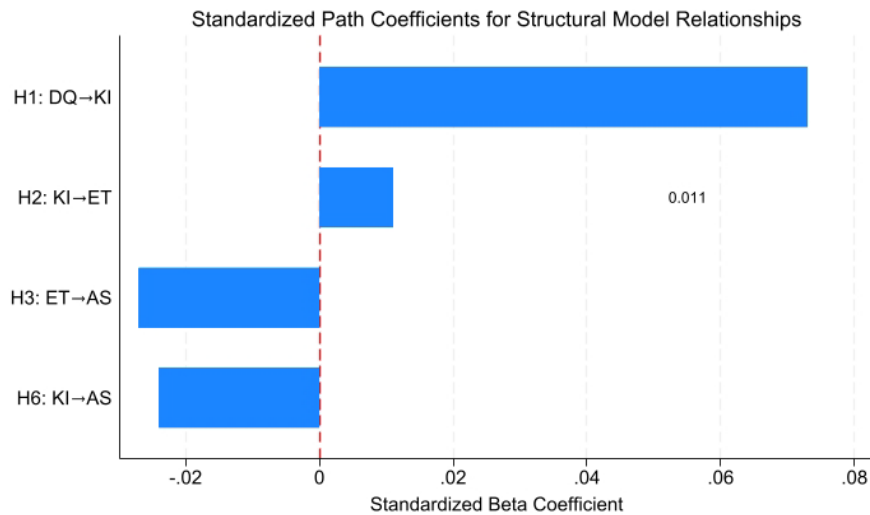


Figure 3. Standardized path coefficients for structural model relationships

MODERATION ANALYSIS

As shown in Table 10, neither interaction term was statistically significant ($H4: \beta = 0.080$, $p = 0.170$; $H5: \beta = -0.050$, $p = 0.351$), indicating that OR does not moderate the relationships between DQ and KI or ET and AS. Furthermore, the overall models were not statistically significant ($H4: F = 2.12$, $p = 0.096$; $H5: F = 1.17$, $p = 0.322$). The R^2 values were extremely low (0.0055 and 0.0041, respectively), suggesting that the models explain a negligible proportion of variance in the dependent variables.

Table 10. Moderation analysis results

Hypothesis	Model	R ²	F	p-value	Interaction β	p-value	Supported?
H4	KI ~ DQ + OR + DQ×OR	0.0055	2.12	0.096	0.080	0.170	No
H5	AS ~ ET + OR + KI + ET×OR	0.0041	1.17	0.322	-0.050	0.351	No

SUMMARY OF KEY FINDINGS

The analysis shows that only Hypothesis 1 (DQ → KI) was supported. All other hypothesized direct and moderating relationships were non-significant. The measurement model demonstrated excellent fit, and all constructs met reliability and validity thresholds.

DISCUSSION

This study proposed and tested the DKAT-EIS model. The results present a nuanced picture, confirming a foundational hypothesis while challenging several assumed pathways in technology adoption literature. The discussion situates these findings within established theories such as ISSM, UTAUT, and KM theory, while engaging with recent empirical work on AI in education.

THEORETICAL INTEGRATION AND EMPIRICAL VALIDATION

The findings provide a nuanced validation of DKAT-EIS, showing both confirmatory and contradictory evidence. The significant positive relationship between DQ and KI (H1: $\beta = 0.073$, $p = 0.032$) aligns with ISSM (DeLone & McLean, 2003, 2004) and supports Liu et al. (2016) and Elouataoui (2024), confirming that high-quality data is essential for meaningful AI outputs. Conversely, the non-significant KI → ET pathway (H2) challenges assumptions in Explainable AI literature. This aligns with Habib et al. (2021) and Viberg et al. (2025), highlighting that trust is influenced by factors beyond interpretability, such as self-efficacy and comprehension.

THE TRUST-INTERPRETABILITY PARADOX IN EDUCATIONAL AI

The lack of support for H2 and H3 reveals a “trust-interpretability paradox.” While XAI emphasizes transparency for trust (Hassija et al., 2024), interpretability alone was insufficient to foster ET in educational contexts. This echoes Choi et al. (2023), where pedagogical beliefs and ease of use outweighed technical transparency in influencing adoption. Trust may develop through iterative engagement, proven utility, and alignment with institutional and pedagogical values rather than through static interpretability features (Räsänen et al., 2024).

These null findings suggest several boundary conditions for DKAT-EIS. First, interpretability does not produce trust (H2 unsupported). The insignificant KI → ET path indicates that users may need more than interpretability to trust AI systems. As prior ethics-based AI research shows, trust is influenced by transparency, fairness, perceived risk, and accountability. Second, ethical trust does not directly predict adoption success (H3 unsupported). The non-significance of ET → AS suggests that trust alone may be insufficient for adoption in university settings, where organizational culture and leadership support may play stronger roles. Third, knowledge interpretability does not directly influence adoption success (H6 unsupported). Interpretability may be necessary to understand AI outputs, but it is not a strong enough factor to drive adoption behavior on its own.

