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Artificial Intelligence and Human Decision-Making: A Multidisciplinary Study on Governance, Business, Healthcare and Education

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Abstract: *Artificial intelligence (AI) has rapidly evolved from a specialised computational tool into a pervasive decision-support infrastructure that influences how individuals, organisations and governments make choices. While sector-specific studies on AI adoption are abundant, comparatively few works examine how AI reshapes human decision-making simultaneously across multiple domains. This paper presents a multidisciplinary, mixed-methods study of the influence of AI on human decision-making in four critical sectors: public governance, business, healthcare and education. A structured questionnaire was administered to a stratified random sample of 480 professional decision-makers (120 per sector), complemented by semi-structured interviews with 32 domain experts. A composite Decision Quality Index (DQI) integrating accuracy, efficiency, transparency, trust and fairness was developed, and the data were analysed using descriptive statistics, one-way ANOVA and multiple linear regression. The results indicate that AI-assisted decisions outperformed human-only decisions in mean accuracy across all four sectors, with the largest improvement observed in healthcare (78.4% to 91.3%) and the smallest in governance (71.2% to 83.6%). Regression analysis shows that perceived system transparency ($\beta = 0.41$, $p < 0.001$) and user trust ($\beta = 0.36$, $p < 0.001$) are the strongest predictors of effective AI adoption in decision processes, while perceived risk exerts a significant negative effect ($\beta = -0.22$, $p < 0.01$). The study also reveals a pronounced generational divide, with trust in AI declining and perceived risk rising with respondent age. The findings imply that human–AI complementarity, rather than substitution, yields the highest decision quality, and that governance frameworks emphasising explainability, accountability and digital literacy are prerequisites for responsible AI-augmented decision-making.*

Keywords: Artificial intelligence; human decision-making; decision support systems; governance; business analytics; healthcare; education technology; human–AI collaboration; trust; explainability

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I. INTRODUCTION

1.1 Background

Decision-making is the central cognitive activity through which individuals and institutions convert information into action. Classical decision theory long assumed that humans behave as rational optimisers; however, the seminal work of Simon [2] on bounded rationality and the later experimental programme of Kahneman [1] demonstrated that human judgement is constrained by limited information-processing capacity, time pressure and systematic cognitive biases such as anchoring, availability and overconfidence. Artificial intelligence—particularly machine learning (ML), natural language processing and predictive analytics—offers a fundamentally different decision substrate: one that can ingest vast heterogeneous data, detect latent patterns and generate recommendations at a speed and scale unattainable by unaided human cognition [3].

Over the last decade, AI has migrated from research laboratories into the operational core of society. Governments deploy algorithmic systems for welfare allocation, fraud detection and urban planning [7], [21]; firms embed AI in pricing, hiring, credit scoring and supply-chain optimisation [5], [6]; hospitals use deep learning for diagnostic imaging, triage and treatment planning [4], [8], [14]; and educational institutions adopt intelligent tutoring systems, automated assessment and learning analytics [9], [10]. In each domain, the locus of decision-making is shifting from purely human judgement towards hybrid configurations in which algorithms filter, rank, predict and sometimes decide.

This shift raises pressing multidisciplinary questions. To what extent does AI actually improve the quality of decisions, and does the magnitude of improvement differ across sectors with different risk profiles and accountability structures? How do transparency, trust, fairness and perceived risk shape the willingness of professionals to rely on algorithmic recommendations [11], [12], [15]? And what organisational and policy arrangements best support productive human–AI complementarity rather than uncritical automation or blanket rejection [13], [16]?

1.2 Problem Statement

Existing research on AI and decision-making is fragmented along disciplinary lines. Public-administration scholars study algorithmic governance, management researchers study AI in firms, medical informaticians study clinical decision support, and education researchers study learning analytics—often using incompatible constructs and metrics. As a result, there is limited empirical evidence that compares, within a single coherent framework, how AI influences human decision-making across sectors. This fragmentation hampers the development of general theories of human–AI decision-making and of cross-sectoral policy instruments. The present study addresses this gap by applying one unified instrument and one composite index of decision quality across four sectors simultaneously.

1.3 Research Objectives

1. To measure and compare the perceived quality of human-only versus AI-assisted decisions in governance, business, healthcare and education.
2. To develop and validate a composite Decision Quality Index (DQI) integrating accuracy, efficiency, transparency, trust and fairness.
3. To identify the factors that significantly predict effective adoption of AI in professional decision processes.
4. To derive sector-specific and cross-sectoral recommendations for responsible AI-augmented decision-making.

