



Research Article

Modeling Human Algorithm Interaction to Improve Trust and Reliability of Intelligent Decision Support Systems in Data Driven Organizations

Siska Narulita ^{1*}, Prihati ², Ahmad Nugroho ³

¹ Universitas Nasional Karangturi Semarang, Indonesia; e-mail : siskanarulita84@gmail.com

² Institut Teknologi dan Bisnis Semarang, Indonesia; e-mail : esterprihati20@gmail.com

³ Universitas Tidar, Indonesia; e-mail : ahmadnugroho@untidar.ac.id

* Corresponding Author : Siska Narulita

Abstract: This research explores the role of human algorithm interaction mechanisms in enhancing trust, reliability, and user confidence in Decision Support Systems (DSS). Traditional DSS models often focus solely on algorithmic accuracy and performance, neglecting crucial factors such as transparency and user engagement, which are essential for building trust. By incorporating explainable AI (XAI) techniques like SHAP and LIME, real-time feedback mechanisms, and user-friendly interfaces, the study develops structured interaction models that improve the interpretability of AI-driven decisions. The results show that transparent decision-making processes and interactive features significantly enhance user trust, making DSS more reliable and easier to adopt. Users interacting with systems that provide clear, understandable explanations of decisions, along with real-time updates on the system's confidence, reported higher levels of decision-making confidence, especially in high-stakes scenarios. These improvements lead to greater user engagement and adoption of the system in various domains, including healthcare and finance. The study also highlights the importance of balancing interpretability with efficiency in user interface design to ensure both trust and usability. The findings contribute to the design of more user-centric DSS that prioritize trust, interpretability, and cognitive factors, providing a framework for the successful integration of intelligent decision support systems in complex decision-making environments. Future research should focus on refining interaction models and exploring the broader applicability of these systems in different sectors.

Keywords: Decision Support Systems; Explainable AI; Human Algorithm Interaction; Trust-Building Mechanisms; User Engagement.

Received: 21, November 2025

Revised: 10, December 2025

Accepted: 29, December 2025

Published: 20, January 2026

Curr. Ver.: 20, January 2026



Copyright: © 2026 by the authors.

Submitted for possible open

access publication under the

terms and conditions of the

Creative Commons Attribution

(CC BY SA) license

(<https://creativecommons.org/licenses/by-sa/4.0/>)

1. Introduction

Decision Support Systems (DSS) play a critical role in modern organizations by providing data driven insights to assist in decision-making, judgments, and planning. These systems are designed to process large datasets to guide organizational decisions across various domains such as healthcare, real estate, and vocational training [1], [2]. DSS can be model-driven, data driven, or a hybrid, with the latter gaining prominence due to its integration of machine learning and statistical analysis. Data driven Decision Support Systems (DD-DSS) use advanced algorithms to process data from multiple sources, such as Enterprise Resource Planning (ERP) systems, Customer Relationship Management (CRM) systems, and data warehouses. These systems enhance decision-making capabilities by providing insights that assist organizations in optimizing resources, improving predictive analytics, and fostering collaborative decision-making [3], [4].

The adoption and effectiveness of intelligent algorithms in DSS heavily rely on the users' trust and the system's reliability. As algorithms become more integrated into decision-making processes, factors such as system transparency, accuracy, and user interaction play pivotal roles in determining the trust users place in these systems [5]. Trust in DSS is often influenced

by system accuracy, which dictates the reliability of algorithmic recommendations, as well as by the system's transparency and the clarity of its operational processes [6]. Transparency ensures that users understand how decisions are made, thus fostering greater trust and encouraging adoption. Without transparency, users may become skeptical of the system's outputs, which can hinder the integration of intelligent DSS into daily operations [7], [8]. Moreover, first impressions during user interactions significantly impact the development of trust. Positive initial experiences can foster trust, which can be reinforced through consistent system performance over time [2].

