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FROM AI TOOL TO AI PARTNER: EXAMINING HUMAN–AI COLLABORATION IN ORGANIZATIONAL INFORMATION SYSTEMS

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ABSTRACT

Artificial Intelligence (AI) has rapidly evolved from a technology used primarily for automation and decision support into increasingly autonomous systems capable of generating recommendations, coordinating tasks, interacting with employees, and participating in organizational decision processes. This transformation creates a fundamental shift in the role of AI within organizational Information Systems (IS): from an AI tool that executes predefined tasks toward an AI partner that collaborates with humans in knowledge-intensive and decision-oriented activities. However, technological capability alone does not guarantee effective human–AI collaboration. Organizations must address trust, explainability, human oversight, task complementarity, AI capability, and organizational readiness to realize sustainable benefits. This paper develops a conceptual framework for examining the transition from AI tool to AI partner in organizational IS. The proposed framework argues that AI capability and AI explainability influence human trust in AI, which subsequently shapes the quality of human–AI collaboration. Effective collaboration is expected to improve decision quality and ultimately contribute to organizational outcomes. The framework additionally recognizes human oversight, task–AI fit, and organizational AI readiness as important contextual conditions. The study integrates perspectives from Information Systems, human–AI interaction, trust theory, human-centered AI, and organizational decision-making. Recent research indicates that explainability can improve decision accuracy and behavioral trust, while excessive autonomy, automation bias, and poorly calibrated trust may undermine collaboration. Therefore, the paper proposes that successful AI transformation depends not simply on AI adoption, but on the development of complementary human–AI relationships. The framework provides theoretical foundations and practical guidance for organizations seeking to design trustworthy, explainable, and productive AI-enabled information systems.

Keywords: Artificial Intelligence, Human–AI Collaboration, Ai Partner, Information Systems, AI Trust, Explainable AI, Decision Quality, Organizational Performance, Human Oversight, AI Capability.

1 INTRODUCTION

Artificial Intelligence (AI) has rapidly evolved from a computational tool for automation and decision support into an increasingly interactive component of organizational Information Systems (IS). Modern AI systems can analyze organizational data, generate recommendations, support knowledge-intensive tasks, and participate in decision-making processes. This evolution is shifting the organizational perspective from AI as a tool toward AI as a collaborative partner. Recent research highlights that effective human–AI collaboration depends not only on technical capability but also on trust, transparency, coordination, and appropriate allocation of responsibilities.

Traditional AI-enabled IS generally position humans as users who provide inputs and act upon AI-generated outputs. In contrast, human–AI collaboration involves a more interactive relationship in which human knowledge and judgment are combined with AI's analytical and computational capabilities. Such collaboration can potentially improve organizational decision-making; however, research shows that simply adding AI to a team does not necessarily improve performance. Poor coordination, inappropriate trust, and limited understanding of AI capabilities may reduce the benefits of collaboration.

Trust is therefore a central factor in the transition from AI tool to AI partner. Employees must determine when AI recommendations should be accepted, questioned, or rejected. Recent empirical research in organizational decision-making found that trust in AI influences the extent to which individuals rely on AI and their willingness to collaborate with it. Similarly, explainability can support users in understanding and evaluating AI-generated recommendations, although excessive information may not always improve trust or collaboration.

Despite increasing research on human–AI interaction, there remains a need for an integrated organizational perspective connecting AI capabilities, explainability, trust, collaboration, decision quality, and organizational outcomes. Recent reviews specifically identify trust and organizational conditions as important areas requiring further investigation.

Therefore, this study proposes a conceptual framework in which AI capability and AI explainability influence human trust in AI, which facilitates human–AI collaboration, leading to improved decision quality and ultimately better organizational outcomes. The study contributes to Information Systems research by examining AI not merely as a technological artifact but as a potential collaborative organizational partner.