1.4 Research Questions and Hypotheses

RQ1: Does AI assistance significantly improve perceived decision accuracy relative to human-only decisions across the four sectors? RQ2: Do the five dimensions of decision quality differ significantly between sectors? RQ3: Which behavioural and system factors predict the Decision Quality Index of AI-assisted decisions? Three hypotheses are tested: H1 — AI-assisted decisions exhibit significantly higher accuracy than human-only decisions in all four sectors; H2 — decision-quality dimensions differ significantly across sectors; H3 — transparency and trust positively, and perceived risk negatively, predict the DQI.

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1.5 Significance and Organisation of the Paper

The study contributes (i) a cross-sectoral empirical comparison conducted with a single validated instrument; (ii) a tractable composite index (DQI) that other researchers can reuse; and (iii) evidence-based recommendations for managers, clinicians, educators and policymakers. The remainder of the paper is organised as follows. Section 2 reviews related work. Section 3 presents the research methodology, the mathematical formulation of the DQI and the analytical models, together with the methodological flowchart. Section 4 reports and discusses the results using tables and charts. Section 5 concludes with implications, limitations and directions for future research.

II. RELATED WORK

2.1 Human Decision-Making and Cognitive Limits

The behavioural foundations of this study rest on bounded rationality [2] and dual-process theory [1], which distinguish fast, intuitive 'System 1' processing from slow, deliberative 'System 2' reasoning. Human decisions are vulnerable to noise and bias, especially under uncertainty and information overload. These limitations motivate the use of computational decision aids, but they also explain why humans may over-rely on (automation bias) or under-rely on (algorithm aversion) machine recommendations, making calibrated trust a central research concern [12].

2.2 AI in Public Governance

Wirtz et al. [7] mapped AI applications in the public sector—chatbots for citizen services, predictive policing, tax-fraud detection and resource allocation—while cataloguing challenges of accountability, legality and societal acceptance. Margetts and Dorobantu [21] argue that governments must 'rethink' policymaking with AI, using machine learning for detection, prediction and simulation of policy outcomes, but warn that opaque models can erode democratic legitimacy. Empirical studies generally report efficiency gains alongside persistent concerns about transparency, contestability and bias in high-stakes administrative decisions [11], [15].

2.3 AI in Business and Organisational Decision-Making

In the management literature, Jarrahi [5] proposed a human–AI symbiosis perspective: AI excels at analytical processing of big data, whereas humans contribute intuition, holistic judgement and ethical sensibility, especially under equivocality. Davenport and Ronanki [6] found that successful enterprise AI initiatives are pragmatic 'augmentation' projects—process automation, cognitive insight and cognitive engagement—rather than moon-shot replacements of managers. Shrestha et al. [13] developed a typology of organisational decision structures (full delegation to AI, hybrid sequential and aggregated human–AI decision-making) and showed that the optimal structure depends on decision specificity, interpretability requirements and time constraints. Brynjolfsson and McAfee [20] situate these micro-level findings within the broader economics of the 'second machine age,' in which digital technologies complement some skills and substitute for others.

2.4 AI in Healthcare

Healthcare offers the most mature evidence of AI decision support. Esteva et al. [8] demonstrated dermatologist-level skin-cancer classification using deep convolutional networks, and Rajkomar et al. [14] reviewed machine-learning applications spanning diagnosis, prognosis and treatment recommendation. Topol [4] synthesised this literature into a vision of 'high-performance medicine' in which the convergence of human and artificial intelligence restores time and attention to the clinician–patient relationship. Nonetheless, clinical adoption is conditioned by regulatory approval, dataset shift, explainability of black-box models and the allocation of liability when human and algorithmic judgements conflict.

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2.5 AI in Education

Zawacki-Richter et al. [9] systematically reviewed AI in higher education, identifying four clusters—profiling and prediction, assessment and evaluation, adaptive systems and personalisation, and intelligent tutoring systems—while noting a striking absence of critical reflection on ethics. Holmes et al. [10] examined the pedagogical promises and perils of AI in education, arguing that AI should support, not supplant, teacher judgement. Studies of learning analytics report improved early identification of at-risk students, but also raise concerns about surveillance, data privacy and self-fulfilling predictions.