Reliability is another essential factor for trust. A DSS that consistently performs well under varying conditions ensures a dependable user experience, leading to increased acceptance and trust in the system [7]. System designers must also account for the cognitive trust factors that influence users' perceptions. For instance, users with higher technological affinity are more likely to trust and adopt these intelligent systems [5]. Therefore, it is crucial to design DSS not only to deliver accurate results but also to ensure that users can understand, interpret, and trust the system's decision-making process.

Decision Support Systems (DSS) are critical tools employed across various sectors to enhance decision-making by processing large volumes of data and providing actionable insights. However, the successful adoption and effectiveness of these systems are often undermined by issues related to transparency and interaction design. Transparency plays a pivotal role in fostering user trust, as it enables users to understand how decisions are made by the system. Without transparency, users may struggle to trust the system's outputs, hindering its overall adoption and utility [1], [3]. Furthermore, poor interaction design, characterized by complex user interfaces and unclear feedback mechanisms, can lead to user frustration, diminished trust, and, ultimately, the rejection of the system [9]. As DSS becomes more integrated into decision-making processes, these barriers to trust and usability must be addressed to maximize the potential of these systems.

One of the main challenges in improving DSS adoption is designing systems that not only offer accurate and reliable recommendations but also make these recommendations understandable and trustworthy to users. The objective of this research is to propose human algorithm interaction mechanisms that can enhance transparency, reliability, and trust in DSS. This includes the integration of Explainable Artificial Intelligence (XAI), which provides clear, understandable explanations of how decisions are made, making the system's processes visible to users [1], [10]. Additionally, the design of intuitive, user-friendly interfaces can reduce cognitive load and enhance user engagement, helping users interact with DSS more effectively [2].

Moreover, the incorporation of dynamic feedback mechanisms that provide real-time updates on the system's confidence in its recommendations can assist in calibrating user trust [11]. These mechanisms can help users adjust their reliance on the system, fostering a balanced relationship between human judgment and algorithmic support [12]. Ultimately, the integration of these mechanisms aims to improve not only the usability of DSS but also the trust users place in these systems, enabling more effective decision-making.

To address these issues, this study focuses on modeling interaction mechanisms that integrate XAI, dynamic feedback, and user-centric design principles to create DSS that are more transparent, reliable, and trust-inspiring. By enhancing these factors, the study aims to improve the decision-making confidence of users, ensuring that DSS are not only trusted but also effectively utilized in organizational decision processes.

In summary, Decision Support Systems (DSS), especially data driven systems, are vital in modern organizations, but their successful adoption largely depends on user trust and system reliability. Transparency in decision-making and effective interaction design are crucial for fostering trust, as users are more likely to embrace systems that are both understandable and reliable. However, issues such as limited transparency and poor user interface design often hinder adoption by reducing trust. The integration of human algorithm interaction mechanisms, such as Explainable AI (XAI) and dynamic feedback, can enhance transparency, improve user confidence, and ultimately support the broader acceptance and successful implementation of intelligent DSS in data driven organizations [1], [2], [9].

2. Literature Review

Existing DSS Models

Decision Support Systems (DSS) have undergone significant evolution, from traditional models to intelligent systems that integrate artificial intelligence (AI) and machine learning (ML). Initially, DSS were computer-based tools designed to assist decision-making by integrating data, models, and user interfaces. Traditional DSS frameworks were primarily rule-based, offering limited capabilities for handling complex decision-making functions [13]. As the need for more advanced decision-making tools grew, Intelligent Decision Support Systems (IDSS) emerged. These systems leverage AI and ML techniques to enhance predictive analytics, real-time decision-making, and adaptability [14]. Modern IDSS utilize various AI techniques, such as reinforcement learning, fuzzy logic, neural networks, and Bayesian methods, to improve decision accuracy and efficiency. These systems are especially effective in dynamic and uncertain environments, providing real-time support and managing multiple information flows [1], [15]. IDSS are applied across various domains, including medical diagnosis, financial risk management, and business decision-making, where their AI-driven capabilities enhance decision outcomes [16].

