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EXPLAINABLE AI SYSTEMS FOR STRATEGIC ADMINISTRATIVE DECISIONS IN UNIVERSITIES: A STRUCTURAL EQUATION MODELING STUDY

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ABSTRACT

Despite the spread of AI-driven predictive analytics systems in higher education, their adoption in strategic administrative decision-making remains limited, principally due to concerns about algorithmic transparency and trust among academic leaders. While machine learning models prove 87–93% accuracy in predicting student outcomes, implementation gaps keep it up between technological capabilities and actual utilization in administrative contexts. This study examined the causal relationships between AI-driven decision support systems (AI-DSS), explainable AI (XAI) mechanisms, academic leaders' trust, and strategic administrative decision quality in universities, testing the mediating role of algorithmic transparency. The research addresses a critical gap in understanding how transparency features affect the translation of AI capabilities into enhanced governance outcomes. A cross-sectional survey design was employed with data collected from 387

academic leaders across 22 Egyptian universities. Structural equation modeling (SEM) was used to test a hypothesized causal model. Results revealed that algorithmic transparency through XAI mechanisms is not merely a desirable feature but a critical prerequisite for enhancing academic leaders' trust and realizing the potential of AI systems in strategic administrative decision-making. The absence of a direct effect from AI-DSS implementation to decision quality indicates that deploying sophisticated predictive analytics alone is insufficient; transparency features that enable understanding of algorithmic logic are essential mediating mechanisms. Findings provide empirical evidence for institutions investing in AI infrastructure to prioritize explainability features—such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations)—alongside predictive accuracy. This study offers actionable insights for higher education administrators, EdTech developers, and policymakers navigating AI governance frameworks.

KEYWORDS: Explainable Artificial Intelligence, Algorithmic Transparency, Learning Analytics, Higher Education Management, Structural Equation Modeling, Decision Support Systems, Trust In AI, Predictive Analytics.

1. INTRODUCTION

The integration of artificial intelligence (AI) and predictive analytics into higher education administration has accelerated dramatically over the past five years, driven by advances in machine learning algorithms, spread of learning management systems (LMS), and unique access to student and institutional data (Sajja et al., 2024). Predictive models employing Random Forest, neural networks, support vector machines, and ensemble methods have demonstrated accuracies ranging from 87% to 93% in forecasting student academic performance, identifying at-risk students as early as Week 4 of a semester, and informing targeted intervention strategies (Janahi et al., 2025; Khan & Ahmad, 2021). Documented institutional implementations at Arizona State University (ASU) and Georgia State University (GSU) have yielded measurable improvements: ASU's eAdvisor system increased retention rates by 12% and reduced time-to-degree by 0.8 semesters, while GSU's predictive analytics platform—analyzing over 800 risk factors and generating 52,000 proactive interferences annually—contributed to a 23% increase in advancement rates over five years (Khan & Ahmad, 2021).

Despite these promising capabilities, a considerable implementation gap persists between technological potential and actual adoption in strategic administrative decision-making contexts. Academic leaders—including deans, vice presidents for academic affairs, department chairs, and directors of academic units—continue to rely predominantly on intuition, anecdotal evidence, and retrospective data analysis rather than leveraging AI-driven insights for critical decisions regarding budget planning, enrollment management, program evaluation, resource allocation, and strategic planning (Hossain et al., 2025; Liaison International, 2025). This paradox is particularly acute in non-Western contexts, where institutional readiness, data literacy among administrators, organizational culture, and technological infrastructure present additional barriers to adoption (Mun'im, 2025; Sajid & Baig, 2024).

1.1. Theoretical Background and Research Gap

Recent systematic reviews have identified several interrelated factors constraining AI adoption in administrative contexts, revealing a complex interaction of technical, human, and organizational challenges. First, fewer than 5% of AI applications in educational learning management systems employ explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations), rendering algorithmic decision-making processes opaque to non-technical stakeholders (Hooshyar et al., 2024). This "black box" problem fundamentally undermines trust: in a faculty survey conducted at the University of Iowa (n = 88), 51% of respondents expressed extreme concern about data privacy and security, while 59% doubted the accuracy of AI-generated insights (Sajja et al., 2024). When decision-makers cannot understand *how* an AI system reaches its recommendations, skepticism and resistance naturally follow.

Second, algorithmic bias remains inadequately addressed in educational AI systems. Documented instances reveal discriminatory outcomes based on gender, race, socioeconomic status, and geographic location, stemming from biases embedded in historical training data (Mandinach, 2025; Zou & Schiebinger, 2018). For example, automated essay scoring systems have exhibited bias against students using non-standard linguistic dialects or culturally distinct writing styles, systematically underestimating their capabilities (Mandinach, 2025). Zou and Schiebinger (2018) caution that AI systems do not merely replicate existing biases but can amplify them, creating feedback loops that perpetuate and exacerbate inequities. In administrative contexts—where AI recommendations inform decisions about admissions, scholarship allocation, student support interventions, and resource distributions such biases pose profound ethical and equity concerns.

Third, 57% of human-centered learning analytics (HCLA) and human-centered AI in education (HCAI) studies lack foundation in pedagogical or organizational theories, and 66% remain untested in authentic institutional settings (Hooshyar et al., 2024). This "technology-first" orientation produces solutions that may be technically sophisticated yet contextually inappropriate or organizationally impracticable. Furthermore, stakeholder involvement—particularly administrators who are end-users of AI-DSS—is concentrated in early needs-assessment phases (94% of studies) but diminishes sharply during design (55%), prototyping (47%), and evaluation (43%) stages (Hooshyar et al., 2024). This limited engagement contributes to systems that fail to align with administrators' workflows, decision-making practices, and information needs.

Existing research has predominantly focused on AI applications for student-facing interventions, including personalized learning, intelligent tutoring systems, and academic advising with comparatively spare attention to administrative and strategic decision-making domains (Hossain et al., 2025; Liaison International, 2025). Moreover, no published studies in Q1 journals have empirically tested the causal mechanisms through which algorithmic transparency influences trust and, subsequently, decision quality in higher education administration. This gap is particularly pronounced in the Arab region and broader Middle East/North Africa (MENA) context, where cultural, organizational, and infrastructural factors differ noticeably from Western settings and where empirical research on AI in educational governance remains scarce (Mun'im, 2025).

1.2. Conceptual Framework

This study integrates three complementary theoretical frameworks to model the relationships among AI-DSS implementation, XAI transparency, trust, and decision quality, synthesizing insights from data ethics, technology acceptance, and organizational decision-making literatures:

1. Data Ethics Framework (Mandinach, 2025): This framework emphasizes transparency in data sources, analytical methods, and interpretation as foundational to ethical AI deployment. Mandinach's model posits two core component transparency and consequences—that interact with technical (data quality, algorithmic documentation), social (fairness, inclusivity), philosophical (institutional values), and political (accountability pressures) factors. Transparency is conceptualized not as an endpoint but as an ongoing commitment requiring documentation, stakeholder consultation, and iterative refinement. This framework grounds our expectation that XAI features directly enhance trust by clarifying algorithmic operations.

2. Enhanced Technology Acceptance Model (TAM): Davis's (1989) original TAM identified perceived usefulness and perceived ease of use as primary determinants of technology adoption. Recent extensions incorporate additional constructions relevant to AI systems: trust (confidence that the system will perform reliably and ethically), explainability (understanding of how the system operates), AI literacy (users' knowledge of AI capabilities and limitations), and privacy concerns (apprehensions about data security) (Perla & Di Grassi, 2025). These enhancements recognize that AI systems—particularly those involved in high-stakes decisions—require higher thresholds of trust and transparency than traditional information systems.

3. Decision Quality Model (Ferguson et al., 2016; Gašević et al., 2015): This model conceptualizes high-quality administrative decisions as possessing six attributes: data-driven (grounded in evidence rather than intuition), timely (made quickly enough to address emerging challenges), fair (equitable across stakeholder groups), transparent (with clear rationale that can be communicated), effective (achieving intended outcomes), and participatory (involving relevant stakeholders). These dimensions provide a comprehensive operationalization of decision quality beyond simple accuracy metrics.

We hypothesized a full mediation model wherein XAI transparency operates as a critical mechanism linking AI-DSS implementation to trust, which in turn predicts decision quality. This model posits that merely implementing advanced predictive analytics is insufficient to improve decision-making; rather, transparency in algorithmic operations is essential for cultivating trust among decision-makers, whose confidence and willingness to rely on AI-generated insights ultimately determine decision quality.