2.6 Trust, Ethics and Fairness in Human–AI Decision-Making

Glikson and Woolley [12] reviewed two decades of empirical research on human trust in AI, distinguishing cognitive and emotional trust and showing that tangibility, transparency, reliability and immediacy of the system shape trust development. Mehrabi et al. [15] surveyed sources of bias and fairness definitions in machine learning, demonstrating that unfairness can enter through data, algorithms and user interaction. At the normative level, Floridi et al. [11] proposed the AI4People framework—beneficence, non-maleficence, autonomy, justice and explicability—as a synthesis of AI ethics principles, and Dwivedi et al. [16] consolidated multidisciplinary perspectives on AI's challenges and research agenda for policy and practice.

2.7 Research Gap

Across these literatures, three gaps persist. First, most empirical studies are single-sector, preventing controlled cross-domain comparison. Second, decision quality is usually operationalised as a single outcome (e.g., accuracy), neglecting transparency, trust and fairness as constitutive components of good decisions in institutional settings. Third, behavioural predictors of effective adoption are rarely modelled jointly with sectoral context. This study addresses all three gaps through a unified multidisciplinary design, a composite Decision Quality Index and a pooled regression framework with sector controls.

III. RESEARCH METHODOLOGY

3.1 Research Design

A convergent mixed-methods, cross-sectional design [19] was adopted. The quantitative strand measures perceptions of decision quality and its antecedents with a structured questionnaire; the qualitative strand uses semi-structured expert interviews to contextualise and triangulate the statistical findings. The unit of analysis is the individual professional decision-maker who routinely uses, or is exposed to, AI-based decision-support tools in one of the four sectors.

3.2 Population, Sampling and Sample Size

The target population comprises mid-level and senior decision-makers: public administrators and policy analysts (governance); managers and business analysts (business); physicians, radiologists and hospital administrators (healthcare); and academic administrators, faculty and instructional designers (education). Stratified random sampling was used with sector as the stratification variable to guarantee equal representation. The minimum sample size was determined using Cochran's formula [17]:

$$n_0 = (Z^2 \cdot p \cdot (1 - p)) / e^2 \quad (1)$$

where Z = 1.96 is the standard normal value at a 95% confidence level, p = 0.5 is the assumed population proportion that maximises variance, and e = 0.05 is the tolerated margin of error. Equation (1) yields $n_0 \approx 384$. To strengthen subgroup (sector-level) analyses and absorb invalid responses, the target was raised to 480 respondents, i.e., 120 per sector. Of 540 questionnaires distributed, 497 were returned and 480 were usable after screening (response rate 92.0%, usable rate 88.9%). In addition, 32 experts (8 per sector) with at least ten years of professional experience participated in interviews of 35–50 minutes.

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3.3 Instrument and Variables

The questionnaire contained three blocks. Block A captured demographics (sector, age, gender, experience, prior AI exposure). Block B measured the five decision-quality dimensions—accuracy, efficiency, transparency, trust and fairness—each with four items on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), separately for human-only and AI-assisted decision contexts. Block C measured behavioural antecedents: perceived system transparency, trust in AI, perceived risk, digital literacy and organisational support. Perceived decision accuracy was additionally elicited as a percentage estimate for recent representative decisions, enabling the comparison shown in Section 4.

3.4 The Decision Quality Index (DQI)

To aggregate the five dimensions into a single comparable measure, a weighted composite Decision Quality Index is defined for respondent i as:

$$DQI_i = w_1A_i + w_2E_i + w_3T_i + w_4R_i + w_5F_i,\quad \Sigma w_{\square} = 1,\quad 0 \le w_{\square} \le 1 \tag{2}$$

where A_i, E_i, T_i, R_i and F_i denote respondent i's mean scores for accuracy, efficiency, transparency, trust and fairness respectively, and $w_{\square}$ are dimension weights. Weights were derived from the expert interviews using a simple rank-sum procedure and fixed at w = (0.30, 0.20, 0.20, 0.15, 0.15). Each dimension score is the mean of its m^k items:

$$X_i^k = (1/m^k) \cdot \Sigma_j\, x_{ij}^k,\quad j = 1, \ldots, m^k \tag{3}$$

3.5 Reliability and Validity

Internal consistency of each multi-item scale was assessed with Cronbach's coefficient alpha [18]:

$$\alpha = (k / (k - 1)) \cdot (1 - \Sigma\, \sigma^2_{\gamma i} / \sigma^2_x) \tag{4}$$

where k is the number of items, $\sigma^2_{\gamma i}$ the variance of item i and σ^2_x the variance of the total scale score. All scales exceeded the conventional 0.70 threshold (Table 2). Sampling adequacy for factor analysis was confirmed by a Kaiser–Meyer–Olkin (KMO) statistic of 0.88 and a significant Bartlett's test of sphericity ($\chi^2 = 3{,}412.6$, $p < 0.001$). Content validity was established through review by five subject-matter experts and a pilot study with 30 respondents.

