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Human–AI Collaboration in Managerial Decision-Making: Examining the Impact of AI Trust, Explainability, and Perceived Usefulness on Decision Quality

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***Abstract*—**Artificial Intelligence (AI) is increasingly being used to help support decision making. The benefits to using AI may depend on how much trust, understanding and perceived usefulness there is toward the recommendations. In this study, we look into the relationship between trust in AI, perceived explainable AI, perceived usefulness, human-AI collaboration and perceived decision quality. A quantitative cross-sectional survey was conducted to gather data, with 201 responses recorded. Each construct was calculated by finding the mean of five Likert scale questions. Descriptive statistics, Cronbach's alpha, Pearson correlation and multiple regression were performed. The means of the constructs ranged from 4.07 to 4.16. The Cronbach's alphas ranged from 0.506 to 0.617. The first regression model showed that 48.8% of the variation in human-AI collaboration could be explained. The second regression model shows a positive relationship between trust in AI, explainable AI, perceived usefulness, and perceived decision quality. The adjusted coefficient for human-AI collaboration was not statistically significant at .05. Due to the low internal consistency and inconsistencies in the screening questions for AI use in the spreadsheet, this is an exploratory study and should be treated with caution.

***Keywords*—**Artificial Intelligence; Human-AI Collaboration; Trust in AI; Explainable AI; Perceived Usefulness; Decision Quality

I. INTRODUCTION

Artificial Intelligence (AI) is now playing a key role in modern decision-making processes. AI based tools can be used to process large volumes of information, identify patterns, provide recommendations and help users compare options. This has become an integral part of many management processes including planning, marketing, financial management, human resources management, operations and risk analysis.

However, this does not necessarily produce better decision making. The user will have to consider if they can trust the recommendation, understand why it has been generated and also decide how best to integrate this with their own knowledge. There could be many problems with AI recommendations including lack of information, biased results and recommendations that are not applicable to the situation.

Trust, transparency and perceived usefulness are important considerations in human-AI collaboration. Trust can affect whether individuals take recommendations from the AI. Transparency can help users judge the reasoning behind outputs. Perceived usefulness describes whether users believe that the AI can help them make decisions. This paper considers how trust, transparency and perceived usefulness impact human-AI collaboration and perceived decision quality. A measure of perceived decision quality is provided.

II. LITERATURE REVIEW

A. AI Trust

The concept of trust can also play a role in determining how much reliance users place on automated systems. The aim of having trust is to be able to use recommendation technology appropriately (Lee and See, 2004). Having trust when using AI can lead to users feeling confident about what they are being recommended; however, it is also important that users understand the limitations of the systems and make their own decisions.

B. AI Explainability

Explainable AI refers to how easy it is for users to understand the factors driving an AI's recommended output. While explanations can provide useful information, helping users understand, identify issues and determine if they should place any trust in the output, it is not guaranteed that the explanation will be accurate or easy to understand. This study looks at perceived explainability.

C. Perceived Usefulness

Perceived usefulness is a key concept within the Technology Acceptance Model (Davis, 1989). It refers to how much a user believes that a specific technology will improve their performance in relation to tasks. Within an AI support decision making context, this could include a perception of increased efficiency, analysis of information, review of options and support with complex problems. This should not be confused with actual improvements in performance.

D. Human–AI Collaboration

Collaborations between humans and AI systems involve working together using the computational powers of AI with human intelligence and knowledge of context. It involves critically considering the recommendations provided by the AI and considering how they can be incorporated. This could rely heavily on the trust, understanding and relevance of the information provided by the AI from the perspective of the user.

E. Perceived Decision Quality

Decision quality can be viewed as how accurate, consistent, well compared and appropriate decisions are. In the current study, decision quality is assessed using self-perceived measures of whether decisions were improved by AI, identified weaknesses and aided in evaluating alternatives. This does not objectively determine how accurate decisions are.

III. RESEARCH GAP

Existing research has looked at how useful a technology is, building trust in automation, explainability and human-AI interaction. This study presents a unified approach with trust in AI, perceived explainability and perceived usefulness and looks at relationships between these factors and human-AI collaboration, as well as perceived decision quality. This looks at how directly each of these AI perception factors relate to decision quality, compared to human-AI collaboration. By providing an integrated analysis this is a new contribution. However, the novelty of this study can be confirmed by reviewing more of the existing empirical work.