Trust in Decision Support Systems

Trust is a critical factor in the adoption and successful implementation of DSS, particularly those powered by intelligent algorithms. Several studies have explored how trust is built in human algorithm interactions and identified key factors influencing this trust. The design of the user interface plays a significant role in fostering trust, with studies showing that conversational interfaces are more likely to build user trust and satisfaction compared to conventional graphical interfaces [17]. System reliability also has a profound impact on trust; users tend to trust systems that consistently perform well and provide accurate outputs [18]. Moreover, trust is heavily influenced by transparency and explainability, as users need to understand how decisions are made by the system. Explainable AI (XAI) techniques have been identified as essential for building trust, as they provide users with clear and understandable explanations of the system's decision-making processes [1], [10].

Furthermore, user characteristics, such as expertise and self-confidence, influence the level of trust in DSS. Experts may exhibit lower trust in AI-based systems due to their preference for relying on personal judgment [19]. Trust can also be calibrated through long-term, error-free system performance and transparency, which allows users to become more reliant on the system over time. Situational stress, however, can negatively affect trust, especially when users rely heavily on automated recommendations in high-pressure situations [20]. In conclusion, building trust in DSS requires a combination of transparent, reliable, and user-friendly designs that cater to both system performance and user expectations.

Interaction Design and Transparency

In the context of artificial intelligence (AI) and decision support systems (DSS), interpretability and transparency are crucial elements for fostering user trust and improving decision-making quality. Transparent systems enable users to understand and verify the decision-making processes behind algorithmic outputs, thereby reducing errors and enhancing system reliability [21], [22]. Tools like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have proven effective in increasing user confidence by providing clear, interpretable explanations of AI decisions, particularly in high-stakes areas such as healthcare and finance [23]. The use of explainable AI (XAI) methods, which offer "white-box" explanations, plays an essential role in demystifying algorithmic processes, making them more accessible to users [24].

Additionally, effective user interface design is pivotal for visualizing algorithmic processes and making transparency more meaningful to users. Interactive interfaces that clearly present the rationale behind algorithmic decisions can significantly improve user comprehension. However, this level of interpretability requires more time and cognitive resources to design and implement [25]. A balance must be struck between interpretability and efficiency in user interface design. For instance, techniques like navigation aids and well-organized data presentations can enhance transparency without compromising user experience [26].

Despite the benefits of interpretability, the complexity of machine learning models often leads to "black-box" behavior, where users cannot easily understand or trust the algorithm's inner workings [21]. This challenge necessitates both model-agnostic and model-specific interpretability techniques to ensure that systems are not only accurate but also comprehensible [15].

Cognitive Trust

The level of trust users place in AI-driven decision support systems is influenced by several cognitive factors, including cognitive load, task characteristics, and personality traits. Cognitive load, which refers to the mental effort required to process information, can affect trust in algorithmic systems. Studies suggest that tasks with high objectivity and time pressure tend to increase trust, while cognitive load has a less significant impact on trust formation [26], [27]. In high-risk scenarios, users are more likely to trust systems when they have sufficient cognitive resources to process information, thus enhancing their confidence in the system's decision-making [25].

Personality traits, particularly locus of control (LOC), also significantly influence trust in AI systems. Individuals with a high internal LOC are more likely to trust AI-based systems, as they tend to have greater confidence in external sources of control. Other traits, such as openness, affect how individuals respond to suggestions from AI systems. Individuals with higher openness tend to react more quickly to AI recommendations, while those with lower openness may be more skeptical [28].

Moreover, algorithmic accountability—the degree to which an algorithm's actions are traceable and explainable—plays a more significant role in shaping trust than accessibility alone [25]. In high-risk situations, the need for algorithmic accountability is paramount, as it influences perceived trustworthiness and user reliance on the system. Furthermore, educational efforts to improve AI literacy and statistical understanding can help users critically evaluate algorithmic decisions, thus enhancing trust in less risky decision-making contexts [21], [29].

