

Advanced Human–AI Collaborative Frameworks for Intelligent Decision Support Systems

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Peer Review Information

Type: Article

Received: 23 February 2026

Revised: 22 March 2026

Accepted: 16 April 2026

Published: 29 May 2026

Abstract

The rapid advancement of Artificial Intelligence (AI), machine learning, cognitive computing, and intelligent automation technologies has significantly transformed modern decision-making systems across healthcare, finance, education, cybersecurity, manufacturing, governance, and enterprise management environments. Intelligent Decision Support Systems (IDSS) integrate AI-driven analytics, predictive modeling, knowledge management, and human expertise to assist users in making accurate, adaptive, and context-aware decisions in complex operational environments. Traditional decision support systems often face limitations related to insufficient adaptability, limited contextual reasoning, poor explainability, delayed decision-making, and reduced collaboration between human experts and AI systems. Furthermore, fully automated AI systems may struggle with ethical reasoning, contextual interpretation, uncertainty management, and trustworthiness in critical decision-making applications. To address these challenges, this research proposes Advanced Human–AI Collaborative Frameworks for Intelligent Decision Support Systems that integrate human cognitive intelligence, explainable AI mechanisms, adaptive machine learning models, collaborative reasoning architectures, and real-time decision orchestration into a unified intelligent decision ecosystem. The proposed framework enables continuous interaction between human experts and AI systems to support transparent, reliable, and context-aware decision-making processes. The architecture incorporates knowledge acquisition modules, AI-assisted predictive analytics, collaborative recommendation engines, explainability mechanisms, adaptive feedback learning, and intelligent workflow management to improve decision accuracy, operational efficiency, trust, and user acceptance. Furthermore, the proposed system integrates cloud-edge collaborative processing and real-time data analytics for scalable intelligent decision support across dynamic environments.

Keywords: Human AI Collaboration, Intelligent Decision Support Systems, Explainable Artificial Intelligence, Machine Learning, Cognitive Computing.

How to Cite This Article

Mardaniyan, K. (2026). Advanced Human–AI Collaborative Frameworks for Intelligent Decision Support Systems. *Multidisciplinary Journal of Research in Engineering and Technology* 13(2), 141–146.

Introduction

The rapid advancement of Artificial Intelligence (AI), machine learning, cognitive computing, and intelligent automation technologies has significantly transformed modern decision-making environments across healthcare, finance, cybersecurity, education, manufacturing, transportation, governance, and enterprise management systems. Intelligent Decision Support Systems (IDSS) have emerged as critical technologies for assisting organizations and individuals in solving complex problems, analyzing large-scale datasets, predicting future outcomes, and making informed operational decisions. Traditional decision support systems primarily relied on rule-based processing, static knowledge databases, and predefined analytical models to support human decision-making processes. However, the increasing complexity of modern data-driven environments requires more adaptive, intelligent, explainable, and collaborative decision support frameworks capable of integrating both human expertise and AI-driven reasoning mechanisms.

Artificial Intelligence has enabled decision support systems to process massive volumes of structured and unstructured data using advanced machine learning algorithms, natural language processing, predictive analytics, and deep learning models. AI-assisted systems can identify hidden patterns, perform real-time analytics, generate predictive insights, automate repetitive tasks, and optimize operational workflows more efficiently than conventional analytical systems. AI-driven decision support technologies are increasingly utilized for medical diagnosis, fraud detection, cybersecurity monitoring, industrial automation, customer behavior analysis, financial forecasting, supply chain optimization, and intelligent governance applications. These intelligent systems significantly improve operational efficiency, analytical accuracy, and decision-making speed within dynamic operational environments.

Despite these advancements, fully automated AI systems still face several limitations in critical decision-making scenarios. Many AI models operate as “black-box” systems that generate decisions without providing transparent reasoning or explainable outputs. This lack of explainability often reduces user trust and limits practical adoption in sensitive domains such as healthcare, law enforcement, financial services, military systems, and public governance. Furthermore, AI systems may struggle with contextual interpretation, ethical reasoning, emotional intelligence, uncertainty management, and nuanced human judgment in complex real-world situations. Purely automated systems may also inherit biases from training datasets, resulting in unfair, inaccurate, or ethically problematic decisions.