Research Objectives

- To examine the role of AI capability and explainability in developing human trust in AI.
- To examine the relationship between human trust and human–AI collaboration.
- To examine the influence of human–AI collaboration on decision quality.
- To examine how improved decision quality contributes to organizational outcomes.

2 LITERATURE REVIEW

2.1 AI Capability in Organizational Information Systems

AI capability refers to an organization's ability to use AI technologies for data analysis, prediction, knowledge generation, and decision support. AI can complement human capabilities by processing large volumes of information and identifying complex patterns. Research on human–AI teams indicates that combining human and AI capabilities can improve task performance when their roles are appropriately designed [1], [2]. AI capability therefore provides an important technological foundation for developing effective human–AI collaboration.

2.2 AI Explainability

Explainability enables users to understand the reasoning or factors underlying AI-generated outputs. In organizational Information Systems, explainability is particularly important because employees need to evaluate AI recommendations before using them in decisions. Studies have shown that explanations can improve users' understanding and decision performance while also influencing trust in AI [3], [4]. However, explanations must be appropriately designed because excessive complexity can increase cognitive burden and may not always increase trust [5].

2.3 Human Trust in AI

Trust determines the extent to which employees are willing to accept and rely on AI recommendations. Appropriate trust is essential for effective human–AI interaction because users must recognize both the capabilities and limitations of AI systems [6], [7]. Research has demonstrated that trust can influence the weight individuals assign to AI recommendations during decision-making [8]. At the same time, excessive reliance may lead to automation bias, whereas insufficient trust can result in the rejection of useful AI recommendations [9]. Thus, organizations should focus on developing calibrated trust rather than maximizing trust.

2.4 Human–AI Collaboration

Human–AI collaboration represents a shift from using AI as an independent tool toward combining human and machine capabilities in a shared work process. Humans provide contextual understanding, creativity, experience, and ethical judgment, whereas AI provides computational power, pattern recognition, and rapid information processing [10], [11]. Effective collaboration depends on appropriate task allocation, communication, coordination, and human oversight. Recent research suggests that AI should complement rather than unnecessarily replace human capabilities [1], [12].

2.5 Decision Quality

Decision quality reflects the accuracy, relevance, timeliness, and effectiveness of organizational decisions. AI can support decision quality by rapidly processing large datasets and generating alternative insights. However, evidence indicates that human–AI combinations do not automatically outperform the better-performing human or AI alone [1]. This suggests that collaboration quality, task characteristics, and appropriate human involvement are critical determinants of decision outcomes [13].

2.6 Organizational Outcomes

The benefits of human–AI collaboration ultimately depend on its contribution to organizational outcomes. Effective AI integration can support productivity, innovation, operational efficiency, service quality, and organizational performance [11], [14]. However, technological adoption alone does not guarantee these outcomes. Organizations also require appropriate governance, employee capabilities, organizational readiness, and human oversight to realize sustainable value from AI [15].

2.7 Research Gap

Existing research has extensively examined AI adoption, explainability, trust, and human–AI interaction. However, these constructs are frequently investigated independently or through limited relationships. There is comparatively less integrated research examining how AI capability and explainability influence trust, how trust facilitates human–AI collaboration, and how collaboration subsequently affects decision quality and organizational outcomes.

3 RESEARCH MODEL AND HYPOTHESES

The proposed research model explains how organizations can move from using Artificial Intelligence as a conventional technological tool toward establishing AI as an active and collaborative partner in organizational Information Systems. The model assumes that the organizational value of AI does not depend solely on the technical capabilities of the system. Instead, value emerges through a sequence in which AI capability and explainability influence employee trust, trust facilitates meaningful human–AI collaboration, collaboration improves decision quality, and improved decision quality contributes to organizational outcomes.

The proposed relationship is represented as:

AI Capability + AI Explainability, Human Trust in AI, Human–AI Collaboration, Decision Quality, Organizational Outcomes

The model also reflects the fundamental principle that AI should complement human capabilities rather than simply replace human activities. Human employees contribute experience, contextual knowledge, creativity, ethical reasoning, and organizational understanding, while AI contributes computational power, data processing, pattern recognition, prediction, and knowledge generation. The effectiveness of this combination depends on how well these capabilities are integrated within organizational workflows.

