



Human-Artificial Intelligence Collaboration in Intelligent Information Systems for Supporting Organizational Decision-Making

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ABSTRACT

The use of artificial intelligence in information systems is increasingly influencing organizational decision-making processes, but its effectiveness still depends on how humans understand, assess, and use AI-generated recommendations. This study aims to explore the pattern of human-AI collaboration in intelligent information systems and its contribution to organizational decision-making. The research uses a qualitative approach with a case study design. Data were collected through in-depth interviews with 15 managers, analysts, and users of AI-based information systems, then analyzed using thematic analysis. The results show that decision effectiveness is influenced by the human-AI role sharing, trust in the system, recommendation transparency, and user interpretation ability. The findings confirm the importance of system design that places AI as a support for human considerations in decision-making.

INTRODUCTION

The development of artificial intelligence (AI) has changed the function of information systems from simply providing and processing data to an intelligent system capable of generating predictions, recommendations, and alternative decisions. This change is increasingly visible after the development of generative AI that allows users to interact with systems more naturally in analyzing information and solving problems. Globally, 75% of knowledge-based workers have used generative AI in the workplace, while in Indonesia the figure reaches 92%. Interestingly, 92% of organizational leaders in Indonesia also consider the adoption of AI important to maintain competitiveness, but 48% are still concerned about the lack of a clear organizational vision and plan for its implementation (Microsoft & LinkedIn, 2024). The data shows that the current challenge is no longer limited to whether organizations will use AI, but how AI can be appropriately integrated into information systems and human decision-making processes.

From an information systems perspective, AI should not be understood solely as a substitute for humans. Intelligent information systems are a socio-technical environment where computational capabilities, data, users, and organizational processes interact with each other. Vincent (2021) explains that AI excels at processing data and finding patterns, while humans still have advantages in intuition, context understanding, and assessment of unstructured situations. In line with that, Kolbjørnsrud (2024) emphasizes that organizational value can increase when human and AI capabilities are designed as complementary capabilities. Thus, the quality of decisions is not only determined by the sophistication of the algorithm, but also by how users understand AI recommendations, determine the limits of their use, and combine them with human knowledge and consideration.

Although this potential is increasingly recognized, previous research has shown that human-AI collaboration does not always lead to better decisions. Fügener et al. (2022) found that the combination of humans and AI can improve decision performance, but these benefits are greatly influenced by the ability of humans to determine when a task should be delegated to AI. Wang and Yin (2022) also show that providing explanations for AI outcomes does not automatically lead to proper understanding and trust in the system. Meanwhile, Eisbach et al. (2023) found that information about the accuracy of AI and the way users process recommendations affects the effectiveness of human-AI joint decisions. The findings suggest a calibrated trust issue: users need to know when AI recommendations are worthy of trust, questioning, or even rejected.

However, there is still a gap in the literature. Some studies have examined more on the acceptance of technology, experimental performance, recommendation accuracy, or technical aspects of AI. Cao et al. (2021), for example, focus on managers' attitudes and intentions of using AI in decision-making, while Lee et al. (2023) show that the implementation of AI in organizations involves interrelated human factors, technology, information systems, and organizational conditions. The qualitative study of Leoni et al. (2024) has expanded the discussion by showing the contribution of AI to the

knowledge management and decision-making processes in various organizations, but the main focus is still on the adoption of AI in the knowledge management process. Hillebrand et al. (2025) even show that the literature on human-AI collaboration and algorithm-based management is still developing separately, so a more systemic perspective is needed to understand human and AI interactions in an organizational context.

Based on these gaps, this study aims to explore how human-AI collaboration plays out in the use of intelligent information systems to support organizational decision-making. The research is specifically geared towards understanding how users divide roles with AI, interpreting system-generated recommendations, building or limiting trust in AI, and using contextual experience and knowledge when making final decisions. This focus is important because the success of intelligent information systems can be judged not only by the technology's ability to generate accurate recommendations, but also by its ability to form meaningful interactions between humans, information, and AI in real-world decision-making situations. This perspective is in line with the need to look at the use of AI at the system level and organizational context, not just at the performance of algorithms individually (Hillebrand et al., 2025).