Technology Integration for Organizational Decision Making

The integration of advanced technologies into organizational processes enables more effective and informed decision making. Technological innovations such as gamification, IoT, and digital learning platforms demonstrate how digital tools can improve engagement and efficiency within organizations. For example, the use of work gamification mechanisms has been shown to enhance employee engagement and performance evaluation processes in organizational environments [30].

Similarly, technology-supported learning systems illustrate how digital platforms can facilitate interactive learning and knowledge sharing within organizations. The development of technology-integrated learning models, such as the SITENAR CERYA platform for English learning, demonstrates how digital tools can merge technological innovation with educational content to improve learning outcomes [31].

In addition, technology integration in community-based educational activities, such as combining hands-on and virtual learning approaches, illustrates the potential of digital technologies to enhance collaborative learning and knowledge transfer processes [32]. These technological integrations highlight how organizations can leverage intelligent systems and digital platforms to support data-driven decision making and strengthen the interaction between humans and technological systems.

3. Proposed Method

This research uses a mixed-methods approach combining interaction modeling, system prototyping, and controlled user experiments to enhance trust, reliability, and decision confidence in Decision Support Systems (DSS). The study focuses on developing structured interaction models that improve transparency and interpretability, using tools like SHAP and LIME to clarify AI decision-making processes. A prototype DSS will integrate explainable AI (XAI) techniques and user-friendly interfaces, along with dynamic feedback mechanisms to calibrate user trust in real time. Controlled user experiments will measure trust, reliability, and decision confidence, using indicators like trust calibration and decision confidence to assess the impact of human algorithm interactions on system adoption and user engagement.

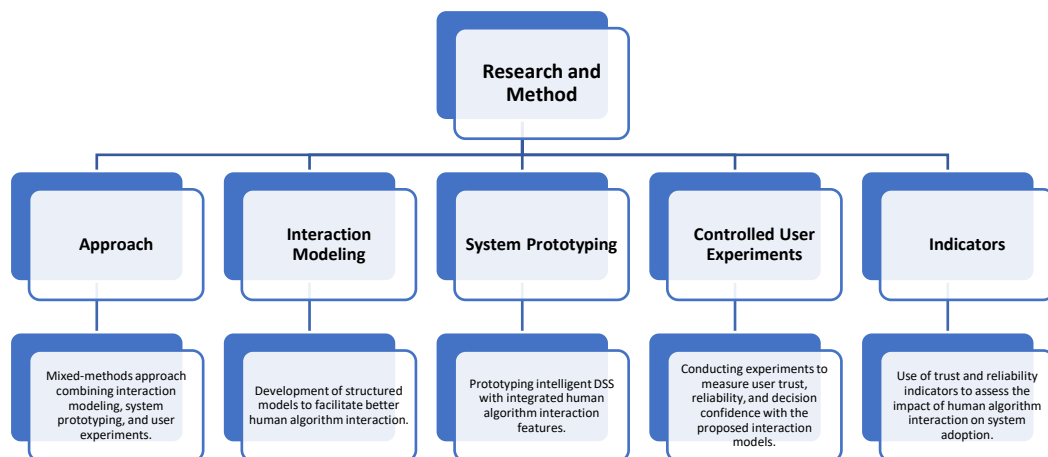


Figure 1. Research Methodology Flowchart Structure.

Approach

The research adopts a mixed-methods approach that combines interaction modeling, system prototyping, and user experiments. This approach allows for a comprehensive analysis by integrating both qualitative and quantitative methods, enabling the development of a robust framework to address both technical and human factors involved in decision support systems (DSS). By combining these methods, the research provides deeper insights into the effectiveness of human algorithm interaction mechanisms in enhancing trust, reliability, and decision confidence in DSS.

Interaction Modeling

Interaction modeling involves the development of structured models designed to facilitate better communication between users and algorithms. These models aim to enhance transparency and interpretability, which are essential for building trust and improving decision-making confidence in intelligent DSS. The use of techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) is central to the interaction modeling process, as these tools provide clear, understandable explanations of AI decisions. The goal of this phase is to create structured models that demystify the decision-making process, making it easier for users to comprehend and trust the system's recommendations.