3.6 Analytical Models

Three analytical procedures were employed. First, paired comparisons of human-only versus AI-assisted accuracy used paired-samples t-tests within each sector. Second, cross-sector differences in the DQI were tested with one-way analysis of variance (ANOVA), whose test statistic is the ratio of between-group to within-group mean squares:

$$F = MS\_between / MS\_within = [\Sigma\, n_j(\bar{x}_j - \bar{x})^2 / (g - 1)] / [\Sigma\, \Sigma\, (x_{ij} - \bar{x}_j)^2 / (N - g)] \tag{5}$$

where g = 4 sectors and N = 480. Significant omnibus effects were followed by Tukey HSD post-hoc tests. Third, the determinants of AI-assisted decision quality were estimated with a multiple linear regression model:

$$DQI_i = \beta_0 + \beta_1 TR_i + \beta_2 TS_i + \beta_3 PR_i + \beta_4 DL_i + \beta_5 OS_i + \Sigma\, \gamma_{\square} SEC_{i\square} + \varepsilon_i \tag{6}$$

where TR is trust in AI, TS is perceived system transparency, PR is perceived risk, DL is digital literacy, OS is organisational support, SEC are sector dummy variables (governance as reference), and ε is a random error term assumed to satisfy $E(\varepsilon) = 0$ and $Var(\varepsilon) = \sigma^2$. Model adequacy was assessed via the coefficient of determination:

$$R^2 = 1 - (SS\_residual / SS\_total) \tag{7}$$

Multicollinearity was screened using variance inflation factors (all VIF < 2.4), and residual diagnostics supported the normality and homoscedasticity assumptions. Qualitative interview transcripts were analysed thematically, and themes were triangulated against the quantitative results. All statistical tests used a significance level of 0.05.

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3.7 Methodological Flowchart and Explanation

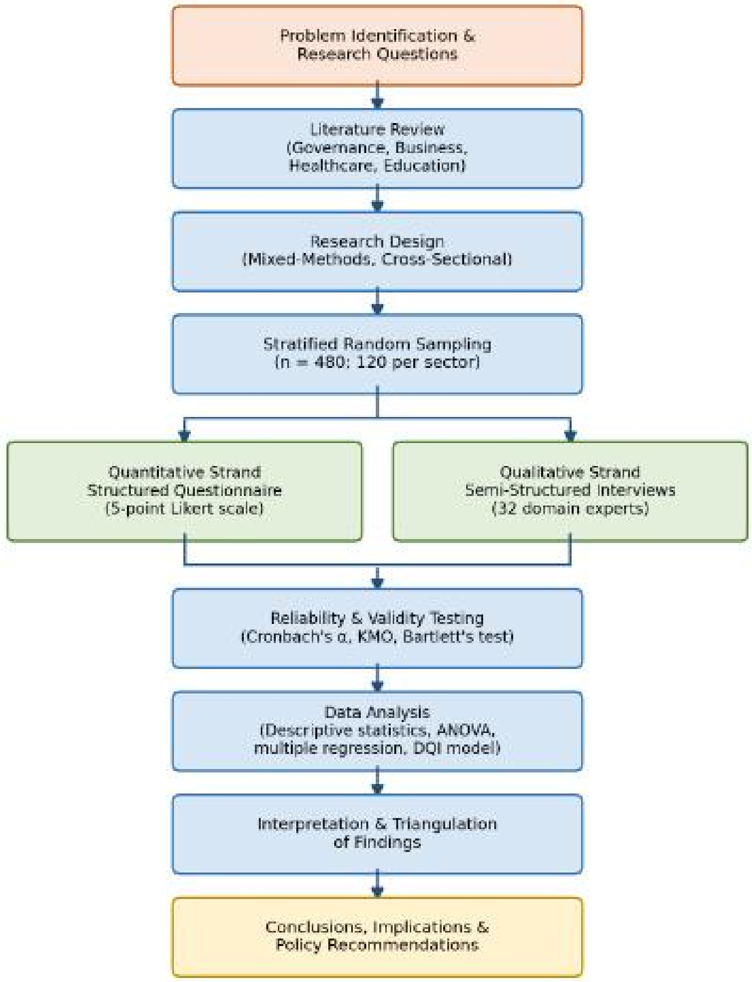

Figure 1. Flowchart of the research methodology.

