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A Hybrid Fuzzy AHP–Entropy–TOPSIS and SEM Framework for Adoption and Impact Assessment of Intelligent Decision Support Systems in Business Management

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Abstract

Intelligent Decision Support Systems (IDSS) integrate artificial intelligence, machine learning, and advanced analytics to enhance organisational decision-making. While IDSS adoption has grown considerably in recent years, a unified framework addressing both adoption drivers and measurable performance outcomes across multiple business sectors remains lacking. To address this gap, this study introduces the Multi-Criteria Adoption Assessment Model (MCAAM). The framework integrates fuzzy Analytical Hierarchy Process (AHP), Shannon entropy weighting, TOPSIS, and covariance-based structural equation modelling (CB-SEM) to evaluate adoption determinants, organisational ranking, and causal relationships. Unlike existing approaches such as TAM and UTAUT, MCAAM integrates subjective expert judgment with objective empirical data within a single evaluation structure. Survey data were collected from 387 business organisations across India, Southeast Asia, and the Middle East, spanning manufacturing ($n = 112$), finance ($n = 98$), healthcare ($n = 89$), and supply chain ($n = 88$) sectors during March–September 2024. Findings indicate that the strongest predictors of adoption are trust in AI-driven outcomes ($\beta = 0.412$, $p < 0.001$) and data infrastructure maturity ($\beta = 0.387$, $p < 0.001$). Organisations implementing IDSS achieved a 34.7% improvement in decision accuracy and a 28.3% reduction in decision latency. Limitations include the cross-sectional design, geographic concentration, and reliance on self-reported data, which may affect generalisability. Future research should incorporate longitudinal designs, broader geographic coverage, and integration of generative AI capabilities.

Keywords: Intelligent Decision Support Systems (IDSS); Multi-Criteria Decision-Making (MCDM); Fuzzy AHP; TOPSIS; Structural Equation Modelling (SEM); Data Infrastructure; AI Adoption.

1. Introduction

As business environments become increasingly complex, organisations are adopting decision-making tools that extend beyond the limits of human cognition. Onwujekwe and Weistroffer [4] identified four core categories of Intelligent Decision Support Systems (IDSS)—knowledge-based, data-driven, model-driven, and hybrid—and highlighted the absence of unified evaluation frameworks across these types. Wang et al. [5] demonstrated that contextual reasoning in IDSS can be enhanced through retrieval-augmented generation combined with knowledge graphs. Chechnev [6] further developed a taxonomy of decision-making automation levels, ranging from system-assisted suggestions to fully autonomous execution. Despite these advancements, the literature lacks a coherent framework capable of simultaneously assessing adoption determinants and measurable performance impacts across multiple business sectors.

Early IDSS applications were largely domain-specific. Liu et al. [1] proposed multi-agent architectures for cooperative decision-making, while Wang and Liu [2] applied group intelligence techniques to power system restoration. Guan et al. [3] implemented intelligent decision support systems for power grid dispatching, and Han [13] developed computational approaches for financial decision-making. Although these studies demonstrated strong domain-level performance, they did not provide generalised frameworks for cross-sector evaluation or organisational impact assessment.

Recent advances in generative AI [11], business process management [7], and chatbot integration [8] have significantly expanded the capabilities of IDSS. Batz et al. [9] provided empirical evidence on machine learning adoption in business environments, while Montealegre-Lopez [10] identified trust as a key barrier to adoption. However, existing research typically examines technological capability and organisational readiness separately, without integrating both dimensions into a unified quantitative framework. Recent studies have begun to explore integrated analytical approaches combining risk assessment and process optimisation techniques; however, these are largely confined to specific industrial domains and do not address cross-sector decision intelligence systems [27].

Three key gaps remain in the current literature. First, most technology adoption studies rely on single-method frameworks such as TAM or UTAUT. While TAM [25] captures individual acceptance through perceived usefulness and ease of use, and UTAUT incorporates social influence and facilitating conditions, neither framework enables the assignment of multi-dimensional weights across organisational, technological, and data-related factors simultaneously. Second, impact assessment remains largely qualitative or limited to individual performance metrics, leaving composite quantitative evaluation underdeveloped. Third, the moderating roles of trust in AI-driven outcomes and data infrastructure maturity in the adoption–impact relationship have not been adequately modelled in multi-sector contexts.