System Prototyping

System prototyping involves the creation of an intelligent DSS that incorporates human algorithm interaction features. This prototype will integrate explainable AI (XAI) techniques that provide transparent, understandable explanations of the system's decision-making processes. Additionally, it will include interactive user interfaces that are intuitive and user-friendly. The prototype also incorporates dynamic feedback mechanisms that update users on the system's confidence in its recommendations, allowing for real-time calibration of trust. Prototyping serves as a critical step in testing and refining interaction mechanisms in a controlled environment, ensuring that these features support user engagement and decision-making.

Controlled User Experiments

The research includes controlled user experiments to measure user trust, reliability, and decision confidence in the proposed interaction models. These experiments are designed to assess how different interaction models, such as those integrating XAI or providing real-time feedback, affect users' perceptions of system trustworthiness. Specifically, the experiments will examine how users' reliance on DSS varies with task complexity and time pressure, providing empirical evidence of the influence of interaction design on trust and decision

outcomes. The goal is to evaluate how well these interaction models enhance user confidence and reliability in the DSS.

Indicators

To evaluate the impact of human algorithm interaction on system adoption, the study uses trust and reliability indicators. These indicators include trust calibration measures, which track how users' trust in the system develops over time with consistent performance and transparency. The experiments also measure decision confidence, assessing how confident users feel in their decisions when supported by the DSS. By using these indicators, the study aims to quantify the effectiveness of different interaction mechanisms in improving system reliability and enhancing user trust, ultimately influencing the adoption of intelligent DSS.

4. Results and Discussion

The study found that structured interaction models significantly enhanced user trust, algorithm interpretability, and acceptance of DSS recommendations. Transparent tools like SHAP and LIME, along with real-time feedback mechanisms, helped users understand the decision-making process, increasing their trust in the system's outputs. This transparency improved decision-making confidence, especially in high-risk tasks. User feedback highlighted that clear explanations and user-friendly interfaces made the system more accessible, fostering greater system engagement and acceptance. Overall, the findings suggest that DSS that prioritize transparency, real-time updates, and intuitive design are more likely to gain user trust and be successfully adopted in decision-making processes.

Results

The study's results show that the structured interaction models significantly improved user trust, algorithm interpretability, and the acceptance of recommendations. Users who interacted with the DSS featuring explainable AI (XAI) techniques, such as SHAP and LIME, reported a higher understanding of how decisions were made by the system. These tools provided transparent, understandable explanations, allowing users to verify the system's decisions and, as a result, increasing trust in the system's outputs. Moreover, the integration of real-time feedback mechanisms allowed users to receive updates on the system's confidence in its recommendations, which helped calibrate their trust and reliance on the system. The interactive and user-friendly interfaces, designed to balance interpretability with efficiency, played a vital role in improving overall system acceptance and engagement.

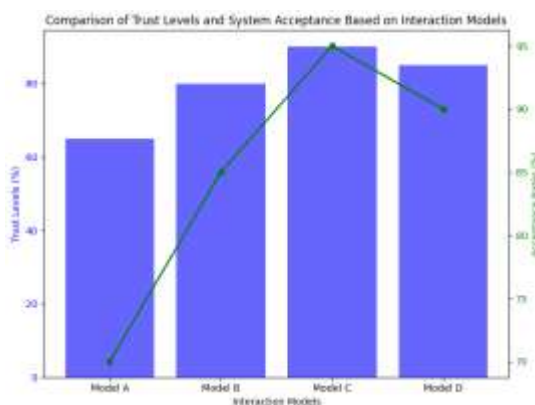


Figure 2. Comparison of Trust Levels and System Acceptance Based on Interaction Models.