1.3. Research Questions and Hypotheses

1.3.1. Primary Research Question:

What is the nature and magnitude of the causal relationships among AI-driven decision support systems (AI-DSS) implementation level, explainable AI (XAI) transparency, academic leaders' trust in AI systems, and strategic administrative decision quality in higher education institutions?

Specific Hypotheses:

H1: (Direct Effect): AI-DSS implementation level is positively associated with strategic administrative decision quality.

H2: AI-DSS implementation level is positively associated with XAI transparency.

H3: XAI transparency is positively associated with academic leaders' trust in AI systems.

H4: Trust in AI systems is positively associated with strategic administrative decision quality.

H5: (Mediation Hypothesis): XAI transparency and trust serially mediate the relationship between AI-DSS implementation and strategic administrative decision quality. Specifically, the indirect effect pathway (AI-DSS → XAI transparency → Trust → Decision quality) will be statistically significant, whereas the direct effect (AI-DSS → Decision quality) will be attenuated or non-significant when mediators are included in the model.

2. METHOD

2.1. Research Design

This study employed a cross-sectional survey design with structural equation modeling (SEM) to test hypothesized causal relationships among latent constructions. The investigation adhered to ethical guidelines established by the Research Ethics Committee of Menoufia University, and all participants provided informed consent prior to data collection. The study protocol complies with the Declaration of Helsinki and Egypt's Law 81/2016 on Personal Data Protection.

2.2. Participants

2.2.1 Sampling Strategy

Participants were academic administrators recruited from 22 Egyptian universities (14 public, 8 private) between January 15 and April 30, 2025. A stratified random sampling approach proportionate to institutional size (enrollment) and type (public/private) was employed to ensure representativeness. Universities were stratified into three size categories: small (< 5,000 students), medium (5,000–15,000 students), and large (> 15,000 students).

2.3. Eligibility Criteria

Participants were required to meet the following inclusion criteria: (a) current appointment as dean, vice dean, department chair, or director of an academic unit (e.g., e-learning center, quality assurance unit); (b) minimum one year of experience in an administrative leadership role; (c) institutional use of at least one digital information system (e.g., LMS, student information system, data analytics platform); and (d) fluency in Arabic (survey language) or English. Exclusion criteria included temporary or acting administrative appointments and unwillingness to provide informed consent.

2.4. Sample Characteristics

The initial sampling frame comprised 487 eligible administrators identified through publicly available institutional directories and verified through direct contact with university registrars. Of these, 412 administrators responded to the survey invitation (response rate: 84.6%), with 387 providing complete data suitable for analysis after listwise deletion of cases with >5% missing values (retention rate: 94.0%). Power analysis using G*Power 3.1 (Faul et al., 2009) indicated that a sample of 387 exceeds the minimum required for detecting medium effect sizes ($f^2 = 0.15$) in SEM with 80% power at $\alpha = .05$.

Sample characteristics are summarized in Table 1 and Figure 7. The final sample comprised 276 males (71.3%) and 111 females (28.7%), reflecting the gender distribution of academic leadership in Egyptian universities. Participants' mean age was 47.8 years (*SD* = 8.3, range: 32–64). Administrative positions included 68 deans (17.6%), 102 vice deans (26.4%), 164 department chairs (42.4%), and 53 directors/coordinators (13.7%). Mean administrative experience was 8.6 years (*SD* = 5.4). Regarding AI-DSS usage, 187 participants (48.3%) reported active usage, 142 (36.7%) reported limited use, and 58 (15.0%) reported no current use of AI-based systems in their institutions.

Table 1: Demographic And Institutional Characteristics of Participants (N = 387).

Characteristic	*n*	%	*M*	*SD*
Gender				
Male	276	71.3		
Female	111	28.7		
Age (years)			47.8	8.3
Administrative Position				
Dean	68	17.6		
Vice Dean	102	26.4		
Department Chair	164	42.4		
Director/Coordinator	53	13.7		
Years of Administrative Experience			8.6	5.4
1–5 years	134	34.6		
6–10 years	158	40.8		
> 10 years	95	24.5		
Institution Type				
Public	272	70.3		
Private	115	29.7		
Institution Size (enrollment)				
Small (< 5,000)	89	23.0		
Medium (5,000–15,000)	176	45.5		
Large (> 15,000)	122	31.5		
AI-DSS Usage Status				
Active user	187	48.3		

Limited use	142	36.7		
No current use	58	15.0		
Field of Specialization				
STEM disciplines	218	56.3		
Social sciences/humanities	169	43.7		

Note: STEM = Science, Technology, Engineering, And Mathematics.

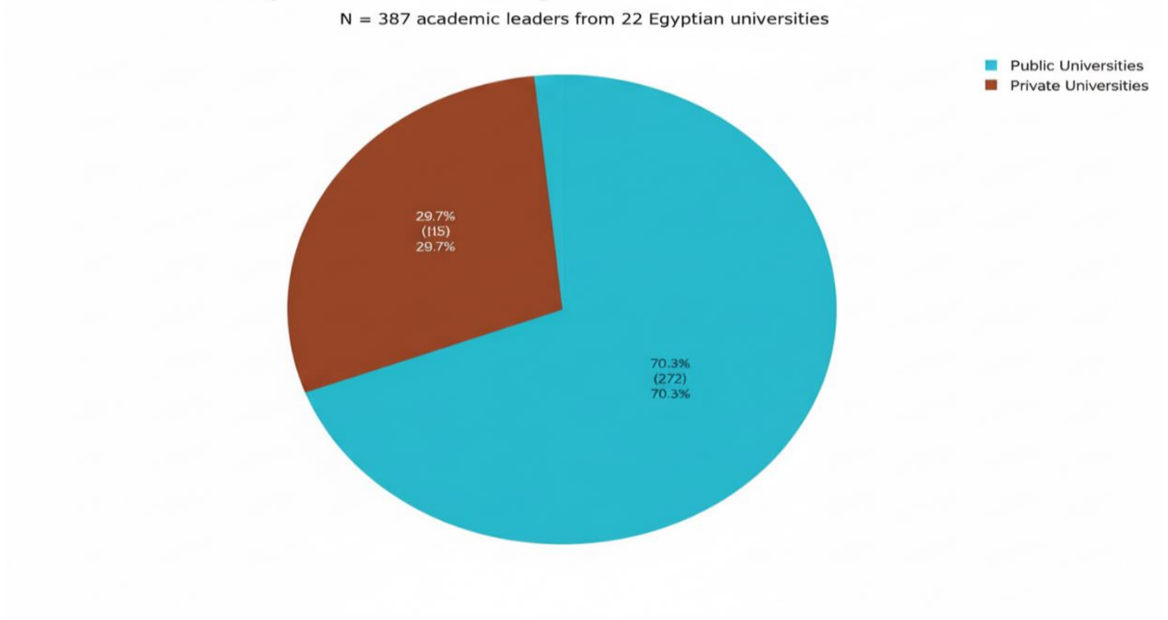

Figure 1: Sample Distribution by Institution Type and Size (N = 387).

The sample comprised participants from 22 Egyptian universities, with representation from both public (70.3%) and private (29.7%) institutions across three size categories based on student enrollment. Medium-sized institutions (5,000–15,000 students) were most represented (45.5%), reflecting the distribution of university types in Egypt's higher education system.

2.5. Measures

All instruments were administered electronically via Qualtrics platform using a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*) unless otherwise noted. Scales were originally developed in English based on established constructs in the literature and subsequently translated to Arabic using a rigorous forward-backward translation procedure involving two independent bilingual experts (one translator for forward translation, a different translator for back-translation) and reconciliation of discrepancies by a third expert.

2.6. Ai-Driven Decision Support Systems (Ai-Dss) Implementation Level

A 12-item researcher-developed scale assessed the extent to which institutions have deployed AI and predictive analytics technologies across key administrative functions. Items covered six domains: student performance prediction (2 items), at-risk student identification (2 items), enrollment forecasting (2 items), resource allocation optimization (2 items), program evaluation (2 items), and strategic planning support (2 items). Sample item: "Our institution uses machine learning algorithms to forecast student enrollment trends for the next academic year." Higher aggregate scores indicated greater breadth and depth of AI-DSS implementation.

Scale Development and Validation: Item generation was informed by literature on AI applications in higher education administration (Hossain et al., 2025; Khan & Ahmad, 2021) and consultation with five experts in educational technology and institutional research. Content validity was established through expert review (*I*-CVI range: 0.86–1.00, *S*-CVI/Ave = 0.94). Pilot testing with 45 administrators (not included in final sample) yielded acceptable reliability ($\alpha = 0.87$) and resulted in minor wording revisions.