This study addresses these gaps by integrating fuzzy multi-criteria decision-making (MCDM), entropy-based objective weighting, and covariance-based structural equation modelling (CB-SEM) into a unified assessment framework. The proposed Multi-Criteria Adoption Assessment Model (MCAAM) enables the simultaneous evaluation of adoption determinants and organisational impact across multiple sectors.

Research Questions

RQ1: What are the dominant determinants of IDSS adoption in business management, and what are their relative weights?

RQ2: How does IDSS adoption influence measurable decision quality, latency, and strategic alignment?

RQ3: Do trust in AI-driven outcomes and data infrastructure maturity moderate the relationship between adoption intent and realised impact?

Hypotheses

Based on the literature synthesis [4], [10], [22], the following hypotheses are formulated:

H1: Trust in AI-driven outcomes has the strongest positive effect on IDSS adoption intent.

H2: Data infrastructure maturity positively predicts IDSS adoption intent.

H3: IDSS adoption intent positively predicts measurable impact scores.

H4: Trust and data maturity moderate the adoption–impact relationship.

2. Literature Review and Research Gap Analysis

The evolution of Intelligent Decision Support Systems (IDSS) has progressed from rule-based expert systems [1] to advanced AI-driven platforms [4]. Liu et al. [1] introduced multi-agent cooperative architectures for decision-making, while Wang and Liu [2] and Guan et al. [3] demonstrated domain-specific applications in power systems. Han [13] extended these approaches to financial decision support. Although these studies established foundational contributions, they remain limited to domain-specific implementations and do not provide quantifiable cross-sector adoption frameworks.

Wang et al. [5] proposed the integration of retrieval-augmented generation with knowledge graphs to enhance contextual reasoning in IDSS. While this approach improves system intelligence, it lacks empirical validation across multiple business sectors. A common limitation across these studies is their focus on isolated domains, which restricts comparative multi-factor evaluation.

Fettke and Di Francescomarino [7] examined the integration of artificial intelligence into business process management, identifying process mining and predictive analytics as key capabilities. Rejeb and Rejeb [8] reported rapid growth in AI-driven business applications, while Batz et al. [9] provided empirical evidence on machine learning adoption, primarily through qualitative case studies. Montealegre-Lopez [10] identified trust as a significant barrier to adoption but did not quantify its relative importance.

Further contributions include Bag et al. [11], who analysed generative AI in financial decision-making, and Aljohani [12], who developed a fuzzy multi-criteria decision-making model for healthcare applications. However, these studies are limited to specific domains and do not support cross-sector evaluation. The inconsistency between qualitative and quantitative approaches further highlights the need for an integrated framework.

Karim and He [16], Chung et al. [17], and Lyu [18] explored data-driven decision-making across various domains, while Staudinger et al. [19] demonstrated the application of knowledge graphs in analytics. Al-Omoush et al. [20] examined business analytics adoption, and Miao et al. [21] analysed sociotechnical factors influencing organisational change. Despite these contributions, most studies remain descriptive and do not provide prescriptive decision-support frameworks for optimising adoption strategies.

Overall, the existing literature supports the importance of multi-factor adoption modelling but lacks an integrated approach that combines subjective expert weighting with objective data-driven weighting. This limitation is addressed in the proposed MCAAM framework.

3. Proposed Mathematical Framework

3.1. Multi-Criteria Adoption Assessment Model (MCAAM) Overview

The MCAAM integrates three mathematical components: (1) fuzzy AHP for subjective criterion weight determination based on expert judgment, (2) Shannon entropy for objective weight calibration from empirical data, and (3) TOPSIS for alternative ranking. Adoption determinants are validated through covariance-based structural equation modelling (CB-SEM) with confirmatory factor analysis (CFA).

Let $C = \{C_1, C_2, \dots, C_n\}$ denote the set of adoption criteria and $A = \{A_1, A_2, \dots, A_m\}$ denote the set of organisational alternatives.