The graph above illustrates the relationship between Trust Levels and System Acceptance Rates across different interaction models. As shown, Model C had the highest trust level and system acceptance rate, indicating that its structured interaction models significantly influenced both trust and adoption. Meanwhile, Model A, which had the lowest trust level and acceptance rate, highlights the importance of transparency and clear

explanations in user interaction. The trends demonstrate that as trust in the system increases, so does the likelihood of its acceptance and continued use by users.

In addition, users found that having clear explanations of algorithmic processes directly contributed to greater system acceptance. The real-time feedback on the system's confidence level in its recommendations reassured users and built their trust in the system's outputs. These findings highlight that when users can clearly understand how decisions are made, they are more likely to accept and rely on the system's recommendations, especially in high-stakes decision-making situations, such as healthcare or financial assessments. The results indicate that structured interaction models that prioritize transparency and real-time feedback lead to a stronger connection between users and the system.

Discussion

The findings suggest that enhanced interaction models significantly influence user decision-making confidence. When users are provided with transparent explanations of the decision-making process, their trust in the system increases, which in turn improves their confidence in making decisions based on the system's recommendations. This is particularly important in complex or high-risk tasks, where decision-makers need to understand the rationale behind the recommendations to feel assured about the decisions they make. The transparency offered by tools like SHAP and LIME, which offer clear explanations of AI decisions, directly contributed to users' ability to trust and confidently use the system's outputs in these contexts.

The real-time feedback mechanism incorporated into the DSS also played a crucial role in enhancing user decision-making confidence. By continuously updating users about the system's confidence in its recommendations, users were able to adjust their reliance on the system's advice according to their understanding of its reliability. This dynamic feedback fosters a more informed decision-making process, especially when facing uncertain or complex scenarios. This ability to calibrate trust in real-time is essential for systems that aim to be used in a variety of domains where decision-making certainty varies depending on the context and task complexity.

Furthermore, qualitative feedback from users revealed a positive shift in their overall experience with the system. Many users reported feeling more in control of the decision-making process due to the clear and transparent explanations provided by the system. They also noted that the interactive features of the system, including the ability to provide real-time updates on system confidence, helped them engage with the DSS more effectively. The combination of interpretability, transparency, and feedback resulted in a user-friendly experience that increased trust and reliability in the system. Users with varying levels of technological affinity found the system's interface intuitive and accessible, which further contributed to their positive experience and willingness to adopt the system in future decision-making tasks. These insights indicate that the adoption of DSS can be significantly enhanced when the system is designed with transparency, clear explanations, and real-time feedback mechanisms.

5. Comparison

Traditional algorithm-centric systems primarily focus on improving the accuracy and performance of the algorithms without considering the importance of user trust and cognitive factors. These systems prioritize computational efficiency and output precision, often operating as "black-box" models, where the decision-making process is not transparent to the user. While such systems can deliver highly accurate results, their lack of interpretability and transparency can lead to low user engagement, as users may struggle to understand or trust the decisions made by the system. This focus on algorithmic performance without addressing trust factors can hinder the adoption of decision support systems, especially in complex or high-stakes domains where users must feel confident in the system's recommendations.

Human centered interaction models, in contrast, prioritize transparency, interpretability, and user trust, significantly enhancing user engagement and system adoption. These models emphasize the importance of clear, comprehensible explanations of the decision-making process, which increases user trust and confidence in the system's outputs. By incorporating

explainable AI (XAI) techniques, real-time feedback mechanisms, and user-friendly interfaces, human algorithm interaction models provide users with the tools they need to understand and interact with the system more effectively. Unlike traditional DSS frameworks, which may overwhelm users with technical details or fail to provide clear explanations, human centered systems create an environment where users can engage with the system in a more intuitive and transparent way. This, in turn, leads to greater acceptance of the system's recommendations and a higher likelihood of long-term adoption.