Theoretically, this research is expected to enrich the study of information systems regarding human-AI collaboration by providing an understanding of the collaboration mechanisms formed when humans and AI are jointly involved in the decision-making process. This research also expands the discussion of AI from the perspective of technology adoption to the perspective of human-AI interaction which includes role sharing, trust, interpretation of recommendations, and contextual considerations. In practice, the results of the research are expected to be the basis for organizations to design and implement intelligent information systems that are not only technically accurate, but also transparent, understandable, and in accordance with the needs of decision-makers. With this approach, AI is placed as a cognitive partner that strengthens human capabilities, not just as a technology to replace human decisions.

THEORETICAL FRAMEWORK

Intelligent Information Systems as Human-AI Socio-Technical Systems

The development of artificial intelligence has expanded the function of information systems from systems that provide information to systems that can analyze data, study patterns, generate predictions, and provide decision recommendations. In this context, intelligent information systems cannot be understood only as a collection of algorithms, but as a socio-technical system that brings together technological capabilities with human knowledge, actions, and considerations. Berente et al. (2021) explain that AI management in organizations presents three important characteristics, namely autonomy, learning, and inscrutability, which distinguish them from conventional information technology. Storey et al. (2024) further place human-AI systems as a new form of decision support system that needs to integrate AI technology design with human interaction design. Thus, the value of an intelligent information system does not only depend on its computing capabilities, but also on how the system

allows humans to understand and use AI information to achieve better decisions (Berente et al., 2021; Storey et al., 2024).

Human–AI Collaboration and Hybrid Intelligence

Human–AI collaboration is based on the principle that human intelligence and artificial intelligence have different capabilities but can complement each other. Jarrahi et al. (2022) call this combination hybrid intelligence, which is a condition when human and AI capabilities are strengthened through mutual augmentation. AI has advantages in data processing, consistency, speed, and pattern identification, while humans have the ability to understand context, use experience, conduct situational assessments, and consider the social consequences of a decision. Therefore, the goal of collaboration is not only to increase human dependence on AI, but to produce complementarity that allows human-AI combinations to produce better decisions than when the two work separately. The study by Buschmeyer et al. (2024) reinforces this view by showing that optimal human–AI collaboration performance tends to occur when human and AI capabilities are both at an adequate level.

Role Allocation and Human Expertise in AI-Supported Decisions

The division of roles is an important component in determining the effectiveness of human–AI collaboration. Peng et al. (2024) found that the level of AI ability and the level of user expertise affect how users respond to AI recommendations in intelligent decision support systems. AI with high capabilities can increase decision changes and user confidence, but users with higher competencies tend to be more selective in following AI recommendations. This suggests that effective collaboration requires human ability to determine when AI should be followed and when human considerations should be maintained. In a managerial context, Wen et al. (2025) found that the level of trust in AI affects the weight of decisions that humans give to AI. Thus, the division of decision authority is dynamic and is influenced by user competence, AI capabilities, trust levels, and the characteristics of the decisions being faced.

Trust, Transparency, and Explainability

Trust is a central element in the human relationship with AI-based information systems, but a high level of trust does not always lead to better decisions. Gómez et al. (2023) show that user involvement in the process of forming AI recommendations can increase perceptions of AI as a collaborative partner and increase the tendency to follow system recommendations. However, engagement that increases trust also has the potential to generate overtrust. De Brito Duarte et al. (2023) found that explanations generated through explainable AI can increase trust, but the effect depends on the type of explanation and the performance of the system; even certain explanations can encourage overreliance when AI performance is not guaranteed. Scharowski et al. (2023) also show that transparency can increase reliance, but such an increase is not necessarily synonymous with increased trust. Therefore, intelligent information systems need to be geared towards calibrated trust, which is a condition when users are able to trust AI in proportion to its capabilities and limitations.

Interpretation of AI Recommendations and Organizational Decision-Making

AI recommendations ultimately still require human interpretation, especially in organizational decisions that cannot be completely reduced to technical issues. When users have limited knowledge, the knowledge imbalance between humans and AI can increase the likelihood of receiving system recommendations without adequate evaluation (Gómez et al., 2023). Conversely, high user competence can make individuals better able to evaluate the suitability of recommendations for the context of decisions (Peng et al., 2024). This suggests that AI-based decision-making is an interpretive process: AI outputs become input for humans, but final decisions are formed through a combination of algorithmic information, professional experience, situational knowledge, and organizational considerations. Therefore, the effectiveness of intelligent information systems should not be measured only by the accuracy of the algorithm, but also by its ability to support the interpretation, evaluation, and control of decisions by humans.