The hybrid structure is selected to balance subjectivity and objectivity. Fuzzy AHP captures expert preferences but may introduce inconsistency, whereas Shannon entropy provides data-driven weighting based on variability. TOPSIS is adopted because it evaluates alternatives relative to both ideal and anti-ideal solutions, resulting in improved discrimination. CB-SEM is employed due to the presence of reflective constructs, a sufficiently large sample size (n = 387), and theory-driven relationships.

Five criteria are defined based on literature synthesis:

C_1: Technological Readiness (TR),

C_2: Organisational Compatibility (OC),

C_3: Perceived Strategic Value (PSV),

C_4: Data Infrastructure Maturity (DIM),

C_5: Trust in AI-Driven Outcomes (TAO).

All criteria are treated as benefit criteria. Therefore, the index sets are defined as $J^+ = \{1,2,3,4,5\}$ and $J^- = \emptyset$, which are used in the TOPSIS formulation.

3.2. Fuzzy AHP Weight Determination

Expert judgments are expressed using triangular fuzzy numbers (TFNs), denoted as

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}),$$

where l_{ij}, m_{ij}, and u_{ij} represent the lower, middle, and upper bounds of the fuzzy comparison, respectively.

The fuzzy pairwise comparison matrix is constructed as:

$$\tilde{A} = [\tilde{a}_{ij}]_{n\times n} \qquad (1)$$

To derive criterion priorities, the fuzzy geometric mean for each criterion is computed as:

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{a}_{ij} \right)^{\frac{1}{n}} \qquad (2)$$

The fuzzy weights are then obtained by normalising the geometric means:

$$\widetilde{w}_i = \tilde{r}_i \otimes \left(\bigoplus_{i=1}^{n} \tilde{r}_i \right)^{-1} \qquad (3)$$

Since fuzzy weights are not directly interpretable, defuzzification is performed using the centroid method:

$$w_i^{def} = \frac{l_i + m_i + u_i}{3} \qquad (4)$$

Finally, the subjective weights are normalised as:

$$w_i^s = \frac{w_i^{def}}{\sum_{j=1}^{n} w_j^{def}}$$

3.3. Entropy-Based Objective Weighting

To complement subjective weights, Shannon entropy is used to derive objective weights based on the variability of data in the decision matrix $X = [x_{ij}]$.

First, the decision matrix is normalised:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

The entropy value for each criterion is calculated as:

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln (p_{ij}) \qquad (5)$$

The degree of diversification is defined as:

$$d_j = 1 - E_j$$

Criteria with higher dispersion have greater importance. Thus, the objective weights are computed as:

$$w_j^o = \frac{d_j}{\sum_{j=1}^{n} d_j} \qquad (6)$$

3.4. Combined Weight Integration

To balance subjective and objective contributions, a convex combination is used:

$$w_j^* = \lambda w_j^s + (1 - \lambda) w_j^o, \lambda \in [0,1] \qquad (7)$$

The parameter $\lambda$is optimised using 5-fold cross-validation on a held-out dataset (20% of the sample). The optimal value $\lambda = 0.55$minimises the root mean squared error (RMSE = 0.0423), indicating an effective balance between expert judgment and data-driven weighting.

3.5. TOPSIS-Based Impact Ranking

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is applied to rank organisational alternatives.

The decision matrix is first normalised using vector normalisation:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

The weighted normalised matrix is then computed as:

$$v_{ij} = w_j^* \cdot r_{ij} \qquad (8)$$

The positive ideal solution A^+ and negative ideal solution A^- are defined as:

$$A^+ = \left\{ \max_i \ v_{ij} \mid j \in J^+ \right\} \qquad (9)$$
$$A^- = \left\{ \min_i \ v_{ij} \mid j \in J^+ \right\} \qquad (10)$$

The separation measures from the ideal and anti-ideal solutions are calculated as:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \qquad (11)$$

Finally, the relative closeness coefficient is obtained as:

$$RC_i = \frac{S_i^-}{S_i^+ + S_i^-}, 0 \leq RC_i \leq 1$$

Higher values of RC_i indicate better performance of alternatives.

3.6. Structural Equation Model

The causal relationships among variables are estimated using covariance-based SEM (CB-SEM) with maximum likelihood estimation.