The findings from this study have significant implications for the future design of DSS. Human algorithm interaction models, with their focus on transparency, interpretability, and user trust, offer a promising path for improving DSS trustworthiness and user adoption. As decision support systems become increasingly integrated into various high-stakes environments, the need for user-centric designs that prioritize trust and cognitive factors will become more critical. The broader applicability of human algorithm interaction designs suggests that future DSS will need to be more than just accurate and efficient—they must also be transparent and user-friendly. This shift towards more interactive and trustworthy systems could lead to more widespread adoption, especially in domains where decision-making confidence is paramount. By addressing both the technical and human aspects of DSS, future systems can better meet the needs of users, fostering trust and improving decision outcomes across diverse fields.

6. Conclusions

The study highlights the significant impact of human algorithm interaction mechanisms in enhancing trust, reliability, and user confidence in Decision Support Systems (DSS). By incorporating transparency, interpretability, and real-time feedback, the proposed interaction models improved users' understanding of the system's decision-making process, leading to higher levels of trust and confidence. The use of explainable AI (XAI) techniques, such as SHAP and LIME, along with user-friendly interfaces, facilitated a more transparent interaction, allowing users to verify and understand the system's recommendations. The real-time feedback on system confidence further calibrated trust, ensuring users felt more confident in relying on the DSS for decision-making.

This research contributes to the ongoing evolution of Decision Support Systems by introducing human centered interaction models that prioritize user trust and cognitive factors. By focusing on transparency, interpretability, and user engagement, this study presents a more user-centric approach to DSS design, addressing the common pitfalls of traditional algorithm-centric systems. The findings emphasize the importance of creating systems that are not only accurate but also understandable and reliable, offering valuable insights into the design of more effective and trustworthy DSS for various high-stakes environments.

Future research should focus on further refining human algorithm interaction models, especially in terms of enhancing real-time feedback mechanisms and improving explainability techniques to better address user concerns. Additionally, the broader application of these interaction models across diverse sectors, such as healthcare, finance, and public administration, could provide deeper insights into how transparency and trust affect system adoption and user decision-making. Future studies could also explore the integration of emotional and social factors in human algorithm interactions, examining how these dimensions influence user trust and system effectiveness. Ultimately, continued advancements in user-centered DSS design will be crucial in ensuring the successful adoption and long-term use of intelligent decision support systems across industries.