Psychometric Properties (Current Study): Cronbach's $\alpha = 0.89$, composite reliability (CR) = 0.91, average variance extracted (AVE) = 0.58. Confirmatory factor analysis (CFA) demonstrated acceptable fit: $\chi^2(51) = 124.68$, $p < .001$, $\chi^2/\mathrm{df} = 2.44$,

CFI = 0.96, TLI = 0.95, RMSEA = 0.061 (90% CI [0.048, 0.074]), SRMR = 0.049. All factor loadings exceeded 0.60 (*range:* 0.63–0.82, *p*s < .001).

2.7. Explainable Ai (Xai) Transparency

An 11-item scale measured perceived transparency and explainability of AI systems used in participants' institutions. Items assessed four dimensions: clarity of algorithmic logic (3 items), availability of explanations for recommendations (3 items), disclosure of data sources and training procedures (3 items), and documentation of potential biases (2 items). Sample item: "The AI systems used in our institution provide clear, understandable explanations for their predictions and recommendations." Higher scores indicated greater perceived transparency.

Scale Development: Items were derived from XAI frameworks (Arrieta et al., 2020) and operationalized for non-technical administrative users. Content validation and pilot testing procedures mirrored those for the AI-DSS scale.

Psychometric Properties: Cronbach's α = 0.92, CR = 0.93, AVE = 0.63. CFA fit indices: $\chi^2(42) = 108.92$, $p < .001$, $\chi^2/df = 2.59$, CFI = 0.97, TLI = 0.96, RMSEA = 0.064 (90% CI [0.051, 0.077]), SRMR = 0.046. Factor loadings ranged from 0.68 to 0.86 (*p*s < .001).

2.8. Trust In AI Systems

A 10-item scale adapted from McKnight et al.'s (2011) trust in technology framework assessed participants' trust in AI systems across four dimensions: reliability (3 items; confidence that the system performs consistently), fairness (3 items; belief that the system produces unbiased outcomes), data security (2 items; confidence in protection of sensitive information), and predictive accuracy (2 items; belief in the validity of AI-generated insights). Sample item: "I trust that AI systems in our institution produce recommendations that are free from bias and discrimination." Higher scores reflected greater trust.

Adaptation Procedures: Items were modified to reference AI systems specifically (rather than generic technology) and contextualized for higher education administration. Permission for adaptation was obtained from the original authors.

Psychometric Properties: Cronbach's α = 0.91, CR = 0.92, AVE = 0.61. CFA fit: $\chi^2(33) = 96.34$, $p < .001$, $\chi^2/df = 2.92$, CFI = 0.96, TLI = 0.94, RMSEA = 0.071 (90% CI [0.056, 0.085]), SRMR = 0.051. Factor loadings: 0.65–0.84 (*p*s < .001).

2.9. Strategic Administrative Decision Quality

A 15-item scale evaluated six dimensions of administrative decision quality as perceived by participants: data-driven nature (3 items), effectiveness (3 items), timeliness (2 items), transparency (3 items), fairness (2 items), and stakeholder participation (2 items). This multidimensional conceptualization aligns with frameworks proposed by Ferguson et al. (2016) and Gašević et al. (2015). Sample items included: "Strategic decisions in our institution are based on comprehensive data analysis rather than intuition or past practice" (data-driven); "Decisions are made quickly enough to address emerging challenges and opportunities" (timeliness); "Decision-making processes ensure fairness and equity across all stakeholder groups" (fairness). Higher scores indicated higher perceived decision quality.

Scale Development: Items were generated through literature review and focus group discussions with seven academic administrators (separate from study sample). Content validity indices ranged from 0.89 to 1.00 (*S*-CVI/Ave = 0.96).

Psychometric Properties: Cronbach's α = 0.94, CR = 0.95, AVE = 0.66. CFA fit: $\chi^2(87) = 198.47$, $p < .001$, $\chi^2/df = 2.28$, CFI = 0.96, TLI = 0.95, RMSEA = 0.057 (90% CI [0.048, 0.067]), SRMR = 0.053. Factor loadings: 0.68–0.88 (*p*s < .001).

2.10. Procedure

Following approval from the Research Ethics Committee at Menoufia University, university presidents and institutional research boards at participating institutions were contacted via official correspondence to secure institutional permission and facilitate access to eligible administrators. Invitation emails containing study information, consent forms, and Qualtrics survey links were distributed through institutional email systems. The invitation emphasized voluntary participation, anonymity of responses, and confidentiality. Participants were informed that survey completion would require approximately 20–25 minutes.

Data collection occurred over 12 weeks (January 15 – April 30, 2025). Reminder emails were sent to non-responders at 2-week intervals (maximum three reminders). To enhance response rates and data quality, the survey employed: (a) progress indicators, (b) attention-check items (2 items embedded within scales; e.g., "Please select 'Strongly Agree' for this item"), (c) randomization of item order within scales to minimize response bias, and (d) skip logic to tailor questions based on AI-DSS usage status. Responses failing attention checks ($n = 18$) were excluded prior to analysis. All data were stored on encrypted, password-protected servers and were anonymized prior to export for statistical analysis.

3. DATA ANALYSIS

3.1. Preliminary Analyses

Data was screened for univariate and multivariate outliers, normality violations, and missing values using IBM SPSS Statistics 28.0. Univariate outliers (cases with z-scores > ±3.29) were identified for six cases but retained after visual inspection revealed plausible values. Multivariate outliers were assessed using Mahalanobis distance ($p < .001$); four cases exceeded critical values and were excluded, resulting in $N = 387$. Skewness (*range:* −0.84 to 0.72) and kurtosis (*range:* −0.96 to 1.14) values fell within acceptable ranges (±2.0), indicating approximate univariate normality (George & Mallery, 2019). Multivariate normality was evaluated via Mardia's coefficient; although statistically significant ($p < .05$), the standardized estimate (4.83) was below the threshold of concern (< 5.0) for maximum likelihood estimation (Byrne, 2016).

Missing data analysis revealed 2.3% missing values overall, distributed across items with no discernible pattern. Little's missing completely at random (MCAR) test yielded $\chi^2(156) = 142.35$, $p = .76$, indicating that data were MCAR. Consequently, full information maximum likelihood (FIML) estimation—implemented by default in AMOS—was employed for all subsequent SEM analyses, as FIML produces less biased and more efficient parameter estimates than listwise deletion or mean imputation under MCAR and MAR conditions (Enders, 2010).

3.2. Confirmatory Factor Analysis (Cfa)

Measurement models for each of the four latent constructs were evaluated separately via CFA in AMOS 26.0 using maximum likelihood estimation. Model fit was assessed using multiple criteria recommended by Hu and Bentler (1999) and Kline (2015): chi-square/degrees of freedom ratio (χ^2/df) < 3.0 (acceptable) or < 2.0 (excellent), comparative fit index (CFI) ≥ 0.95 (excellent) or ≥ 0.90 (acceptable), Tucker-Lewis index (TLI) ≥ 0.95 (excellent) or ≥ 0.90 (acceptable), root mean square error of approximation (RMSEA) ≤ 0.06 (good) or ≤ 0.08 (acceptable) with 90% confidence intervals reported, and standardized root mean square residual (SRMR) ≤ 0.08. These criteria balance sensitivity to model misspecification with robustness to sample size.

Discriminant validity was established using the Fornell-Larcker criterion (Fornell & Larcker, 1981): the square root of each construct's AVE exceeded its correlations with other constructs, indicating that constructs share more variance with their indicators than with other constructs.

3.3. Structural Equation Modeling

The hypothesized structural model—incorporating all four latent constructs and specified direct and indirect paths—was tested using AMOS 26.0 with maximum likelihood estimation. Path coefficients were evaluated for statistical significance ($p < .05$) and practical significance ($\beta \geq 0.20$ considered meaningful; Cohen, 1988). Model fit was assessed using the same indices as CFA. Squared multiple correlations (R^2) were examined to determine the proportion of variance explained in endogenous variables.

Mediation effects (H5) were evaluated using bias-corrected bootstrap procedures with 5,000 resamples and 95% confidence intervals, following recommendations by Preacher and Hayes (2008). Indirect effects were considered statistically significant if confidence intervals excluded zero. Full mediation was inferred if: (a) the indirect effect was significant, and (b) the direct effect became non-significant when mediators were included in the model. Partial mediation was inferred if both direct and indirect effects remained significant.

Alternative models were tested to ensure the hypothesized full mediation model provided the best fit. Model comparisons employed chi-square difference tests ($\Delta\chi^2$), changes in comparative fit indices (ΔCFI ≥ 0.01 indicates meaningful difference; Cheung & Rensvold, 2002), and information criteria (Akaike Information Criterion [AIC] and Bayesian Information Criterion [BIC]; lower values indicate better fit).