The structural model for adoption intent is expressed as:

Adoption Intent (AI)

$$(AI) = \beta^1 TR + \beta^2 OC + \beta^3 PSV + \beta^4 DIM + \beta^5 TAO + \zeta \quad (12)$$

The impact model incorporating moderation effects is defined as:

Impact Score (IS)

$$(IS) = \gamma^1 AI + \gamma^2 (AI \times DIM) + \gamma^3 (AI \times TAO) + \varepsilon \quad (13)$$

where ζ and ϵ represent error terms.

3.7. Decision Quality Index

To evaluate organisational performance, the Decision Quality Index (DQI) is defined as:

$$DQI = \alpha^1 \cdot Accuracy + \alpha^2 \cdot \left(\frac{1}{Latency}\right) + \alpha^3 \cdot Alignment + \alpha^4 \cdot Consistency \quad (14)$$

The weights are determined using the Delphi method with expert input:

$$\alpha_1 = 0.30, \alpha_2 = 0.25, \alpha_3 = 0.25, \alpha_4 = 0.20, \sum \alpha_i = 1$$

All components are normalised to the range [0, 1], ensuring comparability across metrics.

4. Research Methodology

4.1. Research Design and Sampling

A cross-sectional quantitative research design was employed to investigate IDSS adoption and its organisational impact. The target population consisted of organisations from India, Southeast Asia (Malaysia, Thailand, Indonesia), and the Middle East (UAE, Saudi Arabia) with a minimum of two years of IDSS implementation experience.

Stratified random sampling was used to ensure representation across both industry sectors and geographic regions. A total of 620 questionnaires were distributed, of which 412 responses were received, yielding a response rate of 66.5%. After excluding incomplete responses (n = 25), a final sample of 387 valid responses was retained.

The sectoral distribution of the sample was as follows: manufacturing (n = 112, 28.9%), finance (n = 98, 25.3%), healthcare (n = 89, 23.0%), and supply chain (n = 88, 22.7%). Data collection was conducted over the period March–September 2024.

4.2. Survey Instrument

The survey instrument comprised 47 items measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). The items were adapted from established sources, including TAM constructs [25], trust measurement scales [10], data maturity indices [17], and organisational readiness frameworks [22].

The instrument development followed a three-stage process:

i. item generation based on literature,
ii. expert panel review involving 12 specialists, and
iii. pilot testing with a sample of 45 respondents.

The Content Validity Index (CVI) exceeded 0.85 for all constructs, indicating strong content validity.

4.3. Fuzzy AHP Expert Panel

Fifteen domain experts participated in the fuzzy AHP evaluation process, comprising 5 IDSS developers, 5 business strategists, and 5 academic researchers.

Each expert provided pairwise comparisons using triangular fuzzy numbers. The consistency ratio (CR) was verified for all comparison matrices and found to be below the acceptable threshold of 0.10, indicating reliable judgments.

4.4. Measurement Model Validation (CFA)

The measurement model was evaluated using confirmatory factor analysis (CFA). Table 1 presents the results, including factor loadings (FL), Cronbach's alpha (α), composite reliability (CR), average variance extracted (AVE), variance inflation factor (VIF), and heterotrait–monotrait ratio (HTMT).

All factor loadings are greater than or equal to 0.68, indicating adequate indicator reliability. Cronbach's alpha values range from 0.821 to 0.912, and composite reliability values range from 0.872 to 0.921, confirming strong internal consistency.

All AVE values exceed the threshold of 0.50, establishing convergent validity. Discriminant validity is supported as all HTMT values are below 0.85, and the Fornell–Larcker criterion is satisfied. Additionally, all VIF values are below 3.0, indicating the absence of multicollinearity.

Table 1: *CFA measurement model results*

Construct	Items	FL Range	α	CR	AVE	VIF	HTMT
TR	8	0.71–0.89	0.87	0.89	0.61	2.1	<0.85
OC	7	0.68–0.86	0.82	0.87	0.58	1.9	<0.85
PSV	9	0.74–0.91	0.89	0.91	0.64	2.4	<0.85
DIM	12	0.72–0.88	0.91	0.92	0.63	2.5	<0.85
TAO	11	0.76–0.92	0.91	0.92	0.66	2.4	<0.85

4.5. Common Method Bias Assessment

To assess common method bias, three statistical tests were applied. First, Harman's single-factor test showed that the largest factor accounted for 29.4% of the total variance, which is below the threshold of 50%.