Recent international research reinforces this view. Viberg et al. (2025) found that teachers’ self-efficacy, not objective interpretability, was the strongest predictor of trust across six countries. Similarly, Call et al. (2026) suggest that trust depends on whether users perceive AI as enhancing professional autonomy rather than threatening it; a dynamic that the present study’s quantitative measures could

not capture. Xing et al. (2026) document how users positioned merely as “system operators” experience role alienation that erodes trust, even when systems are interpretable.

The non-significant ET→AS pathway contrasts with Abdelazim et al. (2025), who found that trust significantly predicted AI adoption among school administrators in Oman; a difference that may reflect the broader stakeholder sample or the Saudi higher education context.

Together, these findings suggest that interpretability is necessary but not sufficient for trust, and trust alone does not guarantee adoption, pointing to critical boundary conditions for DKAT-EIS.

ORGANIZATIONAL READINESS: NECESSARY BUT NOT SUFFICIENT

Fourth, the moderation effects of organizational readiness were unsupported (H4, H5). Neither DQ×OR nor ET×OR interactions were significant, implying that readiness operates at a broader institutional level rather than through individual-level interactions (Tornatzky & Fleischer, 1990). Infrastructure and training alone did not strengthen relationships within the model. This aligns with Allam et al. (2025), who argue that static readiness measures fail to capture the “living intelligence” needed for dynamic human-AI collaboration. Similarly, Verboom et al. (2025) emphasize that successful adoption depends on ongoing adaptation rather than one-time preparation. Thus, OR functions as a contextual enabler, shaping culture and leadership support rather than a direct statistical moderator.

METHODOLOGICAL AND THEORETICAL CONTRIBUTIONS

The DKAT-EIS measurement model addresses the data quality (DQ) issues highlighted by Liu et al. (2016) and Sinha et al. (2025), demonstrating exceptional psychometric properties (CFI = 1.000, TLI = 1.000, RMSEA = 0.000). Reliability indices (CR > 0.89, AVE > 0.67) and strong factor loadings (>0.79) illustrate the value of integrating multiple theoretical frameworks into a single measurement tool.

More importantly, this study moves beyond measurement validation to offer a theoretical contribution. DKAT-EIS is not merely a model-testing exercise; it is a novel mid-range theory (Corley & Gioia, 2011) that synthesizes and reconfigures established constructs into a unified explanatory system. The core contribution lies in proposing data-to-knowledge alignment as the central mechanism through which AI adoption succeeds or fails in educational contexts. Unlike prior models that focus narrowly on technology acceptance (e.g., TAM, UTAUT) or information quality (e.g., IS Success Model), DKAT-EIS provides an integrated socio-technical framework explaining how technical inputs DQ are transformed into KI, which then interacts with human factors ET and OR to influence AS.

The mixed structural findings critically refine this theory and advance the field by identifying boundary conditions and challenging linear assumptions. In AI-specific educational contexts, unsupported pathways (e.g., KI → ET, ET → AS) reveal that interpretability does not lead to trust, giving rise to the “trust-interpretability paradox.” This finding does not invalidate DKAT-EIS; instead, it demonstrates the theory’s explanatory utility by providing a coherent framework for understanding complex, non-linear adoption dynamics. The result shows that trust is multi-faceted and that organizational readiness functions as a broad contextual enabler rather than a direct statistical moderator.

Thus, DKAT-EIS fulfills the key roles of a theory: it (1) integrates constructs from disparate domains into a novel explanatory structure, (2) generates testable propositions about their relationships, (3) provides a lens to interpret both confirmatory and contradictory evidence, and (4) offers a portable diagnostic framework, not just a predictive model, for researchers and practitioners to analyze AI adoption challenges across diverse institutional settings. The contribution of this work is therefore twofold: a robust measurement instrument and a refined theoretical understanding of the socio-technical mechanisms underpinning AI integration in education.

BROADER RELEVANCE AND PRACTICAL IMPLICATIONS FOR EDUCATIONAL AI

As a portable diagnostic framework, DKAT-EIS's relevance extends beyond Jazan University or Saudi higher education. The framework's findings provide actionable insights, frameworks, and guidance for institutions, policymakers, and researchers worldwide engaging with AI adoption in complex socio-technical environments.

Core constructs and global significance

DKAT-EIS addresses universal pillars of AI integration: DQ, KI, ET, and OR. Universities face challenges in data integrity, algorithmic transparency, user skepticism, and institutional capacity. The framework provides a common lens for diagnosing and addressing these factors. The empirical confirmation of the DQ→KI link in this study (H1) underscores that the imperative to begin with high-quality data is a universal prerequisite, not a context-specific recommendation.

Key insights

- *Data Quality as a Foundation:* The strongly supported DQ → KI pathway demonstrates that high-quality data is essential for meaningful AI-generated knowledge – a global imperative.
- *Trust–Interpretability Paradox:* Interpretability alone does not ensure trust, highlighting the need for strategies addressing fairness, accountability, and alignment with pedagogical and ethical values.
- *Organizational Readiness:* OR acts as a cultural enabler; infrastructure alone is insufficient. Successful adoption requires a supportive culture, strategic alignment, and leadership commitment.