Figure 1 summarises the research workflow. The process begins with problem identification and formulation of the research questions, followed by a multidisciplinary literature review spanning the four sectors, which informs the constructs and hypotheses. The mixed-methods, cross-sectional design is then specified, and stratified random sampling is applied to obtain 480 respondents balanced across sectors. Data collection proceeds in two parallel strands: the quantitative strand administers the structured Likert-scale questionnaire, while the qualitative strand conducts semi-structured interviews with 32 domain experts. The two strands converge at the reliability and validity stage, where Cronbach's alpha (Equation 4), the KMO statistic and Bartlett's test verify the psychometric soundness of the instrument. The validated data then enter the analysis stage—descriptive statistics, paired t-tests, ANOVA (Equation 5), multiple regression (Equation 6) and computation of the DQI (Equation 2). Quantitative results and qualitative themes are jointly interpreted and triangulated, and the workflow terminates with conclusions, practical implications and policy recommendations. This sequential-with-parallel-strands structure ensures that every inferential claim is grounded in a validated instrument and corroborated by expert testimony.

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3.8 Ethical Considerations

Participation was voluntary and based on informed consent. Responses were anonymised, stored on encrypted media and used solely for research purposes. The study protocol followed institutional ethical guidelines for research involving human participants.

IV. RESULTS AND DISCUSSION

4.1 Respondent Profile

Table 1 presents the demographic profile of the 480 respondents. The sample is balanced by design across sectors and reasonably balanced by gender (56.5% male, 43.5% female). Most respondents (62.7%) have more than five years of professional experience, and 71.5% report prior hands-on exposure to at least one AI-based decision-support tool, indicating that the sample is well positioned to evaluate AI-assisted decision-making.

Variable	Category	Frequency	Percent (%)
Sector	Governance / Business / Healthcare / Education	120 each	25.0 each
Gender	Male	271	56.5
	Female	209	43.5
Age group	18–25 years	58	12.1
	26–35 years	164	34.2
	36–45 years	139	29.0
	46–55 years	82	17.1
	56 years and above	37	7.7
Experience	Less than 5 years	179	37.3
	5–15 years	208	43.3
	More than 15 years	93	19.4
Prior AI exposure	Yes	343	71.5
	No	137	28.5

Table 1. Demographic profile of respondents (n = 480).

4.2 Reliability of the Measurement Scales

Table 2 reports Cronbach's alpha (Equation 4) for each construct. All values lie between 0.79 and 0.91, comfortably exceeding the 0.70 benchmark and indicating high internal consistency of the measurement instrument.

Construct	Items	Cronbach's α	Decision
Accuracy	4	0.87	Reliable
Efficiency	4	0.84	Reliable
Transparency	4	0.81	Reliable
Trust	4	0.91	Reliable

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Fairness	4	0.79	Reliable
Perceived risk	4	0.83	Reliable
Digital literacy	4	0.85	Reliable
Organisational support	4	0.80	Reliable

Table 2. Reliability analysis of the constructs.

4.3 Human-Only versus AI-Assisted Decision Accuracy (RQ1, H1)

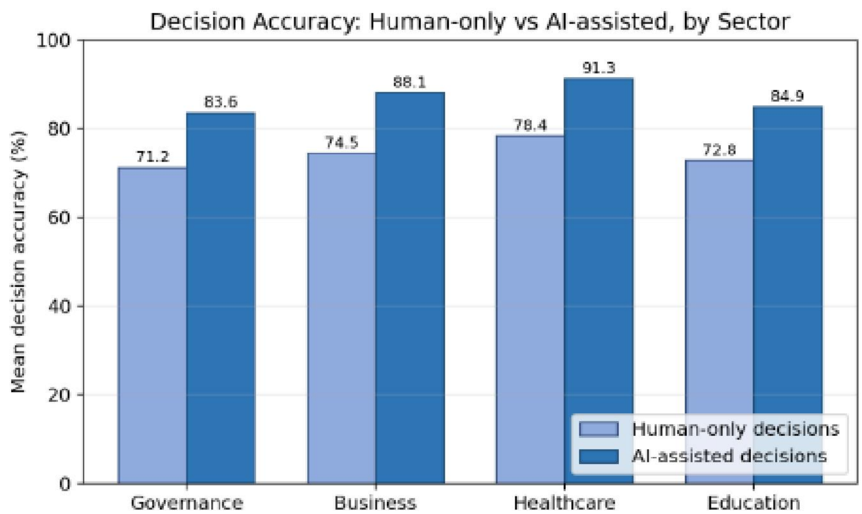

Figure 2. Mean perceived decision accuracy of human-only and AI-assisted decisions by sector.