Second, full collinearity assessment indicated that all inner VIF values were below 3.3, suggesting no pathological common method variance.

Third, the marker variable technique was applied using a theoretically unrelated variable (job tenure). The average correlation between the marker variable and study constructs was 0.037 ($p > 0.10$), confirming the absence of significant common method bias.

4.6. Normality Assessment

Multivariate normality was evaluated using Mardia's coefficient, with skewness = 14.32 and kurtosis = 187.6. Although the kurtosis value exceeds the recommended threshold, maximum likelihood estimation in CB-SEM is considered robust to moderate non-normality when sample size exceeds 200.

To further validate robustness, the Bollen–Stine bootstrap method (2000 replications) was applied, yielding a p-value of 0.067, which confirms acceptable model fit under non-normal conditions.

5. Results and Analysis

5.1. Criterion Weights

The integrated criterion weights obtained through the hybrid fuzzy AHP–entropy approach are presented in Table 2. The results indicate that Trust in AI-Driven Outcomes (TAO) and Data Infrastructure Maturity (DIM) are the most influential factors in IDSS adoption.

Data Infrastructure Maturity (DIM) (C_4) ranks first with a final weight of 0.237, followed by Trust in AI-Driven Outcomes (TAO) (C_5) with a weight of 0.218. Perceived Strategic Value (PSV) and Technological Readiness (TR) occupy intermediate positions, while Organisational Compatibility (OC) has the lowest weight.

To assess robustness, sensitivity analysis was conducted by varying the balance parameter λbetween 0.40 and 0.70. The rank order of criteria remained unchanged, confirming the stability and reliability of the weighting scheme.

Table 2: *Integrated criterion weights*

Criterion	TFN	w_def	w^s	w^o	w^* ($\lambda = 0.55$)	Rank
C_1: TR	(0.15, 0.21, 0.28)	0.213	0.2	0.18	0.188	4
C_2: OC	(0.10, 0.16, 0.23)	0.163	0.15	0.16	0.155	5
C_3: PSV	(0.16, 0.22, 0.29)	0.223	0.21	0.2	0.202	3
C_4: DIM	(0.19, 0.25, 0.32)	0.253	0.23	0.24	0.237	1
C_5: TAO	(0.17, 0.24, 0.31)	0.24	0.22	0.22	0.218	2

5.2. TOPSIS Sector Impact

The sector-wise impact of IDSS adoption is evaluated using TOPSIS, and the results are presented in Table 3. The relative closeness coefficient (RC_i) and Decision Quality Index (DQI) are used to assess performance across sectors.

Finance demonstrates the highest performance with $RC_i = 0.760$and DQI = 0.823, followed by healthcare ($RC_i = 0.687$, DQI = 0.779). Manufacturing ranks third, while supply chain exhibits the lowest performance among the sectors analysed.

A one-way ANOVA test confirms statistically significant differences across sectors ($F(3, 383) = 8.74$, $p < 0.001$, $\eta^2 = 0.064$). Tukey's HSD post-hoc analysis indicates that the finance sector performs significantly better than supply chain and manufacturing sectors, while healthcare shows moderate differences.

Table 3: *TOPSIS impact assessment and ANOVA comparison*

Sector	S_i^+	S_i^-	RC_i	DQI	Rank	Post-hoc
Manufacturing	0.03	0.06	0.63	0.74	3	b
Finance	0.02	0.07	0.76	0.82	1	a
Healthcare	0.03	0.06	0.69	0.78	2	a,b
Supply Chain	0.04	0.06	0.6	0.7	4	c

5.3. Structural Equation Modelling Results

The structural model was evaluated using CB-SEM. The model fit indices indicate a good fit: $\chi^2/df = 2.31$, CFI = 0.967, TLI = 0.958, RMSEA = 0.048, and SRMR = 0.041. These values satisfy recommended thresholds, confirming model adequacy. Post-hoc power analysis based on RMSEA yields a statistical power of 0.97 for n = 387, indicating sufficient sample size for hypothesis testing.