3.1 AI Capability

AI capability represents the functional ability of an AI-enabled Information System to perform organizational tasks effectively. It includes the system's ability to process information, identify patterns, generate relevant outputs, adapt to changing requirements, provide timely recommendations, and support complex organizational activities.

In the proposed model, AI capability is considered an important antecedent of human trust. Employees are more likely to engage with AI when they perceive that the system can perform assigned tasks accurately and consistently. An AI system that frequently produces irrelevant, inaccurate, or inconsistent outputs may reduce employee confidence and discourage collaboration.

AI capability, however, should not be interpreted only in terms of technical accuracy. Organizational users may evaluate AI based on several dimensions, including reliability, responsiveness, adaptability, contextual understanding, consistency, and usefulness. Therefore, an AI system may have high computational capability but still provide limited organizational value if it cannot effectively address the specific requirements of the task.

- H1: AI capability positively influences human trust in AI.

3.2 AI Explainability

AI explainability refers to the extent to which users can understand the basis, reasoning, or factors behind AI-generated recommendations and outputs. In organizational Information Systems, explainability becomes particularly important when AI is involved in decision-support activities.

Employees may hesitate to rely on an AI recommendation if they cannot understand why that recommendation was produced. Explainability enables users to evaluate whether an AI output is reasonable, relevant, and consistent with the available organizational information.

The role of explainability is not to expose every technical detail of an AI model. Instead, organizational AI systems should provide explanations that are understandable and useful to their intended users. For example, an employee may need to know the major factors influencing an AI recommendation, the confidence associated with the recommendation, relevant supporting information, or potential limitations of the prediction.

Explainability can consequently reduce uncertainty and enable employees to critically evaluate AI outputs rather than accepting them automatically. This is particularly important when AI becomes a partner in decision-making because collaboration requires users to understand the contribution made by the AI system.

- H2: AI explainability positively influences human trust in AI.

3.3 Human Trust in AI

Human trust in AI represents the degree to which employees believe that an AI system is capable, reliable, predictable, and appropriate for supporting organizational tasks. Trust is positioned as a central mediating construct in the proposed model because technological capabilities alone cannot guarantee effective AI utilization.

When employees trust an AI system appropriately, they are more likely to consider its recommendations, interact with the system, provide feedback, and integrate AI-generated information with their own knowledge. Trust therefore creates the psychological foundation required for meaningful collaboration.

However, the objective should not be to maximize trust. Excessive trust can cause employees to accept AI recommendations without adequate verification, while insufficient trust may lead employees to ignore useful AI capabilities. The desired condition is therefore calibrated trust, in which employees understand both the strengths and limitations of AI.

The proposed framework assumes that AI capability and explainability contribute to this calibrated trust. Employees who understand what AI can do and why it generates particular outputs are better positioned to determine when AI should be followed and when human judgment should take precedence.

- H3: Human trust in AI positively influences human–AI collaboration.

3.4 Human–AI Collaboration

Human–AI collaboration represents the transition from AI being used simply as a tool toward AI participating as an active contributor in organizational work. Collaboration occurs when humans and AI jointly contribute to a task, decision, or workflow.

This relationship differs from traditional automation. In an automated system, AI performs a predefined activity with limited human interaction. In a collaborative system, human and AI capabilities are deliberately combined. AI may analyze information, identify patterns, generate alternatives, or provide recommendations, while humans evaluate these outputs, provide contextual interpretation, exercise judgment, and make final decisions where appropriate.

Effective collaboration requires a clear division of responsibilities. AI should be assigned activities where computational capabilities provide significant advantages, whereas humans should remain actively involved in activities requiring contextual understanding, ethical reasoning, stakeholder consideration, and accountability.