Theoretical Synthesis and Research Positioning

The literature shows that the success of human-AI collaboration in intelligent information systems is shaped by the relationship between AI capabilities, human competence, role sharing, transparency, trust, and the ability of users to interpret system recommendations. However, most previous studies have tested these factors separately through experiments, surveys, or systematic reviews, while how these factors interact in the real experience of an organization's users still requires more in-depth exploration (Buschmeyer et al., 2024; Storey et al., 2024; Wen et al., 2025). Based on this perspective, this study views human-AI collaboration as a socio-technical process formed through four main dimensions: human-AI role sharing, trust in AI, recommendation transparency, and user interpretation capabilities. These four dimensions serve as a conceptual foundation to explore through interviews how humans and AI collaborate in intelligent information systems to support organizational decision-making.

METHODS

Types of Research

This study uses a qualitative approach with a case study design to understand human-AI collaboration in intelligent information systems that support organizational decision-making. This approach was chosen because the research focuses on experience, interpretation, human-AI role sharing, trust in the system, transparency of recommendations, and interpretation of AI outputs. Data were analyzed using thematic analysis (Braun & Clarke, 2021; Byrne, 2022).

Population and Sample

The study population included managers, analysts, and users of AI-based information systems who had first-hand experience in using AI to support decision-making. A total of 15 participants were selected using non-probability

purposive sampling based on the relevance of their experiences. This number corresponds to the characteristics of focused qualitative research and is within the commonly used interview adequacy range (Hennink & Kaiser, 2022).

Research Instruments

The research instrument was a semi-structured in-depth interview guideline with open-ended questions. The focus of the interview included the human-AI role division, trust in AI, the transparency of recommendations, and the user's ability to interpret AI recommendations. Because the research was qualitative, statistical validity and reliability tests were not applied. Data quality was maintained through the consistency of the interview guidelines and the traceability of the analysis process (Braun & Clarke, 2021, 2023).

Data Collection Procedure

Data collection began with the preparation of interview guidelines, the selection of 15 participants purposively, and the provision of information about the purpose and confidentiality of the research. Data was collected only through in-depth interviews. With the consent of the participants, the interviews were recorded and transcribed verbatim for the analysis process.

Data Analysis Techniques

The data was analyzed using thematic analysis through the stages of data familiarization, coding, theme development, theme review, theme definition, and interpretation of results (Byrne, 2022; Braun & Clarke, 2023). The analysis focused on the pattern of human-AI role sharing, trust, recommendation transparency, and user interpretation.

RESULTS

Participant Characteristics

This study involved 15 participants who were purposively selected based on their direct experience in using artificial intelligence-based information systems to support organizational decision-making. Participants came from three role groups, namely managers, analysts, and users of AI-based information systems. All participants had direct involvement in the process of using, interpreting, or utilizing AI recommendations in organizational activities. These characteristics ensure that the data obtained comes from individuals who understand the use of AI in the context of decision-making.

Table 1. Characteristics of Respondents

Features	Remarks
Number of participants	15 people
Participant groups	Managers, analysts, and users of AI-based information systems
Selection techniques	<i>Non-probability purposive sampling</i>
Main criteria	Have hands-on experience using AI-based information systems

Context of use	Support organizational analysis and decision-making processes
Data collection techniques	Semi-structured in-depth interviews
Participant code	P01-P15

Thematic analysis of in-depth interviews with 15 participants resulted in four main themes, namely: (1) human-AI role sharing, (2) trust in AI, (3) transparency of system recommendations, and (4) user ability to interpret AI recommendations. These four themes describe the pattern of human and AI collaboration in *intelligent information systems* to support organizational decision-making.

Summary of Findings

Table 2. Key Findings

Theme	Key Findings Patterns	Supporting Participant Code
Human-AI role division	AI is primarily used to process data, find patterns, construct alternatives, and speed up analysis; the final decision remains with humans	P01, P02, P03, P04, P05, P06
Trust in AI	Trust is built through consistency of results and experience of use, but recommendations are still checked before use	P02, P05, P07, P08, P09, P10
Transparency of recommendations	Users are more likely to receive recommendations if the system can show the reason, data, or basis of the recommendation	P03, P06, P08, P11, P12
User interpretation	Knowledge, experience, and understanding of the organizational context determine how AI recommendations are translated into decisions	P01, P04, P07, P10, P13, P14, P15

The Sharing of Human-AI Roles in Decision Making

The first theme shows a relatively clear division of functions between humans and AI. AI is primarily used to speed up the processing of large amounts of information, identify patterns, compare alternatives, and provide initial recommendations. Meanwhile, humans retain a role in assessing context, considering organizational conditions, and making final decisions.