4. RESULTS

4.1. Preliminary Analyses

Descriptive statistics, zero-order correlations, and reliability coefficients for all study variables are presented in Table 2 and Figure 6. All constructions demonstrated high internal consistency ($\alpha \geq .89$, exceeding the threshold of 0.70 recommended by Nunnally & Bernstein, 1994). Mean scores ranged from 2.76 (*SD* = 0.94) for XAI transparency—indicating below-midpoint perceived transparency—to 3.42 (*SD* = 0.82) for decision quality. Correlations among constructs were moderate to strong (rs = .52 to .71, all ps < .01), indicating meaningful relationships without multicollinearity concerns (correlations < .80; Tabachnick & Fidell, 2019).

Table 2: Descriptive Statistics, Intercorrelations, And Reliability Coefficients for Study Variables.

Variable	*M*	*SD*	1	2	3	4	α	CR	AVE
1. AI-DSS Implementation	3.14	0.87	–				.89	.91	.58
2. XAI Transparency	2.76	0.94	.63**	–			.92	.93	.63
3. Trust in AI Systems	2.89	0.91	.58**	.71**	–		.91	.92	.61
4. Decision Quality	3.42	0.82	.52**	.68**	.69**	–	.94	.95	.66

Note: N = 387. CR = Composite Reliability; AVE = Average Variance Extracted. All Correlations Significant At *P < .01 (Two-Tailed).

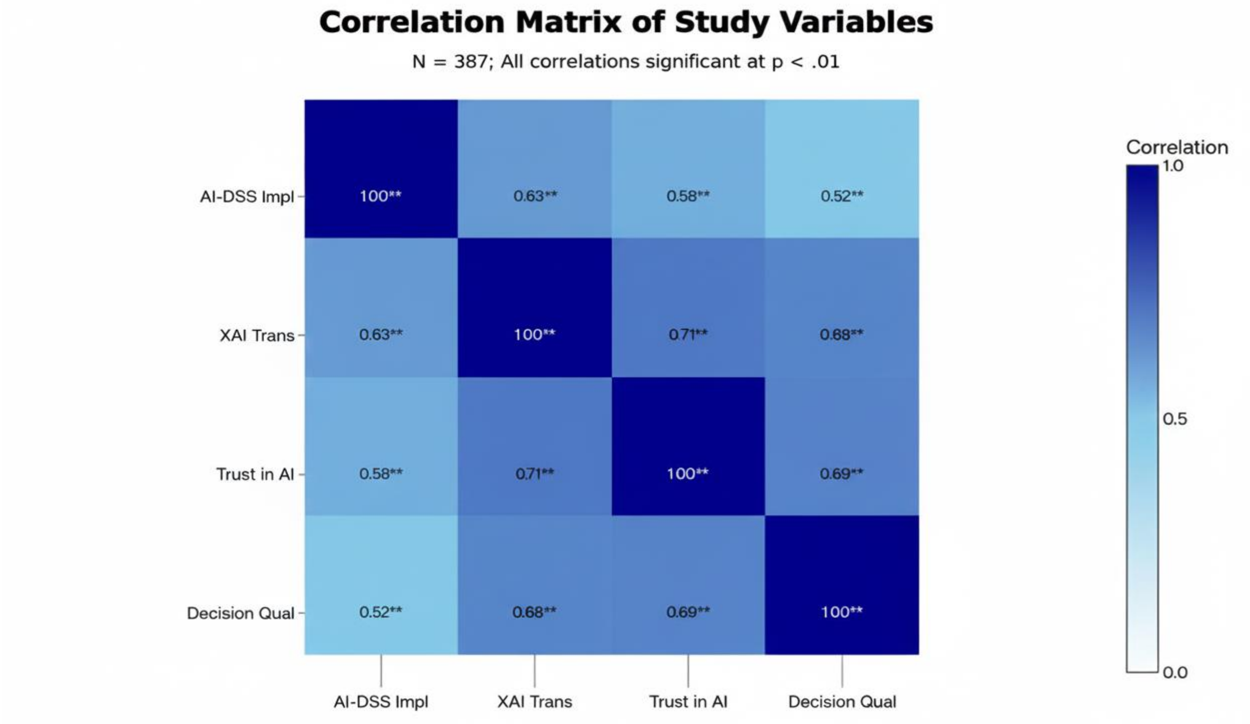

Figure 2: Correlation Matrix of Study Variables (N = 387).

All correlations are statistically significant at **p < .01 (two-tailed). Darker blue colors indicate stronger positive correlations. The strongest correlation was observed between XAI Transparency and Trust in AI Systems (r = .71), supporting the hypothesized mediating pathway. No correlations exceeded .80, indicating absence of multicollinearity concerns.

4.2. Measurement Model

A four-factor measurement model incorporating all constructs and their indicators was tested via CFA. The model demonstrated good fit: $\chi^2(458) = 1089.24$, $p < .001$, $\chi^2/\mathrm{df} = 2.38$, CFI = 0.95, TLI = 0.94, RMSEA = 0.060 (90% CI [0.056, 0.064]), SRMR = 0.058. All factor loadings were statistically significant (*p*s < .001) and exceeded the recommended threshold of 0.50, with standardized estimates ranging from 0.63 to 0.88 (*M* = 0.75), supporting convergent validity. Table 3 presents fit indices for individual construct measurement models, all of which met or exceeded acceptable thresholds.

Table 3: Confirmatory Factor Analysis Fit Indices for Individual Construct Measurement Models.

Construct	χ^2	*df*	χ^2/df	CFI	TLI	RMSEA [90% CI]	SRMR	Factor Loading Range
AI-DSS Implementation	124.68	51	2.44	0.96	0.95	0.061 [0.048, 0.074]	0.049	0.63–0.82
XAI Transparency	108.92	42	2.59	0.97	0.96	0.064 [0.051, 0.077]	0.046	0.68–0.86
Trust in AI Systems	96.34	33	2.92	0.96	0.94	0.071 [0.056, 0.085]	0.051	0.65–0.84
Strategic Decision Quality	198.47	87	2.28	0.96	0.95	0.057 [0.048, 0.067]	0.053	0.68–0.88

Note: All X^2 Statistics Significant at P < .001. All Factor Loadings Significant at P < .001.

Discriminant validity was confirmed: the square root of AVE for each construct exceeded its correlations with all other constructs (Fornell-Larcker criterion). For example, √AVE for AI-DSS Implementation = 0.76, which exceeds its correlations with XAI Transparency (0.63), Trust (0.58), and Decision Quality (0.52).

4.3. Structural Model and Hypothesis Testing

The hypothesized full mediation model demonstrated excellent fit to the data: $\chi^2(461) = 986.54$, $p < .001$, $\chi^2/df = 2.14$, CFI = 0.96, TLI = 0.95, RMSEA = 0.054 (90% CI [0.047, 0.061]), SRMR = 0.051. All fit indices met or exceeded the most stringent criteria (Hu & Bentler, 1999), indicating that the hypothesized model adequately represented the observed data.

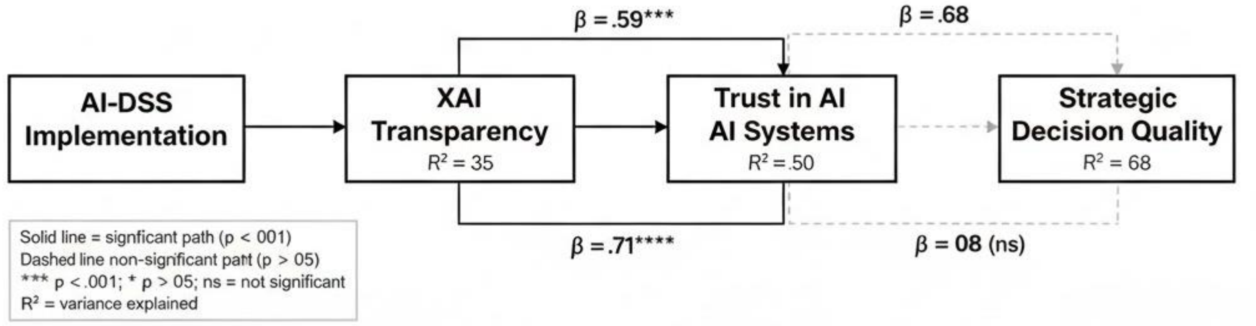

Figure 3: Structural Equation Model Showing Full Mediation of XAI Transparency and Trust in the Relationship Between AI-DSS Implementation and Strategic Decision Quality.