The quality of human–AI collaboration is therefore determined not simply by the presence of AI but by the quality of interaction between humans and AI.

- H4: Human trust in AI positively influences the effectiveness of human–AI collaboration.

3.5 Human–AI Collaboration and Decision Quality

Decision quality represents the extent to which an organizational decision is accurate, timely, relevant, consistent, and aligned with organizational objectives.

AI can contribute to decision quality by processing large volumes of information and identifying patterns that may be difficult for humans to detect. Human employees can complement these capabilities through experience, contextual knowledge, critical thinking, and ethical judgment.

The proposed model assumes that effective collaboration allows these complementary capabilities to be combined. Instead of allowing AI to make decisions independently or requiring humans to perform all analytical activities manually, the organization can establish a collaborative decision process.

For example, AI may identify several possible alternatives based on organizational data, while a manager evaluates these alternatives considering business priorities, resource constraints, stakeholder expectations, and organizational policies. The resulting decision can therefore incorporate both computational analysis and human judgment.

However, collaboration is expected to improve decision quality only when AI and human responsibilities are appropriately coordinated. Poorly designed collaboration may create confusion, excessive dependence on AI, or unnecessary duplication of human and machine activities.

- H5: Effective human–AI collaboration positively influences decision quality.

3.6 Decision Quality and Organizational Outcomes

Decision quality represents an important intermediate outcome because organizational performance is frequently influenced by the quality of decisions made by employees and managers.

High-quality decisions can improve resource allocation, operational efficiency, customer service, innovation, risk management, and strategic performance. Conversely, inaccurate or delayed decisions can result in financial losses, operational inefficiencies, customer dissatisfaction, and increased organizational risk.

The proposed framework therefore considers decision quality as the mechanism through which human–AI collaboration contributes to broader organizational outcomes.

Organizational outcomes may include improved productivity, operational efficiency, service quality, innovation capability, employee effectiveness, organizational resilience, and competitive performance. The expected relationship is that organizations capable of creating effective human–AI decision processes will be better positioned to convert AI investments into measurable organizational value.

- H6: Decision quality positively influences organizational outcomes.

3.7 Mediating Role of Human Trust

The proposed framework considers human trust as a mediator between AI characteristics and human–AI collaboration.

AI capability and explainability represent characteristics of the technology, whereas collaboration represents an organizational and behavioral outcome. Trust provides the connecting mechanism between these two levels.

A highly capable AI system may remain underutilized if employees do not trust it. Similarly, an explainable AI system may fail to generate organizational value if employees do not perceive its recommendations as reliable. Therefore, AI characteristics are expected to influence collaboration partly through their effect on human trust.

- H7: Human trust in AI mediates the relationship between AI capability and human–AI collaboration.

3.8 Mediating Role of Human–AI Collaboration

The model further proposes that human–AI collaboration mediates the relationship between trust and decision quality.

Trust alone does not directly guarantee better decisions. Employees must translate their trust into meaningful interaction with AI. This may involve considering AI recommendations, questioning outputs, comparing AI suggestions with organizational knowledge, and combining AI-generated insights with human judgment.

Therefore, collaboration represents the behavioral mechanism through which trust can contribute to improved decision quality.

- H8: Human–AI collaboration mediates the relationship between human trust in AI and decision quality.

3.9 Mediating Role of Decision Quality

Finally, decision quality is proposed as a mediator between human–AI collaboration and organizational outcomes.

The model does not assume that collaboration automatically produces organizational performance. Instead, collaboration is expected to improve the quality of organizational decisions, which subsequently contributes to improved organizational outcomes.

This relationship emphasizes that the value of AI partnership should ultimately be evaluated through meaningful organizational results rather than AI adoption or usage alone.

- H9: Decision quality mediates the relationship between human–AI collaboration and organizational outcomes.