Figure 2 compares mean perceived decision accuracy under the two decision modes. AI assistance is associated with higher accuracy in every sector: governance improves from 71.2% to 83.6% (+12.4 percentage points), business from 74.5% to 88.1% (+13.6), healthcare from 78.4% to 91.3% (+12.9) and education from 72.8% to 84.9% (+12.1). Paired-samples t-tests confirm that each within-sector difference is statistically significant (all $t(119) > 9.4$, $p < 0.001$), supporting H1. The healthcare result echoes clinical evidence that algorithmic pattern recognition complements expert judgement in diagnosis [4], [8], while the comparatively lower governance figures align with interviewees' observations that public-sector data are fragmented and that administrative decisions involve value trade-offs that resist purely statistical optimisation [7], [21].

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4.4 Sectoral Differences in Decision Quality Dimensions (RQ2, H2)

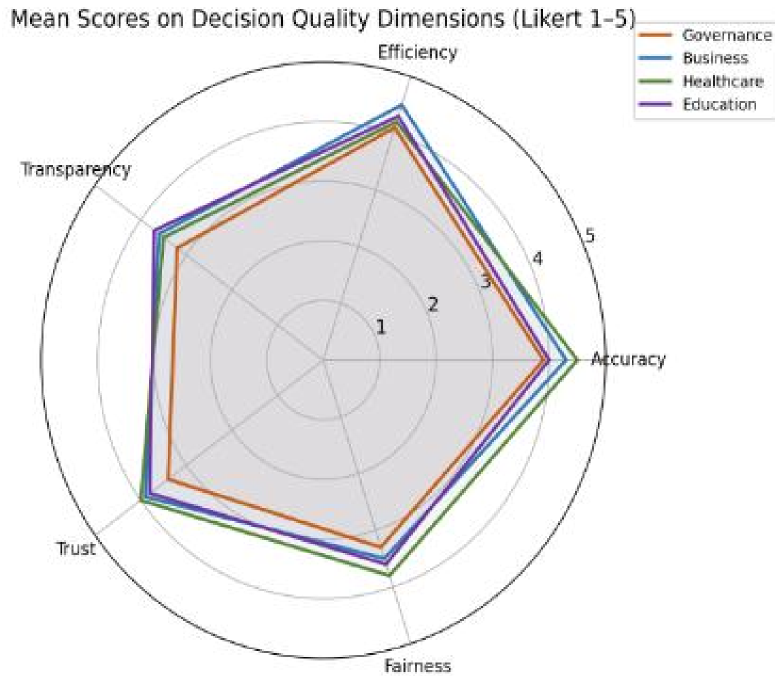

Figure 3. Mean scores on the five decision-quality dimensions for AI-assisted decisions, by sector.

Figure 3 profiles the five DQI dimensions for AI-assisted decisions. Healthcare records the highest accuracy (4.5) and trust (4.0); business leads on efficiency (4.5); education shows the strongest transparency (3.7), plausibly reflecting the pedagogical norm of explaining assessments; and governance trails on transparency (3.2) and fairness (3.3), consistent with the algorithmic-accountability concerns highlighted in the literature [11], [15]. Table 3 reports the composite DQI by sector together with the one-way ANOVA results.

Statistic	Governance	Business	Healthcare	Education
Mean DQI (AI-assisted)	3.62	4.02	4.08	3.91
Standard deviation	0.48	0.41	0.39	0.44
Mean DQI (human-only)	3.31	3.49	3.66	3.42
DQI gain (Δ)	+0.31	+0.53	+0.42	+0.49

Table 3. Composite Decision Quality Index by sector (Likert scale 1–5).

The omnibus ANOVA on the AI-assisted DQI is significant, $F(3, 476) = 28.74$, $p < 0.001$ (Equation 5), supporting H2. Tukey HSD post-hoc tests show that governance differs significantly from each of the other three sectors ($p < 0.001$), whereas the business–healthcare contrast is not significant ($p = 0.62$). Substantively, the AI advantage is therefore not uniform: it is largest where data are structured and feedback loops are fast (business, healthcare) and smallest where decisions are politically contested, multi-stakeholder and explanation-hungry (governance).