Practical applications

Institutions should adopt a phased implementation strategy, prioritizing robust data governance and infrastructure, while developing nuanced strategies to foster trust and adoption. These recommendations complement technical guidance on AI-driven decision-support systems (Mahamad et al., 2025) by emphasizing that human and organizational factors are as critical as system design and architecture. DKAT-EIS also offers a validated survey instrument to assess institutional strengths and weaknesses across the AI adoption pipeline, supporting benchmarking and data-driven strategic planning.

Broader implications

Ethical and effective AI adoption is a socio-technical challenge relevant beyond education, including healthcare, public administration, and finance. Evidence from a non-Western context diversifies and stress-tests AI adoption theories globally, making the insights widely applicable.

LIMITATIONS AND RESEARCH DIRECTIONS

This study has limitations. The study's cross-sectional design prevents causal inference, and the findings may not generalize to other educational systems or cultural contexts. However, they provide insight into the Saudi higher education environment. Future research directions include:

1. *Longitudinal studies:* Track changes in readiness and adoption relationships over time, examining knowledge-action processes across implementation phases (Räsänen et al., 2024).
2. *Extended contexts and stakeholder-specific applications:* Validate the model across different regions and university types (public vs. private, teaching vs. research-focused), and tailor studies for students, faculty, and administrative staff.
3. *Qualitative inquiry:* Use interviews and observations to explore underlying factors not captured quantitatively, such as ethical concerns, experience, and professional identity.

4. *Examining new constructs:* Incorporate variables like algorithmic fairness, perceived strategic alignment, or institutional coercive pressure as potential mediators or moderators to enrich the model.

Although the study is context-specific, the DKAT-EIS framework offers a theoretically grounded perspective on AI adoption by emphasizing the alignment between data quality and knowledge interpretability within broader organizational and socio-technical systems. As such, it provides a useful foundation for future research and a conceptual lens that can be adapted and tested across different higher education environments.

CONCLUSION

This study proposed and tested the Data–Knowledge Alignment Theory for Educational Information Systems (DKAT-EIS), a mid-range framework examining the interplay of data quality (DQ), knowledge interpretability (KI), ethical trust (ET), organizational readiness (OR), and adoption success (AS) in AI-driven educational systems. Drawing on TAM, UTAUT, the IS Success Model, Knowledge Management Theory, explainable AI (XAI) principles, and Socio-Technical Systems Theory, DKAT-EIS extends prior models by emphasizing the alignment of data to actionable knowledge while incorporating organizational, ethical, and interpretability dimensions. The findings provide partial support for the proposed framework, confirming that high-quality data is a critical foundation for generating meaningful and interpretable AI outputs. However, the non-significant relationships among KI, ET, and AS, as well as the absence of moderating effects of OR, suggest a more complex, non-linear adoption process than assumed. This pattern suggests a “trust–interpretability paradox,” in which improved interpretability does not translate into greater trust or adoption, likely due to contextual factors such as institutional culture, professional autonomy, and user self-efficacy.

The study contributes to theory in two key ways. First, it supports the role of data-to-knowledge alignment as a central mechanism in AI adoption, positioning data quality as a prerequisite for interpretability and downstream outcomes. Second, it identifies important boundary conditions by revealing weak and non-linear relationships among interpretability, trust, and adoption, thereby challenging linear assumptions embedded in dominant technology acceptance models and highlighting the need for more context-sensitive and integrative theoretical approaches. These findings do not invalidate DKAT-EIS but rather refine it, demonstrating its explanatory potential in capturing complex adoption dynamics.

Rather than invalidating DKAT-EIS, these findings refine its explanatory scope and demonstrate its value in uncovering complex socio-technical dynamics in educational AI adoption. From a practical perspective, DKAT-EIS offers a diagnostic lens for higher education institutions seeking to implement AI systems effectively. The results underscore the importance of strong data governance while also indicating that successful adoption depends on more than technical transparency; it requires attention to human and organizational dimensions, including professional identity, user competence, and institutional culture. For policymakers and university leaders, the findings highlight the need for balanced socio-technical strategies that combine robust data infrastructures with human-centered implementation practices, supporting a more sustainable, context-aware integration of AI in educational environments.

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DECLARATIONS:

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the present study.

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Data Availability

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

Ethical Approval

The Helsinki Declaration's guiding principles were followed in conducting this study. On December 18, 2025, the Jazan University Local Committee for Research Ethics approved the research protocol (HAPO-10-Z001; Approval No. REC-47/06/1712), guaranteeing adherence to all national and international research ethics standards.

Informed Consent

Every single participant in the study gave their informed consent. Implied consent was considered appropriate due to the survey's anonymous nature and low risk. Participants voluntarily completed the questionnaire after being made aware of the study's objectives, confidentiality procedures, and their right to withdraw at any time.

Contribution

O.S. conceived the study, designed the research methodology, conducted the systematic scoping review and analysis, and drafted the main manuscript. B.A. contributed to the development of the theoretical framework, interpretation of the findings, and critical revision of the manuscript. O.N.A. contributed to survey distribution, data collection, data synthesis, obtaining the necessary approvals, and manuscript review and editing. All authors reviewed, revised, and approved the final manuscript.

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