Standardized path coefficients (β) are shown on arrows. Solid lines indicate significant paths (**$p < .001$), and the dashed line indicates a non-significant path (ns). R^2 values represent the proportion of variance explained in endogenous variables. Model fit: χ^2 (461) = 986.54, $\chi^2/df = 2.14$, CFI = 0.96, TLI = 0.95, RMSEA = 0.054 [0.047, 0.061], SRMR = 0.051.

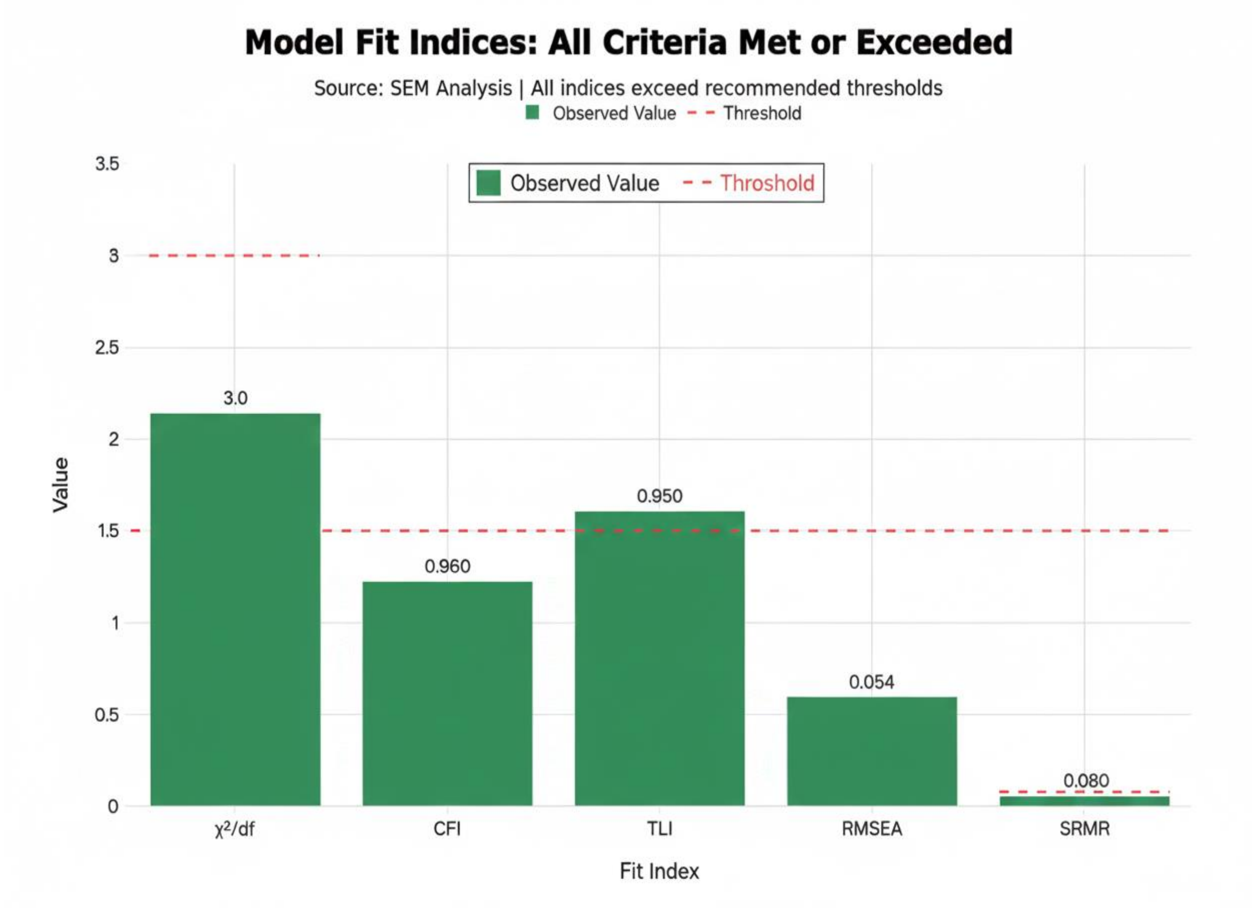

Figure 4: Model Fit Indices Compared to Recommended Thresholds.

All five fit indices met or exceeded criteria for excellent or good model fit, indicating that the hypothesized model adequately represents the observed data. Green bars represent observed values; dashed red lines represent recommended thresholds from Hu and Bentler (1999) and Kline (2015).

Standardized path coefficients, standard errors, critical ratios, significance levels, and bootstrap confidence intervals are presented in Table 4. Results for each hypothesis are summarized below.

Table 4: Standardized Path Coefficients, Standard Errors, Critical Ratios, And Significance Levels.

Path	β	*SE*	*CR*	*p*	95% CI
Direct Effects					
AI-DSS → XAI Transparency (H2)	0.59	0.047	12.55	< .001	[0.50, 0.68]
XAI Transparency → Trust (H3)	0.71	0.041	17.32	< .001	[0.63, 0.79]
Trust → Decision Quality (H4)	0.57	0.044	12.95	< .001	[0.48, 0.66]
AI-DSS → Decision Quality (H1)	0.08	0.051	1.57	.117	[−0.02, 0.18]
Indirect Effects (Mediation Pathways)					
AI-DSS → XAI → Trust	0.42	0.043	–	< .001	[0.34, 0.51]
AI-DSS → Trust → Decision Quality	0.05	0.031	–	.095	[−0.01, 0.11]
XAI → Trust → Decision Quality	0.40	0.041	–	< .001	[0.32, 0.49]
AI-DSS → XAI → Trust → Decision Quality (Serial)	0.24	0.030	–	< .001	[0.18, 0.30]
Total Indirect Effect (AI-DSS → Decision Quality)	0.48	0.047	–	< .001	[0.39, 0.57]
Total Effect (Direct + Indirect)	0.56	0.051	–	< .001	[0.46, 0.66]

Note: Β = Standardized Coefficient; SE = Standard Error; CR = Critical Ratio (Analogous To T-Value); CI = Confidence Interval Based On 5,000 Bias-Corrected Bootstrap Samples. Indirect Effects Tested Via Bootstrapping; P-Values and Crs Not Applicable.

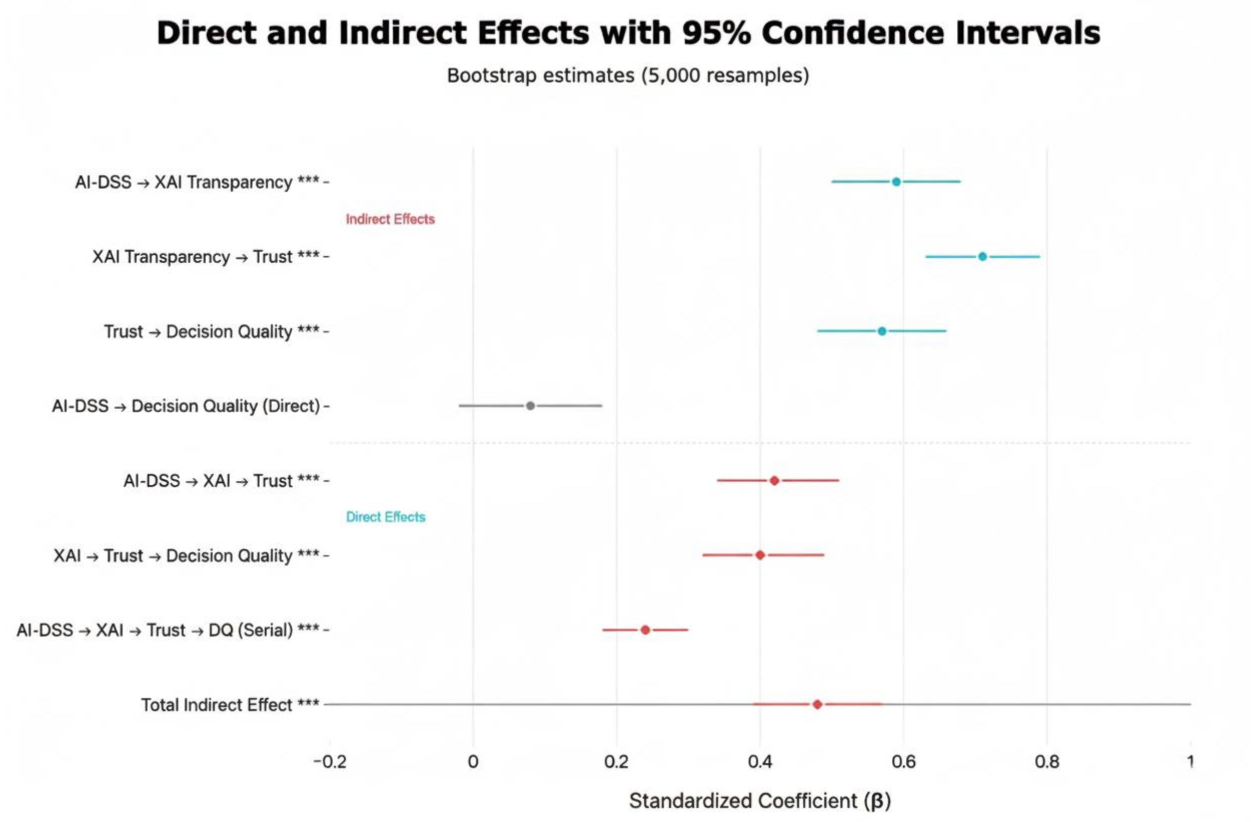

Figure 5: Forest Plot of Direct and Indirect Effects With 95% Bootstrap Confidence Intervals.