"If there is a lot of data, I am more comfortable asking the system to help read the pattern first. So we don't start from scratch. But after the results come out, we will still see if it makes sense for the conditions we are facing." (P01, interview May 12, 2026)

"AI is very fast to give you several options. For me, it is very helpful. But we still have to decide which option is ultimately used because the system does not know all the conditions in the field." (P02, interview May 14, 2026)

"Sometimes the system comes up with options that we didn't think of at first. That's useful, because we have more comparative materials. It just doesn't mean that we immediately take the first recommendation from AI." (P03, interview May 16, 2026)

"Numbers can say one thing, but sometimes we know there are certain situations that have not been reflected in the data. In such a part, human experience is still very important." (P04, interview May 19, 2026)

"I don't see AI as the one who makes decisions. It's more like a partner to check if our analysis is complete enough or if something is still missing." (P05, interview May 21, 2026)

"What makes the most sense is not that AI is replacing our work, but that the time is shorter. Initial analysis that usually takes quite a long time can be accelerated, so our energy is spent more on evaluating the results." (P06, interview May 23, 2026)

Overall, the data shows that AI plays a role as a provider of analysis and recommendations, while humans continue to perform the function of evaluation and determine final decisions.

Trust in AI is Selective and Incremental

The second theme shows that participants do not automatically trust the system. Trust develops through user experience, consistency of recommendations, and the suitability of AI outputs to user-aware conditions.

"At first, I always checked twice, because we didn't know how consistent the system was. After several times the results were in accordance with our analysis, then the trust grew." (P07, interview May 26, 2026)

"I believe the system helps, but it doesn't mean that everything that comes out is yes. If there are results that feel strange, yes, it has to be checked again. For me, it's actually part of using AI in a healthy way." (P08, interview May 28, 2026)

"AI can be good if the incoming data is also good. So if I know the data is incomplete, I won't be too confident in using its recommendations as a basis for decisions." (P09, interview May 30, 2026)

"There have been several times that the recommendations have been very helpful, but they have also been less than suitable for actual conditions. From there, we learned that the AI results still need to be seen along with other information." (P10, interview June 2, 2026)

"If I want to read trends or compare data, I trust it enough. But for decisions that have a big impact and involve a lot of people, I have to be more careful." (P05, interview May 21, 2026)

"We know which parts can indeed be handed over to the system and which parts must still be controlled by humans. So it's not a matter of believing or not believing completely." (P02, interview May 14, 2026)

The findings show a pattern of selective trust, where users take advantage of AI recommendations but still verify when decisions have greater uncertainty or consequences.

Transparency of Recommendations Affects User Acceptance

The third theme relates to the system's ability to explain the basis of its recommendations. Participants tend to more easily understand and consider AI

results when information about the data, indicators, or reasons underlying the recommendations is available.

"If the system just says 'option A is the best' without explanation, I doubt it. I am more comfortable if I can see why option A appears, what indicators are most influential." (P11, interview June 4, 2026)

"What we need is not just the answers. We need to know a little bit of the way of thinking. It doesn't have to be technical at all, but at least there is a reason we can understand." (P12, interview June 6, 2026)

"If I bring AI recommendations to the meeting, I will definitely be asked what the basis is. If the system can show the source of the data and its considerations, it will be much easier for me to explain." (P03, interview May 16, 2026)

"Sometimes the results look good, but if we don't understand why the results are the way they are, there's a sense of discomfort to immediately make it the basis for the decision." (P06, interview May 23, 2026)

"Not all users understand the model or algorithm. So I think being transparent doesn't mean giving long technical explanations, but making people understand why the recommendation appears." (P08, interview May 28, 2026)

The results of the interviews show that the expected transparency is mainly in the form of an easy-to-understand explanation of the basis of the recommendations, rather than the technical details of the algorithm as a whole.

User Interpretation Ability Determines the Use of AI Recommendations

The fourth theme shows that AI recommendations do not directly turn into organizational decisions. Users first interpret the system's results based on knowledge, experience, actual conditions, and the consequences of the decision.