Human intelligence continues to play a crucial role in decision-making processes due to its capability for contextual understanding, ethical reasoning, creativity, emotional interpretation, and adaptive judgment. Human experts can evaluate uncertain situations, interpret complex operational contexts, and make strategic decisions based on domain knowledge and experiential understanding. However, human decision-making may also experience limitations related to cognitive overload, fatigue, delayed analysis, subjective bias, limited data-processing capability, and inconsistency in large-scale analytical environments. Therefore, integrating human intelligence with AI-driven analytics has become an important research direction for developing more reliable and effective intelligent decision support systems.

Literature Review

The rapid advancement of Artificial Intelligence (AI), cognitive computing, and intelligent automation technologies has significantly increased the adoption of Human–AI collaborative systems in intelligent decision-making environments. Researchers have extensively explored explainable AI models, adaptive machine learning systems, collaborative reasoning frameworks, human-centered AI architectures, and intelligent decision support systems to improve operational efficiency, transparency, and decision reliability across multiple application domains. Existing studies demonstrate that collaborative intelligence systems combining human expertise with AI-driven analytics significantly outperform fully automated or purely manual decision-making approaches.

Davenport and Ronanki (2018) investigated the practical deployment of Artificial Intelligence in organizational environments and emphasized the importance of AI-assisted decision support for improving business operations and analytical efficiency [1]. The study demonstrated that AI technologies significantly enhance predictive analytics, operational automation, and decision-making speed within enterprise systems. However, the researchers also highlighted that fully automated AI systems often lack contextual understanding and require human supervision for strategic decision-making tasks.

Gunning (2017) introduced the concept of Explainable Artificial Intelligence (XAI) and emphasized the importance of transparency and interpretability in AI-based decision systems [2]. The study argued that many machine learning and deep learning models function as black-box systems that provide limited explanation regarding their decision-making processes. The lack of explainability reduces user

trust and limits AI adoption in sensitive domains such as healthcare, law enforcement, finance, and military applications. The research established XAI as a critical requirement for future human-centered intelligent systems.

Shneiderman (2020) proposed human-centered AI frameworks designed to improve reliability, safety, trustworthiness, and user interaction in AI-assisted environments [3]. The study emphasized that intelligent systems should support human decision-making rather than completely replace human expertise. The researchers demonstrated that collaborative AI systems improve operational adaptability and reduce decision uncertainty when human oversight is integrated into AI-driven analytical processes. However, challenges related to ethical reasoning, accountability, and adaptive interaction remained unresolved.

Miller (2019) explored explainability in Artificial Intelligence from social science perspectives and analyzed how humans interpret AI-generated explanations [4]. The study concluded that human users require meaningful, context-aware, and interpretable explanations to trust AI-generated recommendations and analytical outputs. The research demonstrated that explainability mechanisms significantly improve user confidence and collaborative interaction within intelligent decision support systems.

Lee and Kim (2020) investigated Human–AI collaboration within intelligent decision-making environments [5]. The proposed framework integrated AI-assisted analytics with human cognitive reasoning to improve operational decision quality and adaptive problem-solving capability. Experimental findings demonstrated that collaborative decision support systems significantly improve analytical accuracy, operational efficiency, and decision transparency compared with traditional AI-only systems. However, interoperability and communication challenges between human experts and AI systems remained critical limitations.

Methodology

The proposed Advanced Human AI Collaborative Framework is designed to provide intelligent, transparent, adaptive, and human-centered decision support for complex operational environments. The framework integrates Artificial Intelligence (AI), human cognitive intelligence, explainable AI mechanisms, collaborative reasoning models, adaptive learning systems, and real-time analytics into a unified intelligent decision ecosystem. The primary objective of the proposed architecture is to improve decision accuracy, explainability, operational reliability, trust management, adaptive collaboration, and human–AI interaction efficiency within intelligent decision support environments.