IV. OBJECTIVES

- Explore the relationship between Trust in AI and Human-AI collaboration.
- Explore the relationship between Explainability in AI and Human-AI collaboration.
- Investigate the relationship between Perceived Usefulness and Human-AI collaboration.
- Examine the relationship between Trust in AI, Explainability in AI, Perceived Usefulness and Perceived Decision Quality.
- Investigate the relationship between Human-AI collaboration and Perceived Decision Quality.
- Evaluate the descriptive properties and internal consistency of the five constructs under investigation.

V. RESEARCH METHODOLOGY

A. Research Design

A cross-sectional survey was used to collect quantitative data. The survey was created on Google Forms. It includes sections for consent, demographics, AI usage and 25 Likert scale (5 point) questions relating to 5 different constructs. Due to the cross-sectional nature of the survey, analysis will show any correlations.

B. Data Collection

The survey contains questions related to participant demographic details (age range, gender, qualification and current status), work experience (industry/field, experience in using AI, how often they use it and which tools they use). Five constructs were used; AI Trust (AT), AI Explainability (AE), Perceived Usefulness (PU), Human-AI Collaboration (HAIC) and Perceived Decision Quality (DQ). Each construct comprised of 5 items that were scored on a Likert scale with scores ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

C. Sample

The study included 201 responses. The sample was non-probability based; therefore, it should not be assumed to represent all managers or organisations. All available rows of data were included in the calculations for exploratory purposes.

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D. Data Analysis

Descriptive statistics including frequencies and percentages were calculated for categorical variables. Construct scores were calculated by taking the average of the five items within each construct. Means and standard deviations were calculated for all constructs. A Cronbach's alpha was also conducted to assess the reliability of the constructs. Analysis included Pearson correlations and two standard ordinary least squares regression models. The first model assessed how much AI trust, explainability and perceived usefulness predicted human-AI collaboration. The second assessed how much AI trust, explainability and perceived usefulness predicted perceived quality of decision making, with human-AI collaboration as a mediator.

E. Data-Quality Considerations

There were some inconsistencies between the single select AI usage question and the multiple select AI tool question. Five respondents said they never used AI. Some of the responses to the AI tool question include both specific tools and the response category 'never used'. Due to the inability to verify each individual's response, we have treated them as responses given. Reliability was low, so any statistical findings should be treated as exploratory.

VI. DATA ANALYSIS AND RESULTS

A. Respondent Profile

There were 201 responses in the data set. All responses gave consent. The distribution of demographics can be seen below. Values have been calculated as a percentage of total rows. Category names have been taken directly from the form submissions.

TABLE I. AGE DISTRIBUTION

Category	Frequency	Percentage
18–24	78	38.8%
25–34	77	38.3%
35–44	22	10.9%
45–54	21	10.4%
55 or above	3	1.5%

TABLE II. GENDER DISTRIBUTION

Category	Frequency	Percentage
Female	101	50.2%
Male	95	47.3%
Other	3	1.5%
Prefer not to say	2	1.0%

TABLE III. EDUCATIONAL QUALIFICATION

Category	Frequency	Percentage
Master's Degree	55	27.4%
Diploma	55	27.4%
Bachelor's Degree	50	24.9%
Higher Secondary	30	14.9%
Doctorate	9	4.5%
Other	2	1.0%

TABLE IV. WORK EXPERIENCE

Category	Frequency	Percentage
1–3 years	60	29.9%
Less than 1 year	51	25.4%
4–7 years	46	22.9%
No work experience	22	10.9%
8–12 years	16	8.0%
More than 12 years	6	3.0%

TABLE V. INDUSTRY OR AREA

Category	Frequency	Percentage
Healthcare	37	18.4%
Education	34	16.9%
Finance or Banking	34	16.9%
Manufacturing	28	13.9%
Marketing or Advertising	20	10.0%
Information Technology	18	9.0%
Retail or E-commerce	13	6.5%
Government or Public Sector	11	5.5%
Consulting	4	2.0%
Other	2	1.0%

TABLE VI. AI-USE EXPERIENCE

Response	Frequency	Percentage
Yes	196	97.5%
No	5	2.5%

B. Descriptive Statistics and Reliability

TABLE VII. DESCRIPTIVE STATISTICS AND RELIABILITY

Construct	Mean	SD	Cronbach's α	Items
AI Trust	4.074	0.459	0.506	5
AI Explainability	4.102	0.496	0.563	5
Perceived Usefulness	4.145	0.525	0.617	5
Human–AI Collaboration	4.155	0.488	0.594	5
Perceived Decision Quality	4.152	0.476	0.539	5

The construct had generally medium levels. The Cronbach's alphas were between 0.506 and 0.617 which means they have low levels of internal reliability so care needs to be taken in how we interpret composite scores. We should carry out item analysis and additional validation; however, we should not delete items just to improve our alpha value.