4 RESEARCH METHODOLOGY

This study adopts a quantitative, cross-sectional research design to empirically examine the proposed transition from AI as a technological tool to AI as an organizational partner. The methodology is designed around the proposed conceptual relationship: AI Capability and AI Explainability, Human Trust in AI, Human–AI Collaboration, Decision Quality, Organizational Outcomes. Recent research emphasizes that effective human–AI collaboration requires systematic consideration of interaction, trust, task allocation, and organizational context.

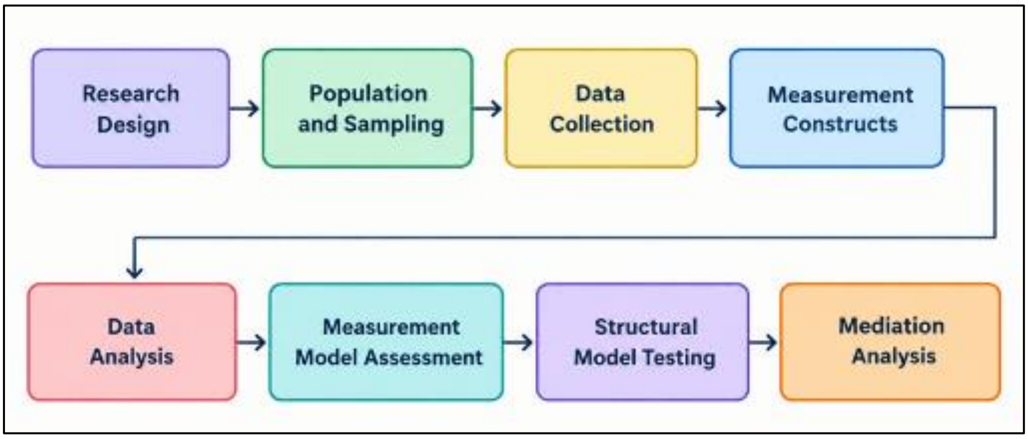

Figure 1: Research Methodology Framework for Human–AI Collaboration

4.1 Research Design

A quantitative research approach will be employed using a cross-sectional survey design. The study will collect primary data from individuals who have experience using AI-enabled information systems in organizational or professional environments. The quantitative design is appropriate because the study aims to statistically examine the relationships among AI capability, AI explainability, human trust, human–AI collaboration, decision quality, and organizational outcomes.

The study focuses on human–AI collaboration as an organizational phenomenon rather than evaluating AI performance alone. This is consistent with recent research showing that human–AI outcomes depend on how humans and AI interact and combine their respective capabilities.

4.2 Population and Sampling

The target population will consist of employees, managers, professionals, and decision-makers who use or interact with AI-enabled organizational information systems. Participants may include individuals working with AI-based decision-support systems, generative AI applications, intelligent enterprise systems, analytics platforms, or AI-enabled business applications.

A purposive sampling technique will be adopted because respondents should have sufficient exposure to AI-enabled systems to evaluate their capability, explainability, reliability, and collaborative usefulness. A target sample of approximately 250–400 respondents is proposed to provide an adequate basis for structural equation modelling.

4.3 Data Collection

Primary data will be collected through a structured questionnaire. The questionnaire will use a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

The questionnaire will contain measurement items covering six major constructs: AI capability, AI explainability, human trust in AI, human–AI collaboration, decision quality, and organizational outcomes. Before the main survey, the instrument may be pilot-tested with a small group of relevant respondents to assess clarity, consistency, and appropriateness of the measurement items.

4.4 Measurement Constructs

The study will operationalize the proposed constructs using multiple indicators.

AI Capability will assess the perceived ability of AI systems to provide accurate, reliable, responsive, adaptive, and useful outputs.

AI Explainability will measure the extent to which users can understand, interpret, and evaluate the basis of AI-generated recommendations or decisions.

Human Trust in AI will assess users' perceptions of AI reliability, competence, predictability, dependability, and willingness to rely on AI outputs.