The path coefficients and hypothesis testing results are presented in Table 4. Trust in AI-driven outcomes (TAO) has the strongest effect on adoption intent ($\beta = 0.412$, $p < 0.001$), followed by data infrastructure maturity (DIM) ($\beta = 0.387$, $p < 0.001$). Perceived strategic value and technological readiness also show significant positive effects.

Adoption intent significantly influences impact score ($\beta = 0.534$, $p < 0.001$). Additionally, the interaction effects $AI \times DIM$and $AI \times TAO$are statistically significant, confirming the moderating roles of data maturity and trust.

The model explains 67.8% of the variance in adoption intent ($R^2 = 0.678$) and 58.3% of the variance in impact score ($R^2 = 0.583$). Predictive relevance is high, with Q^2 values of 0.512 (AI) and 0.437 (IS).

Table 4: *SEM path coefficients*

Path	β	SE	t-value	p	f^2	Decision	Hyp.
TR → AI	0.298	0.047	6.34	<.001	0.091	Supported	—
OC → AI	0.187	0.052	3.596	<.001	0.042	Supported	—
PSV → AI	0.324	0.044	7.364	<.001	0.118	Supported	—
DIM → AI	0.387	0.041	9.439	<.001	0.162	Supported	H2
TAO → AI	0.412	0.039	10.564	<.001	0.194	Supported	H1
AI → IS	0.534	0.036	14.833	<.001	0.398	Supported	H3
AI×DIM → IS	0.176	0.058	3.034	0.002	0.035	Supported	H4a
AI×TAO → IS	0.203	0.054	3.759	<.001	0.048	Supported	H4b

5.4. Performance Comparison

The comparative performance of IDSS-enabled organisations against baseline systems is presented in Table 5. Significant improvements are observed across all performance metrics.

Decision accuracy increases from 61.3% to 82.6%, representing a 34.7% improvement. Decision latency is reduced by 28.3%, indicating faster decision-making. Strategic alignment, consistency, and user satisfaction also show substantial gains. All differences are statistically significant ($p < 0.001$), with effect sizes ranging from medium to large (Cohen's d = 0.76–1.41), indicating strong practical significance.

Table 5: *Performance comparison (IDSS vs baseline)*

Metric	Baseline	IDSS	Relative Δ	Cohen's d	t-stat	p
Decision Accuracy (%)	61.3	82.6	34.70%	1.23	9.87	<.001
Latency (hrs)	18.7	13.4	−28.31%	0.89	7.12	<.001
Strategic Alignment	0.58	0.71	22.40%	0.76	6.04	<.001
Consistency	0.64	0.83	29.70%	1.08	8.41	<.001
Satisfaction (1-7)	3.42	5.18	51.50%	1.41	11.2	<.001

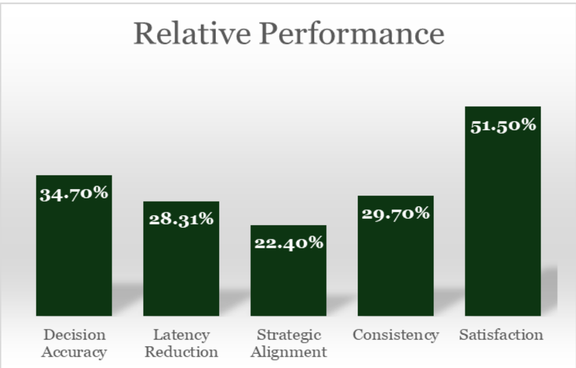

Figure 1: *Relative performance improvement of IDSS over baseline across key metrics*

Figure 1 presents the relative performance improvement of IDSS-enabled systems compared to baseline systems across key decision-making metrics. All values are expressed as percentage change to ensure comparability across different measurement scales.

The results indicate consistent improvement across all dimensions. The highest gain is observed in user satisfaction (51.5%), followed by decision accuracy (34.7%) and consistency (29.7%). Strategic alignment shows a moderate improvement of 22.4%. Latency reduction (28.3%) reflects a significant decrease in decision-making time, indicating enhanced operational efficiency.

Overall, the findings demonstrate that IDSS implementation leads to substantial improvements in both decision quality and efficiency across organisational contexts.

6. Discussion

This study provides a comprehensive evaluation of Intelligent Decision Support Systems (IDSS) adoption by integrating multi-criteria decision-making techniques with structural equation modelling. The findings offer both theoretical and practical insights grounded in the empirical results presented in Tables 2–5 and Figure 1.