C. Correlation Analysis

TABLE VIII. PEARSON CORRELATION MATRIX

Construct	AT	AE	PU	HAIC	DQ
AI Trust	—	0.588	0.540	0.588	0.532
AI Explainability	0.588	—	0.548	0.538	0.513
Perceived Usefulness	0.540	0.548	—	0.617	0.587
Human–AI Collaboration	0.588	0.538	0.617	—	0.531
Perceived Decision Quality	0.532	0.513	0.587	0.531	—

The construct scores showed positive pairwise correlations in the recorded sample. The correlations indicate that more favorable perceptions of trust, explainability, usefulness, collaboration, and decision quality tended to occur together. They do not establish causation, and modest internal consistency may influence the observed associations.

D. Regression Analysis

Model 1 indicated that human and AI cooperation is predicted, $F(3, 197) = 62.61$, $p < .001$, $R^2 = 0.488$ (adjusted $R^2 = 0.480$).

TABLE IX. REGRESSION MODEL 1: PREDICTING HUMAN–AI COLLABORATION

Predictor	B	SE	t	p	95% CI
AI Trust	0.311	0.071	4.388	< .001	[0.171, 0.450]
AI Explainability	0.161	0.066	2.444	0.015	[0.031, 0.291]
Perceived Usefulness	0.344	0.060	5.744	< .001	[0.226, 0.462]

A positive coefficient was shown for AI trust ($B = 0.311$; $p < .001$), AI explainability ($B = 0.161$; $p = 0.015$) and perceived usefulness ($B = 0.344$; $p < .001$).

Perceived decision quality was predicted by Model 2. This model had statistical significance ($F(4,196) = 38.39$, $p < .001$) with $R^2 = 0.439$ (adjusted $R^2 = 0.428$).

TABLE X. REGRESSION MODEL 2: PREDICTING PERCEIVED DECISION QUALITY

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Predictor	B	SE	t	p	95% CI
AI Trust	0.194	0.076	2.554	0.011	[0.044, 0.344]
AI Explainability	0.148	0.069	2.156	0.032	[0.013, 0.283]
Perceived Usefulness	0.283	0.066	4.275	< .001	[0.153, 0.414]
Human–AI Collaboration	0.143	0.073	1.956	0.052	[–0.001, 0.286]

Positive coefficients were observed for AI trust (B = 0.194; p = 0.011), AI explainability (B = 0.148; p = 0.032), and perceived usefulness (B = 0.283; p < .001). A positive coefficient was observed for human-AI collaboration, however it did not reach significance levels (p < .05; B = 0.143; p = 0.052) after controlling for other predictor variables.

E. Hypothesis Summary

TABLE XI. HYPOTHESIS SUMMARY

Hypothesis	Result	Interpretation
H1: AT → HAIC	B = 0.311, p < .001	Positive association
H2: AE → HAIC	B = 0.161, p = 0.015	Positive association
H3: PU → HAIC	B = 0.344, p < .001	Positive association
H4: HAIC → DQ	B = 0.143, p = 0.052	Not significant at .05 in adjusted model
H5: AT → DQ	B = 0.194, p = 0.011	Positive association
H6: AE → DQ	B = 0.148, p = 0.032	Positive association
H7: PU → DQ	B = 0.283, p < .001	Positive association
H8: Mediation	Not tested	No conclusion

VII. DISCUSSION

The exploratory findings indicate that an individual's level of trust in AI systems, explainability and perceived usefulness were all found to be positively related to human-AI collaboration. This could be interpreted to mean that individuals who perceive AI systems to be trustworthy, explainable and useful are more likely to work collaboratively with the AI by combining their own judgment with the AI recommendation. Additionally, perceived usefulness was found to be positively related to perceived quality of decisions. This aligns with the notion that individuals will value AI if they perceive it to be useful for analysing information and considering alternatives.

However, in the modified model, human-AI collaboration did not have a significant effect on perceived decision quality at p < .05 despite having a positive bivariate relationship. This may be due to overlap between this variable and trust, explainability and usefulness, or limitations in measurement. As there was only moderate internal consistency between the five scales, it is not possible to definitively conclude that this pattern of coefficients can be used to determine the relative importance of each construct.

These results are derived from a non-probability self-report study so they cannot be used to show that adding an AI actually improves decision accuracy, or that increasing trust or explainability will improve outcomes. They should be viewed as preliminary and could help provide direction to future studies.