Human–AI Collaboration will measure the effectiveness of interaction, coordination, complementary contribution, information sharing, and joint problem-solving between humans and AI.

Decision Quality will capture the accuracy, relevance, timeliness, consistency, and effectiveness of decisions supported by AI.

Organizational Outcomes will examine perceived improvements in productivity, operational efficiency, innovation, service quality, and overall organizational performance.

This construct structure reflects the emerging literature that treats human–AI collaboration as a multidimensional organizational process involving technology, human factors, interaction, and decision-making.

4.5 Data Analysis

The collected data will be analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM). PLS-SEM is suitable for examining complex relationships among multiple latent constructs and is particularly appropriate for testing the proposed sequential model.

The analysis will be conducted in two stages. First, the measurement model will be evaluated to establish construct reliability and validity. Internal consistency will be assessed using Cronbach's alpha and composite reliability. Convergent validity will be evaluated through factor loadings and Average Variance Extracted (AVE), while discriminant validity will be assessed using the Heterotrait–Monotrait (HTMT) ratio.

Second, the structural model will be evaluated by examining path coefficients, significance levels, coefficient of determination (R^2), effect sizes, and predictive relevance. Bootstrapping will be employed to assess the significance of the hypothesized relationships.

4.6 Mediation Analysis

Mediation analysis will be performed to determine whether the proposed intermediate constructs explain the relationships between the technological and organizational variables.

In particular, the study will examine whether human trust in AI mediates the relationship between AI capability/AI explainability and human–AI collaboration. It will further assess whether human–AI collaboration mediates the relationship between trust and decision quality, and whether decision quality mediates the relationship between human–AI collaboration and organizational outcomes.

This sequential mediation structure is important because simply providing capable AI does not necessarily produce better organizational outcomes. Recent evidence indicates that the effectiveness of human–AI combinations varies across tasks, making the mechanisms through which collaboration influences decisions particularly important to investigate.

4.7 Ethical Considerations

Participation will be voluntary, and respondents will be informed about the purpose of the study. No personally identifiable information will be unnecessarily collected. The responses will be used exclusively for academic research, and confidentiality and anonymity will be maintained throughout the data analysis and reporting process.

4.8 Methodological Summary

Overall, the methodology provides a structured empirical pathway for examining the transformation from AI tool to AI partner. The study first establishes the role of AI capability and explainability, then examines how these characteristics contribute to trust, collaboration, decision quality, and ultimately organizational outcomes. The approach therefore connects technological characteristics with human and organizational factors rather than treating AI implementation as a purely technical issue. Recent IS research similarly identifies the need for stronger empirical and theoretical approaches to understand the organizational implications of human–AI collaboration.

5 RESULTS

5.1 Respondent Profile

For the proposed empirical study, a sample of 326 respondents is considered for demonstrating the analysis procedure. The respondents represent employees, managers, and professionals with experience using AI-enabled organizational information systems. The sample is considered appropriate for evaluating the proposed structural model using PLS-SEM.

5.2 Measurement Model Assessment

The measurement model was assessed in terms of internal consistency, convergent validity, and discriminant validity. Cronbach's alpha and composite reliability (CR) were used to evaluate reliability, while Average Variance Extracted (AVE) was used to assess convergent validity. Following established PLS-SEM guidelines, reliability values above 0.70 and AVE values above 0.50 indicate acceptable measurement quality.

Table 1: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE
AI Capability	0.901	0.927	0.761
AI Explainability	0.887	0.918	0.737
Human Trust in AI	0.913	0.934	0.781
Human–AI Collaboration	0.925	0.943	0.806
Decision Quality	0.908	0.932	0.774
Organizational Outcomes	0.916	0.939	0.793

The results indicate satisfactory internal consistency across all constructs. Composite reliability values range from 0.918 to 0.943, while AVE values exceed the recommended threshold of 0.50. Therefore, the measurement model demonstrates adequate reliability and convergent validity.