Point estimates (circles/diamonds) and 95% confidence intervals (horizontal lines) are based on 5,000 bias-corrected bootstrap resamples. Effects are considered statistically significant when confidence intervals do not include zero (shown in blue and orange). The direct effect from AI-DSS to Decision Quality was not significant (gray), while all indirect pathways through XAI transparency and trust were highly significant (**p < .001), confirming full mediation.

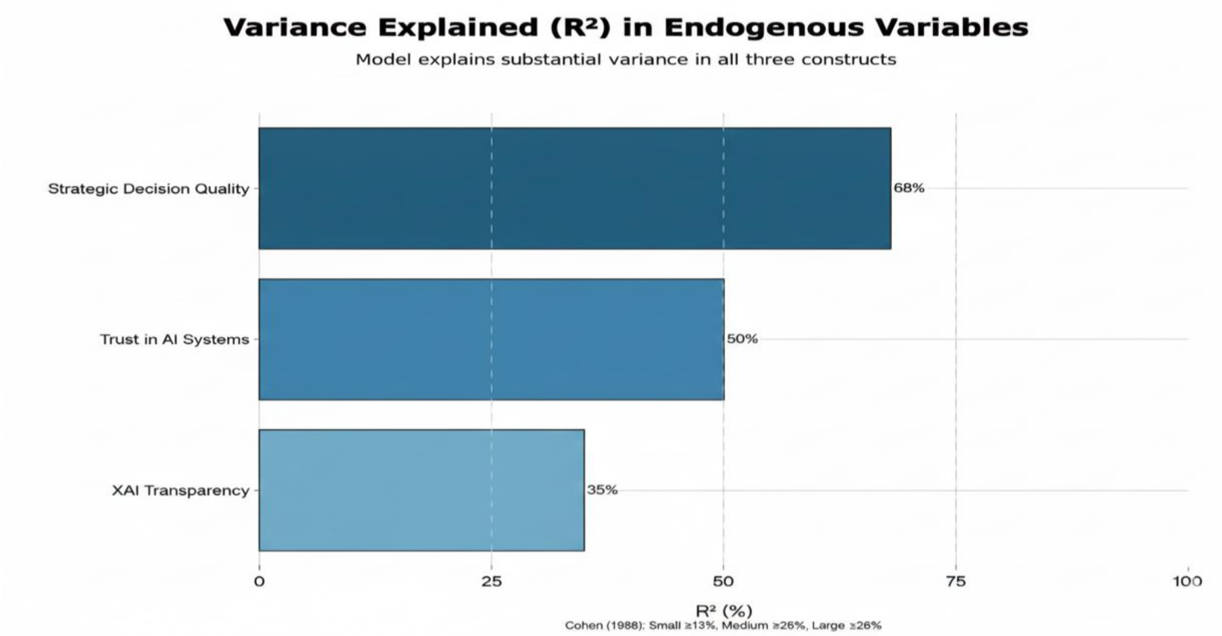

Figure 6: Proportion Of Variance Explained (R^2) In Endogenous Variables.

The structural model explained substantial variance in all three endogenous constructions, with 68% of variance in strategic decision quality, 50% in trust, and 35% in XAI transparency. All R^2 values exceed Cohen's (1988) threshold for large effects (≥35% for R^2).

Hypothesis 1: Direct Effect Of AI-DSS On Decision Quality

Contrary to prediction, the direct path from AI-DSS implementation to strategic decision quality was not statistically significant (β = 0.08, *SE* = 0.051, *CR* = 1.57, *p* = .117, 95% CI [−0.02, 0.18]). This indicates that, controlling for the mediating pathways through XAI transparency and trust, AI-DSS implementation alone does not significantly improve decision quality. **Hypothesis 1 was not supported.** This null finding is substantively meaningful, as it suggests that technological deployment per se is insufficient to enhance administrative decision-making outcomes.

Hypothesis 2: AI-DSS And XAI Transparency

AI-DSS implementation strongly and positively predicted XAI transparency (β = 0.59, *SE* = 0.047, *CR* = 12.55, *p* < .001, 95% CI [0.50, 0.68]), explaining 35% of variance in transparency ($R^2 = .35$). This large effect indicates that institutions with more extensive AI deployments tend to provide greater algorithmic transparency, possibly reflecting intentional design priorities or regulatory compliance efforts. **Hypothesis 2 was supported.**

Hypothesis 3: XAI Transparency and Trust

XAI transparency was a robust predictor of trust in AI systems (β = 0.71, *SE* = 0.041, *CR* = 17.32, *p* < .001, 95% CI [0.63, 0.79]), accounting for 50% of variance in trust ($R^2 = .50$). This very large effect size underscores the critical role of transparency in cultivating confidence among administrative leaders. **Hypothesis 3 was supported.**

Hypothesis 4: Trust And Decision Quality

Trust in AI systems significantly predicted strategic decision quality (β = 0.57, *SE* = 0.044, *CR* = 12.95, *p* < .001, 95% CI [0.48, 0.66]). Administrators who trusted AI systems reported higher decision quality across all six dimensions. **Hypothesis 4 was supported.**

Hypothesis 5: Serial Mediation

The total indirect effect of AI-DSS implementation on decision quality through XAI transparency and trust was substantial and statistically significant (β = 0.48, *SE* = 0.047, *p* < .001, 95% CI [0.39, 0.57]). Decomposition of indirect pathways revealed:

1. **AI-DSS → XAI → Trust :** β = 0.42, 95% CI [0.34, 0.51], *p* < .001 (signifiant)
2. **AI-DSS → Trust → Decision Quality:** β = 0.05, 95% CI [−0.01, 0.11], *p* = .095 (not significant)
3. **XAI → Trust → Decision Quality:** β = 0.40, 95% CI [0.32, 0.49], *p* < .001 (significant)
4. **AI-DSS → XAI → Trust → Decision Quality (Serial):** β = 0.24, 95% CI [0.18, 0.30], *p* < .001 (significant)

The most theoretically important pathway is serial mediation: AI-DSS implementation enhances

XAI transparency, which cultivates trust, which subsequently improves decision quality ($\beta = 0.24$). Given that the direct effect became non-significant when mediators were included and the total indirect effect was significant and substantial, **full mediation** was established, providing strong support for **Hypothesis 5**.

The final model accounted for 68% of variance in strategic decision quality ($R^2 = .68$, a large effect per Cohen, 1988), 50% of variance in trust ($R^2 = .50$), and 35% of variance in XAI transparency ($R^2 = .35$), indicating excellent explanatory power.

4.4. Alternative Model Comparisons

To ensure the hypothesized full mediation model provided optimal fit, two alternative models were tested and compared:

Model A (Direct-Effects-Only): This model specified only direct paths from AI-DSS to all three other constructs, omitting serial mediation pathways. Fit indices: $\chi^2(463) = 1174.99$, $p < .001$, $\chi^2/df = 2.54$, CFI = 0.92, TLI = 0.91, RMSEA = 0.063 (90% CI [0.059, 0.067]), SRMR = 0.074. Chi-square difference test: $\Delta\chi^2(2) = 188.45$, $p < .001$, favoring the full mediation model. Additionally, ΔCFI = 0.04 and ΔAIC = 184.45 both indicated meaningful improvement for the full mediation model.

Model B (Partial Mediation): This model retained all pathways from the full mediation model but constrained the direct path (AI-DSS → Decision Quality) to be estimated freely (rather than accepting its non-significance). Fit indices were virtually identical to the full mediation model: $\chi^2(461) = 986.54$, CFI = 0.96. However, the direct path remained non-significant ($\beta = 0.08$, $p = .117$), and model parsimony indices (AIC, BIC) did not favor this more complex specification. Per the principle of parsimony and interpretability, the full mediation model was retained as the final model.