VIII. CHALLENGES AND ETHICAL CONSIDERATIONS

A. Trust Calibration

Encourage users to trust the AI to an appropriate extent and understand the benefits and limitations of using the AI.

B. Explainability and Transparency

Ensure the AI provides relevant information to the intended users. Ensure explanations are clear and useful.

C. Bias and Fairness

Outputs from AI may contain bias which has been introduced during data collection or development. Outputs should be assessed to ensure they do not cause unfairness, particularly when making decisions.

D. Privacy and Security

AI will be used to assist with workflow processes that may involve personal, private and organisational data. It is important to minimise data, control access, ensure data is handled securely, and ensure compliance with any privacy requirements.

E. Human Oversight and Accountability

Where decisions are important it is important to have human intervention. There should be clear ownership of who is responsible for assessing recommendations, resolving conflicts, and reviewing errors.

F. Research Data Integrity

There was inconsistency in responses to the screening question about using AI in the dataset. Independent contact could not be made with respondents. Findings are based on the data in the spreadsheet.

IX. FUTURE SCOPE

- Conduct larger scale and more representative studies across different sectors and levels.
- Compare perceptions between students, employees, managers and professionals.
- Aim to validate the questionnaire by using item analysis and confirmatory techniques.
- Conduct experiments or use longitudinal designs to investigate how explainability and trust impact performance.
- Compare self reported decision quality to objective measures such as accuracy, consistency and expert ratings.
- Investigate factors such as AI literacy, task complexity, responsibility and organisational controls.
- Test the proposed mediation pathway with an appropriate indirect-effect analysis and stronger measurement evidence.

X. CONCLUSION

This study explored the relationship between trust in AI, explainability, perceived usefulness, human-AI collaboration and perceived decision quality using 201 recorded responses to a survey. An exploratory approach was taken which identified positive relationships between the three AI perceptions and human-AI collaboration. After adjusting for decision quality, there were statistically significant positive coefficients for the AI trust, explainability and perceived usefulness variables. However, the human-AI collaboration variable was not statistically significant at the traditional .05 level.

The results suggest that users' perceptions of AI may be important when considering how they integrate AI into their decision-making process and assess whether it is contributing. However, limitations of the research include the low scale reliability, issues with screening for AI use, and data collection using a cross-sectional self-report design. As well as this, recruitment involved non-probability sampling. Therefore, further validation and research will be needed to make strong claims about the effectiveness of human-AI collaboration based on objective decision outcomes.

REFERENCES

[1] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quarterly, vol. 13, no. 3, pp. 319–340, 1989.

[2] J. D. Lee and K. A. See, "Trust in automation: Appropriately designing trust in automated systems," Human Factors, vol. 46, no. 1, pp. 50–80, 2004.

[3] C. G. Gomez, S. M. Cho, S. Ke, C.-M. Huang, and M. Unberath, "Human-AI collaboration is not very collaborative yet: A taxonomy of interaction patterns in AI-augmented decision making," Frontiers in Computer Science, vol. 6, Art. no. 1521066, 2025.

[4] H. Li and F. Tian, "AI-human collaboration for better decision-making: A systematic review, conceptual framework and future directions," Group Decision and Negotiation, vol. 35, Art. no. 26, 2026.

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ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

[5] M. L. Tielman et al., “Enabling appropriate trust in human-AI interaction: A systematic literature review on trends, opportunities and challenges,” ACM Journal on Responsible Computing, vol. 1, no. 4, Art. no. 26, 2024.

[6] G. Romeo and D. Conti, “Automation bias in human-AI collaboration: A review,” AI & Society, vol. 41, pp. 259–278, 2026.

[7] M. Raees, I. Meijerink, I. Lykourentzou, V.-J. Khan, and K. Papangelis, “From explainable to interactive AI: A literature review on current trends in human-AI interaction,” International Journal of Human-Computer Studies, vol. 189, Art. no. 103301, 2024.

[8] M. Westphal, M. Vössing, G. Satzger, G. B. Yom-Tov, and A. Rafaeli, “Ensuring decision control and explanations in human-AI collaboration,” Computers in Human Behavior, vol. 144, Art. no. 107714, 2023.

[9] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, “User acceptance of information technology: Toward a unified view,” MIS Quarterly, vol. 27, no. 3, pp. 425–478, 2003.

[10] D. L. Goodhue and R. L. Thompson, “The relationship between task-technology fit and individual performance,” MIS Quarterly, vol. 19, no. 2, pp. 213–236, 1995.

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