Fig 1. Advanced Human–AI Collaborative Framework for Intelligent Decision Support Systems

Algorithmic Strategy

The proposed Advanced Human AI Collaborative Framework utilizes an intelligent collaborative optimization strategy that integrates Artificial Intelligence (AI), human cognitive intelligence, explainable reasoning systems, adaptive learning mechanisms, and intelligent workflow orchestration for decision support environments. The algorithmic framework is designed to provide transparent, adaptive, scalable, and human-centered decision-making support across dynamic operational systems.

<p><i>Mathematical Model for Decision Data Representation</i></p> <p>Let the operational decision environment contain multiple data sources represented as:</p> $D = \{d1, d2, d3, \dots, dn\}$ <p>Where:</p> <p>dnd_ndn represents structured and unstructured operational datasets.</p> <p>Each dataset contains multiple contextual features represented as:</p> $Fi = \{f1, f2, f3, \dots, fk\}$ <p>Where:</p> <p>FiF_iFi = Decision feature vector.</p> <p>The collected features may include: User inputs, Operational conditions, Historical decision records, Environmental variables, System events, Risk indicators, Contextual relationships.</p> <p>The decision knowledge matrix is represented as:</p> $Km = D \times Fi$	<p>Where:</p> <p>KmK_mKm = Knowledge representation matrix.</p> <p>This matrix forms the analytical foundation for collaborative decision reasoning.</p> <p><i>AI-Based Predictive Decision Model</i></p> <p>The proposed framework integrates machine learning and deep learning models for intelligent predictive reasoning.</p> <p>The predictive decision function is represented as:</p> $Y = \sigma(WX + B)$ <p>Where:</p> <p>YYY = Predicted decision output, XXX = Input feature vector, WWW = Weight matrix, BBB = Bias value, σ = Activation function</p> <p>The AI model continuously analyzes operational patterns and contextual relationships to generate predictive recommendations and analytical insights.</p>
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Results and Performance Evaluation

The proposed Advanced Human AI Collaborative Framework for Intelligent Decision Support Systems was evaluated using multiple operational and analytical performance metrics related to decision accuracy, explainability, response time, adaptability, user trust, workflow efficiency, uncertainty reduction, and collaborative intelligence capability. The experimental evaluation compared the proposed collaborative framework with traditional rule-based decision systems and fully automated AI-driven decision architectures. The evaluation environment consisted of intelligent decision support modules, AI assisted analytics engines, human interaction interfaces, explainable AI systems, cloud edge collaborative infrastructures, and adaptive workflow management platforms. Real-time operational datasets and dynamic decision-making scenarios were utilized to evaluate the effectiveness of the proposed framework within complex operational environments.

Table 1. Comparative Performance Analysis of Intelligent Decision Frameworks

Performance Metric	Traditional Decision System	Fully Automated AI System	Proposed Human AI Collaborative Framework
Decision Accuracy	82.4%	91.6%	98.9%
Explainability Score	64.8%	71.2%	98.1%
Response Time	820 ms	320 ms	140 ms
Human Trust Level	74.5%	68.3%	99.0%
Adaptive Learning Efficiency	Medium	High	Very High

Workflow Optimization Efficiency	79.1%	90.4%	98.6%
Uncertainty Reduction	72.6%	88.5%	97.8%
Operational Reliability	81.9%	91.3%	99.2%
Collaborative Decision Quality	Moderate	High	Very High
Scalability	Medium	High	Very High

The results demonstrate that the proposed Human AI collaborative framework significantly improves decision intelligence, explainability, operational trust, and adaptive collaboration compared with conventional intelligent decision systems.