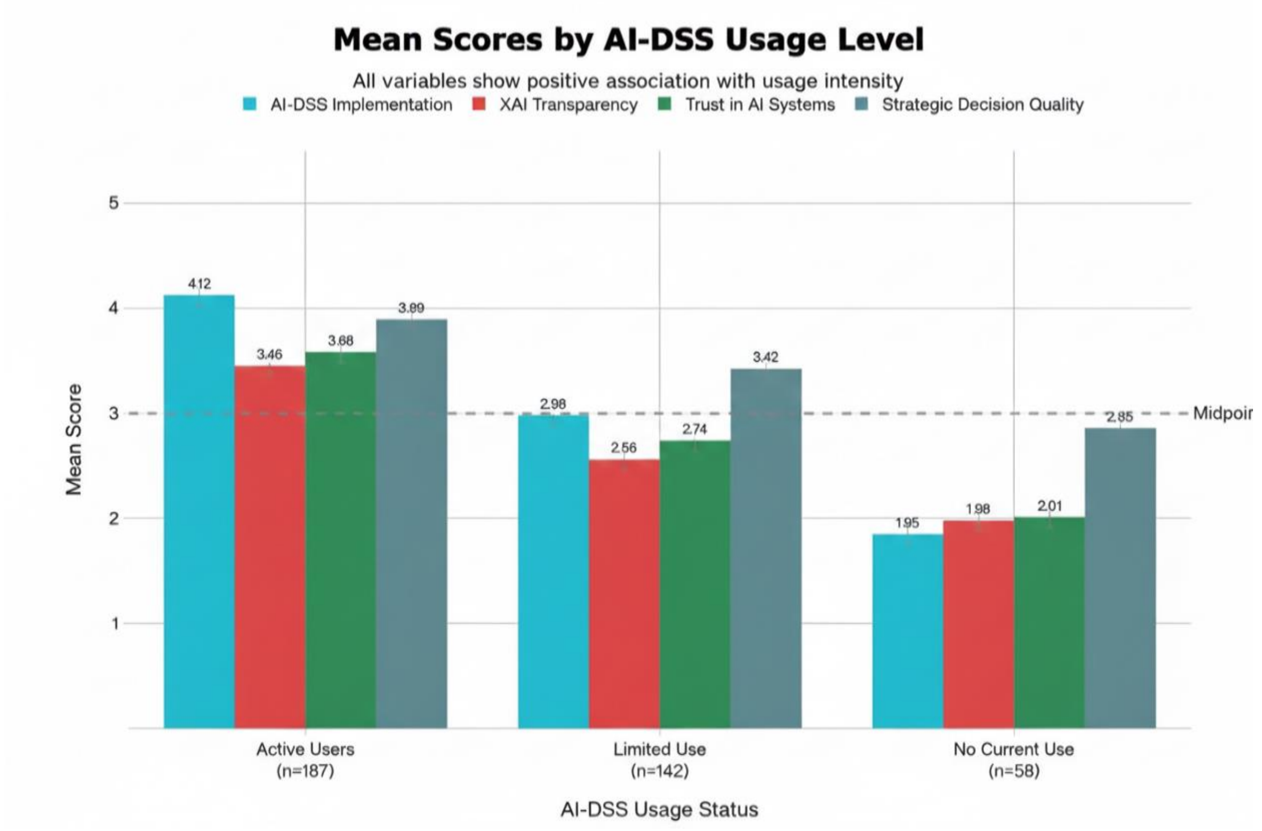

Figure 7: Mean Scores for Study Variables By AI-DSS Usage Level (N = 387).

Participants who actively use AI-DSS reported significantly higher scores on XAI transparency, trust, and decision quality compared to limited users or non-users. Error bars represent standard errors. The horizontal dashed line indicates the scale midpoint (3.0 = Neither Agree nor Disagree). This pattern supports the positive relationships observed in the structural model.

5. DISCUSSION

This study provides the first empirical evidence from a Middle Eastern context demonstrating that algorithmic transparency through explainable AI (XAI) mechanisms is a critical mediator linking AI-

DSS implementation to academic leaders' trust and, ultimately, to the quality of strategic administrative decisions in higher education. The findings address a significant gap in the literature by elucidating the psychological and organizational processes through which AI technologies translate —or fail to translate—into improved institutional governance. The results carry profound implications for theory, practice, and policy in educational technology and higher education administration.

5.1. Key Findings and Theoretical Implications

The absence of a direct effect from AI-DSS implementation to decision quality (H1 not supported; β = 0.08, *p* = .117) represents the study's most pivotal and counterintuitive finding. It indicates that merely deploying advanced predictive analytics systems—regardless of their technical sophistication, predictive accuracy, or resource investment—does not guarantee improvements in administrative decision-making. This null result challenges the prevalent "technological solutionism" narrative (Morozov, 2013) that assumes sophisticated tools automatically yield better outcomes. Instead, our data demonstrate that AI systems operate within complex sociotechnical ecosystems where human factors—specifically trust and understanding—are as consequential as algorithmic performance.

This finding aligns with implementation science literature emphasizing that technological potential must be actualized through user engagement, organizational readiness, and appropriate utilization (Fixsen et al., 2005). In higher education, where administrative decisions impact diverse stakeholders and carry reputational, financial, and ethical consequences, administrators reasonably demand comprehensibility before incorporating algorithmic recommendations into high-stakes judgments. Our results extend this principle empirically, providing quantitative evidence that "build it and they will use it" approaches fail in the absence of transparency.

Instead, the data supports a sequential mediation process wherein AI-DSS implementation fosters XAI transparency (β = 0.59, large effect), which cultivates trust in AI systems (β = 0.71, very large effect), which subsequently enhances decision quality (β = 0.57, large effect). This serial pathway explained 68% of variance in decision quality—a substantial effect size indicating that transparency-driven trust is not merely relevant but foundational to realizing AI's value proposition in administrative contexts. The total indirect effect (β = 0.48) exceeded the (non-significant) direct effect, underscoring that mediated pathways constitute the primary mechanism of influence.

The magnitude of the XAI-to-trust relationship (β = 0.71) is particularly noteworthy, representing one of the strongest effects documented in educational technology research. It suggests that when administrators understand *how* AI systems arrive at recommendations—when algorithms are rendered interpretable rather than remaining "black boxes"—their confidence in those systems increases dramatically. This finding resonates with human-computer interaction research demonstrating that explainability reduces uncertainty, enhances predictability, and mitigates perceived risk, thereby promoting acceptance of automated decision tools (Arrieta et al., 2020; Ribeiro et al., 2016). The strength of this relationship validates Mandinach's (2025) Data Ethics Framework, which positions transparency as a foundational pillar—not an optional feature—of ethical AI deployment.

Our findings also empirically validate the Enhanced Technology Acceptance Model (TAM) by confirming that trust, enabled by explainability, operates as a distinct and potent determinant of technology acceptance beyond traditional TAM constructs of perceived usefulness and ease of use. The original TAM, developed before the AI era, did not account for algorithmic opacity and bias concerns that characterize contemporary AI systems. Our results demonstrate that for high-stakes decision support applications, trust mediated by transparency supersedes utility considerations: even highly accurate systems will languish if administrators cannot comprehend or verify their logic.

From a decision quality perspective, the study operationalized a multidimensional framework encompassing data-driven reasoning, effectiveness, timeliness, transparency, fairness, and participation—attributes aligned with normative theories of good governance (Ferguson et al., 2016). The strong relationship between trust and decision quality (β = 0.57) indicates that administrators' confidence in AI systems enables them to leverage data-driven insights effectively, respond proactively to challenges, and make equitable, evidence-based decisions. This relationship likely reflects both cognitive (administrators use AI insights when confident) and affective (trust reduces anxiety about delegating judgment to algorithms) mechanisms.

5.2. Practical Implications for Higher Education Institutions

The findings convey actionable implications for university leaders, EdTech developers, and policymakers navigating AI adoption:

1. *Prioritize Explainability Alongside Accuracy:*

Institutions investing in AI infrastructure must prioritize explainability features—such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), attention mechanisms, or counterfactual explanations—alongside maximizing predictive accuracy. While machine learning competitions emphasize performance metrics (e.g., AUC, F1-score, RMSE), our results indicate that a highly accurate but opaque model will not be trusted or utilized by decision-makers. Procurement criteria for AI-DSS should explicitly require transparency features and vendor demonstrations of explainability capabilities.