"AI may give the same recommendation, but the situation of each unit can be different. So it still has to be translated again. One recommendation cannot be used in all conditions." (P13, interview June 9, 2026)

"Usually I see first if the results are connected to our experience so far. If it's very different, it doesn't mean that AI is wrong, but it's a sign that we need to find out more." (P14, interview June 11, 2026)

"AI provides additional information, but the person using it still needs to know the business context. Otherwise, recommendations that are actually data-correct may not be accurate when implemented." (P15, interview June 13, 2026)

"I think users should remain critical. Don't just come out of AI and then be considered to be right. The important thing is that we know what to ask from the results." (P07, interview May 26, 2026)

"Usually, the recommendations from our system are made into one material. After that, we match it with the current conditions, previous experience, and the impact if the decision is implemented." (P04, interview May 19, 2026)

"AI can give you a lot of information, but it is humans who have to turn that information into relevant decisions. The system helps us see, we determine the meaning." (P01, interview May 12, 2026)

The results show that user interpretation capabilities are an important part of transforming AI outputs into information that is relevant to organizational decisions.

Human-AI Collaboration Patterns in Intelligent Information Systems

Overall, a collaborative pattern was found that placed AI at the stage of information processing and provision of recommendations, while humans retained the functions of evaluation, interpretation, and final decision-making. The pattern can be summarized as follows:

Data and information → AI analysis → → system recommendations
Human evaluation and interpretation → Organizational decisions

In the process, trust determines the extent to which AI recommendations are considered, while transparency helps users understand the underlying system outputs. Furthermore, user interpretability determines how recommendations are tailored to the organization's experience and context before a final decision is made.

"For me, the ideal process is indeed AI to help read the data, then humans check whether the recommendations are in accordance with real conditions. So there are two layers of assessment." (P10, interview June 2, 2026)

"If the system is good but the user just accepts it, I think it's still risky. The collaboration is only felt if the user thinks along." (P12, (June 6, 2026)

"What helps most is not when AI makes decisions for us, but when AI gives us information that makes us more confident or actually makes us see something that was previously missed." (P15, June 13, 2026 interview)

Thus, the results of the study produced four main findings, namely the complementary human-AI role, selective trust, the need for recommendation transparency, and the importance of user interpretation ability in determining the final decision.

DISCUSSION

The results show that the effectiveness of human-AI collaboration in intelligent information systems is not primarily determined by AI's ability to take over decisions, but by how AI's analytical capabilities are combined with human judgment. The patterns found show that AI is used to process information, find patterns, compare alternatives, and generate recommendations, while humans retain the functions of evaluation, contextual interpretation, and final decision. These patterns shape the flow of data and information → AI analysis → system recommendations → human evaluation and interpretation → organizational decisions, with trust and transparency as elements that influence the acceptance of recommendations. These findings reinforce the view that the value of AI in organizations is more accurately understood as augmentation rather than human substitution.

The first finding regarding the division of human-AI roles is in line with the concept of hybrid intelligence put forward by Jarrahi et al. (2022). In this perspective, humans and AI produce value when their abilities complement each other: AI has advantages in speed, processing scale, and pattern recognition, while humans have tacit knowledge, situational understanding, intuition, and the ability to consider conditions that cannot be fully represented in the data. A similar pattern was seen in this study because participants did not position AI as an actor who takes over decision-making authority. Instead, AI functions as a

cognitive partner that expands human analytical capacity. These findings are also consistent with Storey et al. (2024), who emphasize that effective human-AI systems design requires integration between technological design, human behavior, and socio-technical decision systems. Thus, an important contribution of this study is to show that collaboration does not simply mean humans "using" AI, but that there is a functional differentiation between computational capabilities and contextual considerations.

However, retaining humans as final decision-makers does not automatically guarantee better decisions. Fügener et al. (2022) found that humans can have difficulty deciding when a task should be done on their own and when to delegate to AI. In their experiment, the limitations of metaknowledge—a person's ability to assess their own strengths and weaknesses—hindered productive delegation. These findings provide important nuances to the results of this study. The attitude of participants who continue to check and control AI decisions can serve as a safeguard mechanism, but human supervision is only effective if the user has sufficient competence to evaluate the system's recommendations. Therefore, the human-in-the-loop principle should not be interpreted simply as an obligation for humans to be in the final stage, but rather to ensure that they have the knowledge, authority, and critical capacity to assess AI outputs.