4.5 Predictors of AI-Assisted Decision Quality (RQ3, H3)

Table 4 reports the multiple regression estimates of Equation (6). The model explains 58% of the variance in the AI-assisted DQI ($R^2 = 0.58$, adjusted $R^2 = 0.57$; $F(8, 471) = 81.3$, $p < 0.001$).

Predictor	β (std.)	t-value	p-value	VIF
(Constant)	—	6.21	< 0.001	—
Perceived transparency (TS)	0.41	10.84	< 0.001	1.82
Trust in AI (TR)	0.36	9.47	< 0.001	2.31
Perceived risk (PR)	−0.22	−6.05	< 0.01	1.64
Digital literacy (DL)	0.19	5.12	< 0.001	1.45
Organisational support (OS)	0.14	3.86	< 0.001	1.38
Sector: Business	0.12	3.21	0.001	1.52
Sector: Healthcare	0.15	3.94	< 0.001	1.57
Sector: Education	0.09	2.46	0.014	1.49

Table 4. Multiple regression results predicting the AI-assisted DQI ($n = 480$, $R^2 = 0.58$).

Perceived system transparency is the strongest predictor ($\beta = 0.41$, $p < 0.001$), followed by trust in AI ($\beta = 0.36$, $p < 0.001$); perceived risk is significantly negative ($\beta = -0.22$, $p < 0.01$); and digital literacy and organisational support contribute smaller positive effects. H3 is therefore supported. The dominance of transparency corroborates the explicability principle of Floridi et al. [11] and the trust antecedents identified by Glikson and Woolley [12]: professionals incorporate algorithmic recommendations into their decisions to the extent that they can understand and, if necessary, contest the reasoning behind them. The positive sector dummies confirm that, holding behavioural factors constant, business, healthcare and education realise higher AI-assisted decision quality than governance.

4.6 Generational Patterns in Trust and Perceived Risk

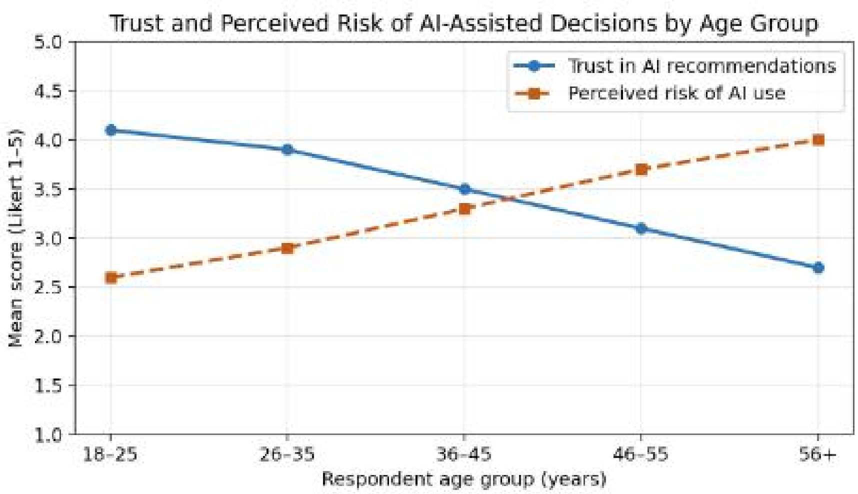

Figure 4. Trust in AI recommendations and perceived risk of AI use across age groups.

Figure 4 reveals a clear generational gradient: mean trust declines monotonically from 4.1 among respondents aged 18–25 to 2.7 among those aged 56 and above, while perceived risk rises from 2.6 to 4.0 over the same range. Interviewees attributed this pattern to differences in digital socialisation, accumulated professional experience of system failures, and accountability exposure—senior decision-makers bear formal responsibility for outcomes and are therefore more sensitive to opaque or unverifiable recommendations. The finding implies that AI deployment strategies should pair

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younger 'digital-native' enthusiasm with senior professionals' calibrated scepticism, for example through mixed-age decision committees and targeted explainability training.