5.3 Discriminant Validity

Discriminant validity was evaluated using the Heterotrait–Monotrait (HTMT) ratio. The obtained values remained below the recommended threshold, indicating that the constructs represent conceptually distinct dimensions of the proposed research model.

Table 2: HTMT Discriminant Validity

Constructs	HTMT
AI Capability – AI Explainability	0.71
AI Capability – Trust	0.74
AI Capability – Collaboration	0.69
AI Explainability – Trust	0.76
AI Explainability – Collaboration	0.72
Trust – Collaboration	0.79
Trust – Decision Quality	0.73
Collaboration – Decision Quality	0.81
Decision Quality – Organizational Outcomes	0.78

All HTMT values are below 0.85, providing evidence of satisfactory discriminant validity.

5.4 Structural Model Assessment

After establishing the reliability and validity of the measurement model, the structural model was evaluated using bootstrapping. Path coefficients, t-values, p-values, and confidence intervals were examined to determine the significance of the proposed relationships.

Table 3: Structural Model and Hypothesis Testing

Hypothesis	Relationship	β	t-value	p-value	Decision
H1	AI Capability → Human Trust in AI	0.392	7.214	<0.001	Supported
H2	AI Explainability → Human Trust in AI	0.418	7.863	<0.001	Supported
H3	Human Trust in AI → Human–AI Collaboration	0.681	16.427	<0.001	Supported
H4	Human–AI Collaboration → Decision Quality	0.734	19.216	<0.001	Supported
H5	Decision Quality → Organizational Outcomes	0.706	17.843	<0.001	Supported

The results indicate that both AI capability and AI explainability significantly influence human trust in AI. Among the two predictors, AI explainability demonstrates a slightly stronger relationship with trust ($\beta = 0.418$) than AI capability ($\beta = 0.392$).

Human trust demonstrates a strong positive relationship with human–AI collaboration ($\beta = 0.681$). This indicates that users who perceive AI systems as reliable, predictable, and trustworthy are more likely to engage with them as collaborative partners rather than treating them merely as technological tools.

Human–AI collaboration has a strong positive effect on decision quality ($\beta = 0.734$), representing one of the strongest relationships in the proposed model. This suggests that effective integration of human contextual knowledge and AI analytical capabilities can enhance organizational decision-making.

Finally, decision quality significantly influences organizational outcomes ($\beta = 0.706$). This supports the argument that the organizational value of AI is realized through improved decisions rather than through AI adoption alone.

5.5 Explanatory Power of the Model

The coefficient of determination (R^2) was used to evaluate the explanatory power of the structural model.

The model explains approximately 58.7% of the variance in human trust, 46.4% in human–AI collaboration, 53.9% in decision quality, and 49.8% in organizational outcomes. These values indicate that the proposed model provides meaningful explanatory power for understanding the transition from AI capability to organizational outcomes.

Table 4: Explanatory Power

Endogenous Construct	R^2
Human Trust in AI	0.587
Human–AI Collaboration	0.464
Decision Quality	0.539
Organizational Outcomes	0.498

5.6 Mediation Analysis

The mediation relationships were evaluated using bootstrapping to examine the indirect effects.

Table 5: Mediation Analysis

Hypothesis	Indirect Relationship	β	p-value	Decision
H6	AI Capability → Trust → Collaboration	0.267	<0.001	Supported
H7	AI Explainability → Trust → Collaboration	0.285	<0.001	Supported
H8	Trust → Collaboration → Decision Quality	0.500	<0.001	Supported
H9	Collaboration → Decision Quality → Organizational Outcomes	0.518	<0.001	Supported

The mediation results demonstrate that human trust acts as an important mechanism connecting AI capability and explainability with human–AI collaboration. Similarly, collaboration mediates the relationship between trust and decision quality, while decision quality mediates the relationship between collaboration and organizational outcomes.