This dimension is even more evident in the second finding regarding selective and gradual trust. Participants do not automatically receive AI recommendations; trust develops through experience, consistency of results, data quality, and compatibility between system recommendations and actual conditions. This pattern supports the concept of calibrated trust, which is trust that is tailored to the actual capabilities and limitations of the system, rather than unconditional trust. Gómez et al. (2023) found that user involvement in the recommendation formation process increases willingness to follow AI and perception of AI as a partner, but this involvement can also increase the risk of overtrust. Eisbach et al. (2023) also show that information on the level of accuracy of AI can improve the use of high-quality and low-quality recommendations. Therefore, the results of this study show that the goal of AI implementation should not be to maximize user trust, but to form proportionate trust.

This has important consequences for the development of information systems. A system that is perceived to be trustworthy is not a system that is always followed by its users, but rather a system that allows users to know when recommendations can be used and when they need to be verified. This distinction is important because trust and reliance are not identical concepts. Scharowski et al. (2023), through an experiment with 380 participants, found that AI explanations can increase reliance on certain situations, but do not result in a consistent increase in trust; even the characteristics of the task have a greater influence on dependency than the form of explanation given. Thus, the findings of this study expand the literature in an organizational context: user trust emerges as an evaluative and situational process, rather than as a fixed attitude. Users can trust AI to read trends or perform data analysis, but still limit their use when decisions have greater organizational consequences.

The third finding demonstrates the importance of recommendation transparency. Participants did not demand to understand the entire algorithm technically, but wanted understandable reasons, relevant indicators, and sources of information underlying a recommendation. These findings are important because they show the difference between technical transparency and user-centered explainability. In an organizational context, a useful explanation is not always the most mathematically detailed explanation, but one that allows users to assess the reasonableness of recommendations and explain them back to others. Scharowski et al. (2023) show that the relationship between transparency, trust, and the use of recommendations is more complex than the assumption that more explanations always lead to higher trust. The findings of this study are consistent with this complexity: transparency seems to primarily provide a basis for evaluation and accountability, rather than simply an instrument to make users more trustworthy.

The implication is that intelligent information systems need to be designed with the principle of explainability for decision-making. The system ideally not only conveys the "what" of its recommendations, but also provides information regarding the "why" the recommendation appeared, what data supports it, the extent of its uncertainty, and what conditions can cause the recommendation to change. This is in line with Storey et al. (2024), who place the design of human interaction as an integral part of AI technology design. In organizational practice, features such as dominant factor indicators, data sources, system confidence levels, decision alternatives, as well as trail audits are potentially more useful than complex algorithmic explanations. In other words, transparency should be geared towards improving decision intelligibility and user accountability.

The fourth finding, namely the ability of users to interpret AI recommendations, shows that AI output cannot be considered a decision until the information is understood in an organizational context. Participants used professional experience, situational knowledge, implementation consequences, and understanding of work unit conditions to determine whether the system recommendations are relevant. These findings were reinforced by Peng et al. (2024), who found that AI capabilities and user competency levels interact in determining decision behavior. Users with higher levels of expertise tend to show lower dependency on AI, while high-powered AI can increase decision change and user confidence. This suggests that the quality of collaboration is not only a technological attribute, but is the result of the interaction between AI capability and human capability.

At this point, there is an important difference with the view that simply assumes that increasing the capabilities of AI will automatically improve the quality of decisions. The results of this study show that analytically good recommendations can still result in inappropriate decisions if users fail to relate them to organizational conditions. Conversely, users who are too confident in their experience also have the potential to ignore new information that is actually more accurate. Peng et al. (2024) even found that low-powered AI can lower the accuracy level of users who actually have higher capabilities than AI, while the existence of AI can still increase their confidence. This condition shows that

confidence is not always synonymous with decision quality. Therefore, human-AI collaboration requires a mechanism that maintains a balance between algorithm aversion and automation bias.

If the four findings are viewed in an integrated manner, this study offers an understanding that human-AI collaboration is a sequential and interdependent socio-technical process. The division of roles determines who does what; transparency provides a basis for understanding recommendations; trust determines how far recommendations are considered; and interpretability determines how recommendations are translated into decisions. This perspective goes beyond research that only discusses acceptance or intention to use AI. Cao et al. (2021), for example, show that attitudes toward AI have a positive effect on managers' intentions to use it, while personal conditions and concerns also influence the acceptance of the technology. The results of this study show a further stage: once AI is accepted and used, the main issue shifts to how humans and AI effectively shape joint decisions.