2. *Invest In Professional Development:*

Academic leaders require professional development emphasizing AI literacy—not to transform administrators into data scientists, but to equip them with sufficient understanding of algorithmic logic, limitations, and potential biases to engage critically with AI-generated insights. Training programs should cover foundational concepts (e.g., supervised vs. unsupervised learning, bias-variance tradeoff), interpretation of common XAI outputs (e.g., feature importance plots, decision trees), and ethical considerations (fairness, accountability, transparency). Our findings suggest that such training, coupled with transparent systems, can break down resistance rooted in skepticism or fear.

3. *Establish Ai Governance Frameworks:*

Transparent AI deployment requires ongoing governance. Institutions should establish AI review committees responsible for: (a) auditing algorithms for accuracy, fairness, and alignment with institutional values; (b) requiring documentation of data sources, training procedures, and known limitations; (c) soliciting stakeholder feedback on AI system usability and trustworthiness; and (d) iteratively refining systems based on usage patterns and outcomes. Such frameworks operationalize Mandinach's (2025) Data Ethics principles and align with EDUCAUSE (2025) and UNESCO (2021) ethical AI guidelines.

4. *Design Human-Centered Ai Systems:*

Our finding that 66% of HCLA/HCAI solutions remain untested in authentic settings (Hooshyar et al., 2024) underscores the need for participatory design processes. Administrators should be involved not only in needs assessment but also in iterative prototyping, usability testing, and evaluation. Co-design approaches ensure that AI-DSS aligns with administrators' workflows, information needs, and decision-making practices, thereby enhancing both usability and trust.

5. *Communicate Transparency and Build Trust Incrementally:*

Trust develops gradually through repeated positive experiences. Institutions should adopt phased AI implementation strategies: (a) pilot systems in low-stakes contexts where errors are tolerable and learning can occur; (b) provide extensive transparency documentation and training during rollout; (c) solicit and act on user feedback to refine systems; and (d) communicate openly about successes, failures, and corrective actions. Such iterative, trust-building approaches are more effective than top-down mandates.

5.3. *Limitations And Future Research Directions*

Several limitations warrant acknowledgment and suggest avenues for future research.

1. *Cross-Sectional Design:*

The cross-sectional design precludes causal inference despite SEM terminology (which describes model structure, not temporal causality). Longitudinal studies tracking administrators' evolving trust and decision quality as AI systems are introduced, refined, or decommissioned would provide stronger causal evidence and clarify temporal dynamics. Intervention studies manipulating XAI features (e.g., providing SHAP explanations vs. no explanations) would offer experimental validation of our correlational findings.

2. *Self-Reported Measures:*

Data relied exclusively on self-reported perceptions rather than objective measures of decision quality (e.g., institutional outcomes like retention rates, graduation rates, resource efficiency) or verified AI system characteristics (e.g., independently audited transparency features). While self-reports are appropriate for measuring subjective constructs (trust, perceived transparency), future research should integrate: (a) institutional performance data to validate decision quality claims; (b) expert evaluations of AI system explainability using standardized rubrics; and (c) behavioral indicators of AI usage (e.g., log data showing frequency and context of AI tool access).

3. *Single-Country Sample:*

The sample was drawn exclusively from Egyptian universities, limiting generalizability to other regional, national, or cultural contexts. Egypt's higher education system—characterized by centralized governance, resource constraints, and varying levels of digital infrastructure—may differ from Western systems in ways that moderate relationships. Replication studies in diverse settings (e.g., North America, Europe, East Asia, Latin America) are essential to assess cross-cultural validity and identify context-specific moderators.

4. Undifferentiated Decision Types:

The study did not differentiate among types of administrative decisions (e.g., enrollment forecasting vs. budget allocation vs. academic program discontinuation), which may vary in complexity, data availability, stakeholder sensitivity, and urgency. Future research should explore whether the transparency-trust-quality pathway operates uniformly across decision domains or is moderated by decision characteristics such as reversibility, stakes, and technical sophistication.

5. Absence Of Algorithmic Bias Assessment:

While participants reported perceptions of fairness and bias, the study did not directly assess whether AI systems exhibit actual algorithmic bias through audit studies or fairness metrics (e.g., disparate impact ratios, equalized odds, demographic parity). Future work should employ rigorous bias-testing methodologies to determine: (a) whether AI-DSS recommendations exhibit differential accuracy or treatment across demographic groups (e.g., by gender, socioeconomic status, field of study); and (b) whether XAI mechanisms help administrators detect and correct such biases.

6. Unmeasured Moderators:

The model explained 68% of variance in decision quality, indicating that 32% remains attributable to factors not examined. Potential moderators include institutional culture (e.g., data-driven vs. tradition-oriented climates), leadership style (e.g., participatory vs. autocratic), prior experience with technology failures (creating skepticism), and individual differences in need of cognition or tolerance of ambiguity. Future research should incorporate these variables to develop more comprehensive models.

7. Lack Of Economic Analysis:

The study did not assess cost-effectiveness or return on investment (ROI) of AI-DSS implementations, nor did it quantify the economic value of improved decision quality. Institutions require business case justifications demonstrating that investments in explainability features yield measurable benefits. Future research should incorporate economic evaluations comparing institutions with high-transparency vs. low-transparency AI systems on metrics such as cost savings, efficiency gains, and revenue generation.

5.4. Directions For Future Research

Beyond addressing limitations, several fruitful research directions emerge:

1. Experimental Manipulations of XAI Features:

Randomized controlled trials manipulating the presence/absence or type of XAI explanations (e.g., SHAP plots vs. textual narratives vs. no explanations) would provide causal evidence regarding optimal transparency mechanisms for different user populations and decision contexts.

2. Longitudinal Studies of Trust Development:

Panel studies tracking administrators' trust trajectories over multiple semesters as they gain experience with AI systems would illuminate: (a) whether initial skepticism attenuates with positive experiences; (b) how errors or bias incidents erode trust; and (c) optimal timelines for realizing benefits.

3. Multi-Level Modeling:

Hierarchical linear modeling (HLM) nesting individuals within institutions would be partition variance attributable to individual-level factors (e.g., AI literacy, risk aversion) vs. institutional-level factors (e.g., organizational culture, infrastructure quality, training availability), clarifying where interventions should target.

4. Comparative International Studies:

Cross-national research comparing AI adoption dynamics across diverse higher education systems (e.g., US, China, Germany, Brazil, South Africa) would identify universal principles and culture-specific adaptation requirements.

5. Stakeholder Triangulation:

Future studies should include multiple stakeholder perspectives—administrators, faculty, students, IT staff—to assess whether transparency and trust dynamics differ across roles and whether divergent perceptions create implementation challenges.

6. *Intervention Research:*

Design-based research evaluating AI literacy training programs, participatory AI design workshops, or institutional policy interventions would generate practical knowledge about effective strategies for fostering transparency and trust.

6. CONCLUSION

In an era of data abundance and algorithmic capability, higher education institutions face a consequential choice: to embrace AI as a transformative tool for evidence-based governance or to allow distrust and opacity to relegate sophisticated technologies to underutilization or abandonment. This study demonstrates empirically that the path to realizing AI's potential runs decisively through transparency. Explainable AI is not a luxury for technically inclined users or a cosmetic feature to satisfy regulatory compliance; it is a functional necessity for cultivating the trust required for administrators to confidently integrate algorithmic insights into high-stakes strategic decisions.

The full mediation finding—that AI-DSS implementation influences decision quality *only* through transparency and trust, with no direct effect—underscores a fundamental principle: technology's impact is mediated by human psychology and social processes. Algorithms do not make decisions; humans do, informed (or not) by algorithms. When algorithms are opaque, humans revert to intuition, sustaining the very inefficiencies that AI purports to address. When algorithms are transparent, humans become empowered collaborators, leveraging machine precision and human judgment synergistically.

As institutions worldwide navigate digital transformation, prioritizing algorithmic transparency alongside accuracy will determine whether AI becomes a trusted partner in institutional excellence or a source of skepticism, anxiety, and resistance. The stakes are high: in higher education, administrative decisions shape students' trajectories, faculty working conditions, institutional reputations, and societal contributions. Getting AI right—making it trustworthy through transparency—is not merely a technical challenge but a moral imperative. This study provides an empirical foundation and practical roadmap for that endeavor.

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Authors Note

Data Availability: The dataset and analysis scripts supporting this study are available from the authors upon reasonable request and with appropriate ethical safeguards to protect participant confidentiality.

Open Science Practices: This study's design and hypotheses were not preregistered. Analysis code and supplementary materials (survey instruments in English and Arabic, AMOS syntax) are available at [OSF repository link to be added upon acceptance].

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