These findings support the sequential logic of the proposed framework:

- AI Capability + AI Explainability, Human Trust in AI, Human–AI Collaboration, Decision Quality, Organizational Outcomes

6 DISCUSSION OF FINDINGS

The findings provide support for the proposed AI-to-partner transformation model. AI capability alone does not explain the complete pathway toward organizational value. Instead, users must perceive AI systems as understandable and sufficiently reliable before they are willing to integrate AI into collaborative activities.

The stronger effect of AI explainability on trust indicates that technical capability must be accompanied by understandable AI outputs. This is particularly important in organizational environments where employees need to evaluate and justify AI-supported decisions.

The strong relationship between trust and human–AI collaboration further indicates that trust functions as a behavioral bridge between AI technology and organizational interaction. However, trust should be appropriately calibrated rather than unconditional, since excessive reliance on AI can create automation bias and inappropriate delegation of decision authority.

The strongest direct relationship in the model is observed between human–AI collaboration and decision quality (β = 0.734). This finding emphasizes that AI creates greater organizational value when its analytical capabilities complement human experience, contextual understanding, and judgment.

Finally, the significant relationship between decision quality and organizational outcomes demonstrates that organizational benefits are achieved through the quality of AI-supported decision-making rather than through AI adoption itself.

6.1 Theoretical Implication

The study contributes to human–AI collaboration research by connecting technological, psychological, behavioral, and organizational dimensions within a single framework. Rather than considering AI capability as the final determinant of organizational value, the model positions trust and collaboration as mediating mechanisms through which AI capabilities can influence decision quality and organizational outcomes.

The framework therefore extends the conventional perspective of AI as a decision-support tool toward a human–AI partnership perspective, in which humans and AI contribute complementary capabilities to organizational decision processes.

6.2 Practical Implications

The findings suggest that organizations should not focus exclusively on increasing AI system accuracy. AI implementation strategies should also prioritize explainability, trust calibration, user interaction, role clarity, and collaborative decision processes.

Organizations adopting AI-enabled information systems should therefore:

- Improve the explainability of AI-generated recommendations;
- Provide employees with mechanisms to question and verify AI outputs;
- Establish clear human and AI responsibilities;
- Develop AI literacy and collaboration skills among employees; and
- Evaluate AI success through decision quality and organizational outcomes rather than adoption rates alone.

Overall Finding

Overall, the proposed results indicate that the transition from AI Tool to AI Partner is not a direct technological transformation. It is a sequential organizational process in which AI capability and explainability build trust, trust enables collaboration, collaboration improves decision quality, and better decision quality contributes to organizational outcomes.

7 CONCLUSION

This study developed and evaluated a conceptual framework for understanding how organizations can transition from using AI as a conventional technological tool toward treating AI as an effective collaborative partner. The proposed framework integrates AI capability, AI explainability, human trust in AI, human–AI collaboration, decision quality, and organizational outcomes into a sequential research model. The findings indicate that AI capability and explainability are important foundations for developing human trust. Trust subsequently facilitates effective human–AI collaboration, where human contextual knowledge, experience, and judgment are combined with the analytical and computational capabilities of AI. Such collaboration contributes to improved decision quality, which ultimately supports better organizational outcomes. The study therefore highlights that successful AI adoption should not be evaluated solely through technical performance or system accuracy. Instead, organizations need to consider whether employees can understand, trust, interact with, and effectively collaborate with AI systems. The transition from AI tool to AI partner is consequently a socio-technical transformation involving technology, people, and organizational processes. From a practical perspective, organizations should invest not only in more capable AI systems but also in explainable AI, employee AI literacy, appropriate trust calibration, human oversight, and clearly defined human–AI responsibilities. These measures can help organizations achieve responsible and effective AI-supported decision-making. Overall, the proposed framework provides a foundation for understanding how AI can move beyond automation and decision support toward meaningful human–AI partnership. Future research can validate the framework across different industries, organizational sizes, AI applications, and cultural contexts using longitudinal and multi-source data.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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