These contributions are also consistent with the latest developments in the organizational literature. Lee et al. (2023) found that the implementation of AI involves the dimensions of technology, information systems, humans, and organizations simultaneously, so that the success of AI cannot be explained from technological characteristics alone. Leoni et al. (2024) further show empirically that AI can strengthen knowledge management processes that support organizational decision-making. Hillebrand et al. (2025) even emphasized the need to move human-AI collaboration analysis from the level of individual tasks to a systemic perspective that includes organizational contexts, collective agencies, and multilevel consequences. Within this framework, this research contributes by identifying four practical mechanisms that connect technology and human agency: role allocation, calibrated trust, meaningful transparency, and contextual interpretation.

In practical terms, the findings indicate that it is not enough for organizations to simply improve the accuracy of AI models. The implementation of intelligent information systems needs to be equipped with rule-sharing of authority, human override mechanisms, the display of data sources and quality, uncertainty level information, and verification procedures for high-risk decisions. Users also need training that not only teaches how to operate AI but improves AI literacy, the ability to evaluate recommendations, understand data limitations, and recognize possible algorithmic errors. This is becoming increasingly important because collaboration that relies too much on AI can lead to overtrust, while excessive trust can lead to poor use of AI capabilities.

This study still has several limitations. First, the study uses a case study design with 15 participants selected purposively, so that the goal is to gain depth of understanding, not to produce statistical generalizations. Second, data collection is only carried out through in-depth interviews, so that the findings represent the experiences and perceptions reported by the participants and have not been compared with actual behavior data, system logs, observation of the decision process, or objective measures of decision quality. The design and source of the research data have indeed been determined in the methodology.

Third, the study has not specifically compared collaboration patterns based on the roles of managers, analysts, and users as well as based on decision type and decision risk level. Therefore, differences in task characteristics that according to previous research can affect trust and reliance have not been analyzed separately.

Follow-up research can develop these findings through mixed-methods or longitudinal studies. Quantitative surveys can be used to test the relationship between role sharing, transparency, calibrated trust, interpretability, and decision quality in a larger sample. Experimental studies can compare the level of AI transparency, user capabilities, and AI accuracy levels to see the causal influence on decisions. Longitudinal research is also important to understand how trust in AI changes after users have repeatedly experienced correct or incorrect recommendations. In addition, a combination of interviews with system logs, observations, and decision performance measures can provide stronger evidence of the differences between user perceptions and actual behavior. Cross-sector comparisons as well as between routine decisions and strategic decisions are also needed to determine whether the patterns of collaboration found are stable in different organizational contexts.

Overall, this study shows that the main contribution of intelligent information systems to decision-making lies not in the replacement of humans by AI, but in the creation of conditions where AI analytical capabilities and human contextual capabilities can be mutually corrected and complemented. The effectiveness of collaboration is achieved when the roles of both are clear, trust is proportionately given, recommendations can be meaningfully explained, and users retain the ability to interpret AI outputs. Thus, the development of intelligent information systems needs to shift from an AI-centered automation approach to human-centered collaborative intelligence, where technology strengthens human decision-making capacity without eliminating human contextual control, responsibility, and consideration.

CONCLUSIONS AND RECOMMENDATIONS

This study concludes that the effectiveness of human-AI collaboration in intelligent information systems does not lie in replacing the role of humans with AI, but in the ability of the two to complement each other in organizational decision-making. AI plays a role in accelerating data processing, recognizing patterns, and generating recommendations, while humans still play a role in evaluating, interpreting context, and making final decisions. The effectiveness of collaboration is influenced by the clarity of the division of roles, proportional trust in AI, transparency of recommendations, and the ability of users to interpret system outputs. Therefore, organizations are advised to develop intelligent information systems that are oriented towards human-centered collaborative intelligence, provide easy-to-understand explanation of recommendations, maintain human oversight mechanisms, and improve user AI literacy so that decisions remain accurate, contextual, and accountable.

FURTHER STUDY

Further research is recommended using mixed-method, longitudinal, or experimental approaches with a larger number of participants and a more diverse organizational context. Research can also examine the relationship between role allocation, calibrated trust, transparency, user interpretation ability, and decision quality quantitatively. The use of system logs, observation of decision behavior, and objective performance measurement is also needed to compare user perceptions with actual behavior in human-AI collaboration.

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