4.7 Qualitative Triangulation

Thematic analysis of the 32 expert interviews produced four convergent themes. (1) Complementarity over substitution: experts in all sectors described the best outcomes as arising when AI narrows the option space and humans make the final, context-sensitive call—mirroring the hybrid structures of Shrestha et al. [13]. (2) Explainability as a precondition: clinicians and administrators reported overriding accurate but unexplainable recommendations, confirming the regression result for transparency. (3) Accountability gaps: governance experts emphasised unresolved questions about who is answerable when an algorithm errs. (4) Capability building: respondents across sectors called for systematic AI literacy programmes, consistent with the significant effect of digital literacy in Table 4.

4.8 Discussion Summary

Taken together, the results support a complementarity model of human–AI decision-making. AI assistance raises perceived accuracy by 12–14 percentage points across very different institutional environments (Figure 2), yet the size of the composite quality gain depends on transparency, trust and risk perceptions (Table 4) and on sectoral characteristics (Table 3, Figure 3). These findings extend single-sector studies [4]–[10] by demonstrating, within one framework, that the behavioural mechanisms of effective AI adoption are largely common across domains, while the institutional ceilings on AI's contribution are sector-specific. For practice, the results suggest that investments in explainable interfaces, audit mechanisms and AI literacy are likely to yield larger decision-quality returns than investments in raw predictive power alone [16].

4.9 Sector-Specific Recommendations

Synthesising the quantitative results and interview themes, Table 5 distils sector-specific recommendations. The common thread is that decision quality is maximised when AI handles pattern detection and option generation while accountable humans retain final authority, supported by explainable interfaces and continuous capability building.

Sector	Primary constraint identified	Recommended intervention
Governance	Low transparency and fairness scores; accountability gaps in algorithmic decisions	Mandatory algorithmic impact assessments, public registers of decision systems, contestability and appeal mechanisms
Business	Risk of automation bias in fast operational decisions	Hybrid sequential decision structures with human review thresholds; periodic model audits and performance dashboards
Healthcare	Liability ambiguity when clinical and algorithmic judgements conflict	Regulated clinical validation, explainable diagnostic interfaces, clear escalation and documentation protocols
Education	Privacy concerns and risk of self-fulfilling predictions from learner profiling	Pedagogy-first deployment, opt-in learning analytics, transparency of grading models to students and faculty

Table 5. Sector-specific constraints and recommended interventions.

V. CONCLUSION

This multidisciplinary study examined how artificial intelligence influences human decision-making in governance, business, healthcare and education using a unified mixed-methods design, a validated instrument and a composite

Decision Quality Index. Three conclusions follow. First, AI-assisted decisions are perceived as significantly more accurate than human-only decisions in all four sectors, with the largest gains in healthcare and business and the smallest in governance. Second, decision quality is multidimensional: sectors differ systematically in transparency, trust and fairness even when accuracy gains are similar, and governance lags on precisely the dimensions—transparency and fairness—that legitimate public decisions require. Third, perceived transparency and trust are the strongest positive predictors, and perceived risk the strongest negative predictor, of AI-assisted decision quality, with digital literacy and organisational support playing reinforcing roles.

The practical implications are direct. Organisations should design AI systems for explainability and contestability, institutionalise human oversight of consequential decisions, build AI literacy across age cohorts, and adopt sector-appropriate governance: lighter-touch augmentation in business analytics, regulated clinical validation in healthcare, pedagogy-first deployment in education, and stringent accountability and audit regimes in public administration. For policymakers, the generational divide in trust signals that public acceptance of algorithmic governance cannot be assumed and must be earned through transparency and demonstrable fairness.

5.1 Limitations and Future Work

The study has limitations that qualify its conclusions. Decision accuracy and quality were measured through validated self-report perceptions rather than objective task outcomes; the cross-sectional design precludes causal inference; and the sample, while stratified and adequately powered, is drawn from a single national context, which may limit generalisability. Future research should (i) combine perceptual measures with objective decision outcomes in field experiments; (ii) track human–AI decision quality longitudinally as systems and users co-adapt; (iii) extend the framework to additional sectors such as law, finance and agriculture; and (iv) examine how emerging generative-AI tools reshape the antecedents identified here, particularly transparency and trust.

In closing, artificial intelligence does not replace human decision-making so much as it reorganises it. The evidence presented here indicates that the societies and organisations that benefit most from AI will be those that treat it neither as an oracle nor as a threat, but as a powerful, fallible collaborator—one whose recommendations must be explainable, whose biases must be audited, and whose place in the decision chain must remain subject to human values, professional judgement and democratic accountability.

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