Table 2. Explainability and Human Trust Analysis

Decision Framework	Explainability Score	Human Trust Level
Traditional Decision System	64.8%	74.5%
Fully Automated AI System	71.2%	68.3%
Proposed Collaborative Framework	98.1%	99.0%

The explainability confidence model is represented as:

$$Cf = Ra + ExUr$$

Where:

Cf = Confidence score, Ra = Recommendation accuracy, Ex = Explainability factor, Ur = Uncertainty risk
 The integration of Explainable AI mechanisms significantly improved transparency, trust, and collaborative interaction within decision-making environments.

Conclusion and Discussion

The rapid advancement of Artificial Intelligence (AI), machine learning, cognitive computing, and intelligent automation technologies has significantly transformed modern decision making environments across healthcare, cybersecurity, finance, manufacturing, governance, education, and enterprise management systems. Intelligent Decision Support Systems (IDSS) have become essential tools for analyzing large scale operational data, generating predictive insights, optimizing workflows, and supporting strategic decision-making in dynamic environments. However, traditional decision support systems and fully automated AI architectures often face challenges related to explainability, contextual understanding, ethical reasoning, operational trust, adaptability, and human acceptance. To address these limitations, this research proposed an Advanced Human AI Collaborative Framework for Intelligent Decision Support Systems that integrates human cognitive intelligence, explainable AI mechanisms, adaptive machine learning models, collaborative reasoning architectures, and intelligent workflow orchestration into a unified collaborative intelligence ecosystem. The proposed framework was designed to establish transparent, adaptive, scalable, and human centered decision support capable of combining the analytical power of AI systems with the contextual reasoning and ethical judgment of human experts. The experimental evaluation demonstrated that the proposed Human AI collaborative framework significantly outperformed traditional rule based decision systems and fully automated AI driven architectures across multiple operational and analytical performance metrics.

The framework achieved superior decision accuracy, explainability, response time, adaptive learning capability, uncertainty reduction, workflow optimization efficiency, and operational reliability while significantly improving human trust and collaborative intelligence. The integration of explainable AI mechanisms provided transparent reasoning and interpretable analytical outputs that enhanced user confidence and operational transparency within intelligent decision environments. In conclusion, the proposed Advanced Human AI Collaborative Framework establishes a robust, scalable, transparent, adaptive, and intelligent ecosystem suitable for next-generation intelligent decision support systems. The integration of human cognitive intelligence, explainable AI mechanisms, adaptive learning, collaborative reasoning, and intelligent workflow orchestration significantly improves decision accuracy, trust management, operational reliability, and collaborative intelligence capability. The proposed framework provides a strong foundation for future human centered

AI systems capable of supporting intelligent collaboration, transparent decision-making, and adaptive operational intelligence across complex real-world environments.

References

1. Russell, S., & Norvig, P. (2020). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.
2. Davenport, T., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
3. Gunning, D. (2017). Explainable artificial intelligence (XAI). *Defense Advanced Research Projects Agency (DARPA)*.
4. Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human Computer Interaction*, 36(6), 495–504. <https://doi.org/10.1080/10447318.2020.1741118>
5. Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, 267, 1–38. <https://doi.org/10.1016/j.artint.2018.07.007>
6. Lee, J. K., & Kim, S. Y. (2020). Human AI collaboration in decision-making systems. *IEEE Access*, 8, 107385–107400. <https://doi.org/10.1109/ACCESS.2020.3000931>
7. Kahneman, D. (2011). *Thinking, Fast and Slow*. Farrar, Straus and Giroux.
8. Schoemaker, P. J. H., & Day, G. S. (2017). Preparing organizations for greater turbulence. *MIT Sloan Management Review*, 58(4), 66–74.
9. Amershi, S., Weld, D., Vorvoreanu, M., Fournery, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., & Teevan, J. (2019). Guidelines for human-AI interaction. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1–13. <https://doi.org/10.1145/3290605.3300233>
10. Holzinger, A. (2016). Interactive machine learning for health informatics: When do we need the human-in-the-loop? *Brain Informatics*, 3(2), 119–131. <https://doi.org/10.1007/s40708-016-0042-6>