The criterion weight analysis (Table 2) indicates that Trust in AI-Driven Outcomes (TAO) and Data Infrastructure Maturity (DIM) are the most influential factors in IDSS adoption. TAO ranks highest, highlighting that organisational confidence in AI outputs plays a decisive role in adoption decisions. DIM follows closely, suggesting that robust data infrastructure is essential for effective system implementation. These findings are consistent with the strong path coefficients observed in the SEM results (Table 4), where TAO ($\beta = 0.412$) and DIM ($\beta = 0.387$) exhibit the largest effects on adoption intent.

The TOPSIS analysis (Table 3) reveals significant sectoral variation in IDSS impact. The finance sector achieves the highest performance ($RC_i = 0.760$, DQI = 0.823), which can be attributed to its advanced data ecosystems and analytical maturity. Healthcare and manufacturing demonstrate moderate performance, while the supply chain sector shows comparatively lower impact. The ANOVA results confirm that these differences are statistically significant, indicating that sector-specific factors influence the effectiveness of IDSS deployment.

The SEM results further validate the structural relationships within the proposed framework. Adoption intent significantly influences impact score ($\beta = 0.534$), confirming that successful implementation translates into measurable organisational benefits. Additionally, the interaction effects (AI × DIM and AI × TAO) are significant, indicating that both data maturity and trust not only drive adoption but also strengthen its impact. This highlights the importance of aligning technological capability with organisational readiness.

The performance comparison (Table 5 and Figure 1) demonstrates substantial improvements across all key metrics. IDSS implementation leads to a 34.7% increase in decision accuracy and a 28.3% reduction in latency, indicating enhanced decision quality and efficiency. Improvements in strategic alignment (22.4%) and consistency (29.7%) suggest better organisational coherence in decision-making processes. The most significant gain is observed in user satisfaction (51.5%), reflecting increased acceptance and usability of IDSS solutions.

Overall, the results confirm that IDSS adoption delivers both operational and strategic benefits. However, these benefits are contingent upon organisational trust in AI systems and the availability of mature data infrastructure. Without these enabling conditions, the effectiveness of IDSS may be limited, particularly in sectors with lower digital maturity.

7. Conclusions

This study proposed the Multi-Criteria Adoption Assessment Model (MCAAM), integrating fuzzy AHP, Shannon entropy weighting, TOPSIS, and CB-SEM to evaluate both the determinants and organisational impact of Intelligent Decision Support Systems (IDSS). The framework provides a unified multi-criteria assessment approach that combines expert judgment with empirical data-driven analysis across multiple business sectors.

The findings indicate that data infrastructure maturity and trust in AI-driven outcomes are the strongest factors influencing IDSS adoption. Organisations implementing IDSS demonstrated notable improvements in decision accuracy, operational efficiency, strategic alignment, consistency, and user satisfaction. Sectoral analysis further showed that the finance sector achieved the highest overall impact, reflecting stronger analytical and data capabilities. In addition, trust and data maturity significantly strengthened the relationship between adoption intent and realised organisational outcomes.

Overall, the study demonstrates that successful IDSS implementation depends not only on technological capability but also on organisational readiness and data preparedness. The proposed MCAAM framework offers a structured foundation for evaluating adoption and performance outcomes within complex business environments.

Future research should employ longitudinal designs, expand geographic coverage, and examine the integration of emerging generative AI capabilities into intelligent decision support systems.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article. The participating organisations had no role in the study design, data collection, analysis, interpretation of results to publish.

Data Availability Statement

The data supporting the findings of this study were collected through a structured questionnaire administered to business organisations across India, Southeast Asia, and the Middle East during March–September 2024. Due to confidentiality agreements with participating organisations, the dataset is not publicly available. However, aggregated results, including CFA measurement model outputs, SEM path coefficients, TOPSIS rankings, and criterion weights, are fully reported in the manuscript. Researchers may request access to anonymised summary-level data by contacting the corresponding author.

Ethics Statement

This study adhered to established research ethics standards. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection. Respondents were assured of anonymity and confidentiality, and no personally identifiable information was collected or stored. The collected data were used exclusively for academic and research purposes.

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