References

- [1] A. Kovari, "AI for decision support: Balancing accuracy, transparency, and trust across sectors," *Inf.*, vol. 15, no. 11, p. 10725, 2024, doi: 10.3390/info15110725.
- [2] M. L. Saremi and A. E. Bayrak, "AGENT-BASED SIMULATION OF OPTIMAL TRUST IN A DECISION SUPPORT SYSTEM IN ONE-ON-ONE COLLABORATION," in *Proceedings of the ASME Design Engineering Technical Conference*, 2022. doi: 10.1115/DETC2022-90770.
- [3] S. Leewis and K. Smit, "What Other Factors Might Impact Building Trust in Government Decisions Based on Decision Support Systems, Except for Transparency and Explainability?," in *Proceedings of the Annual Hawaii International Conference on System Sciences*, 2023, pp. 1633 – 1642.
- [4] S. Monica-Teodora and M. M. Ionela, "Integration of Data Science in Institutional Management Decision Support System," in *International Conference on Enterprise Information Systems, ICEIS - Proceedings*, 2025, pp. 820 – 829. doi: 10.5220/0013352400003929.
- [5] F. J. Roberts, *Decision Support Systems: Types, Advantages and Disadvantages*. 2021.
- [6] J. Wanner, L.-V. Herm, K. Heinrich, and C. Janiesch, "The effect of transparency and trust on intelligent system acceptance: Evidence from a user-based study," *Electron. Mark.*, vol. 32, no. 4, pp. 2079 – 2102, 2022, doi: 10.1007/s12525-022-00593-5.
- [7] K. Appelganc, T. Rieger, E. Roesler, and D. Manzey, "How Much Reliability Is Enough? A Context-Specific View on Human Interaction With (Artificial) Agents From Different Perspectives," *J. Cogn. Eng. Decis. Mak.*, vol. 16, no. 4, pp. 207 – 221, 2022, doi: 10.1177/15553434221104615.
- [8] S. Tolmeijer, U. Gadiraju, R. Ghantasala, A. Gupta, and A. Bernstein, "Second chance for a first impression? Trust development in intelligent system interaction," in *UMAP 2021 - Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization*, 2021, pp. 77 – 87. doi: 10.1145/3450613.3456817.
- [9] J. Li and B. Zhang, "The role of interaction design based on fuzzy decision support system in improving user experience," *Int. J. Fuzzy Syst.*, vol. 27, no. 8, pp. 2585–2601, 2025, doi: 10.1007/s40815-024-01918-6.
- [10] T. Kuflik *et al.*, "TESS 22: Transparency and Explanations in Smart Systems," in *International Conference on Intelligent User Interfaces, Proceedings IUI*, 2022, pp. 16 – 17. doi: 10.1145/3490100.3511165.
- [11] J. Frysak, "Feedback mechanisms for decision support systems: A literature review," *Adv. Intell. Syst. Comput.*, vol. 570, pp. 481 – 490, 2017, doi: 10.1007/978-3-319-56538-5_49.
- [12] E. Ö. Dogru and N. C. Krämer, "Investigating appropriate reliance on AI-Based decision support systems: the role of expertise, trust, and self-confidence," *J. Decis. Syst.*, vol. 34, no. 1, 2025, doi: 10.1080/12460125.2025.2593251.
- [13] A. Kaklauskas, "Introduction to intelligent decision support systems," *Intell. Syst. Ref. Libr.*, vol. 81, pp. 1 – 29, 2015, doi: 10.1007/978-3-319-13659-2_1.
- [14] F. Omar, A. Nabot, and R. Alqirem, "Transforming Decision Support Systems Through Artificial Intelligence: Enhancing Analytics, Automation, and Interaction," *Stud. Syst. Decis. Control*, vol. 597, pp. 479 – 491, 2025, doi: 10.1007/978-3-031-90271-0_34.
- [15] H. Fazlollahtabar and M. Saidi-Mehrabad, "Neuro-fuzzy-regression expert system for AGV optimal path," *Stud. Syst. Decis. Control*, vol. 20, pp. 93 – 115, 2015, doi: 10.1007/978-3-319-14747-5_7.
- [16] F. Gorunescu and S. Belciug, "Intelligent Decision Support Systems in Automated Medical Diagnosis," *Intell. Syst. Ref. Libr.*, vol. 137, pp. 161 – 186, 2018, doi: 10.1007/978-3-319-67513-8_8.
- [17] A. Gupta, D. Basu, R. Ghantasala, S. Qiu, and U. Gadiraju, "To Trust or Not To Trust: How a Conversational Interface Affects Trust in a Decision Support System," in *WWW 2022 - Proceedings of the ACM Web Conference 2022*, 2022, pp. 3531 – 3540. doi: 10.1145/3485447.3512248.
- [18] R. Philipsen, P. Brauner, A. C. Valdez, and M. Ziefle, "Evaluating Strategies to Restore Trust in Decision Support Systems in Cross-Company Cooperation," *Adv. Intell. Syst. Comput.*, vol. 793, pp. 115 – 126, 2019, doi: 10.1007/978-3-319-94196-7_11.

- [19] M. C. Cohen, M. V Mancenido, E. K. Chiou, and N. J. Cooke, "Teamness and Trust in AI-Enabled Decision Support Systems: Current Challenges and Future Directions," in *CEUR Workshop Proceedings*, 2023, pp. 175 – 187.
- [20] K. Litaker and C. B. Mayhorn, "Influences of stress on interactions with decision support," in *Proceedings of the Human Factors and Ergonomics Society*, 2020, pp. 1886 – 1890. doi: 10.1177/1071181320641454.
- [21] N. Kanchepu, *Unveiling the Black Box: The Crucial Role of Interpretability in Machine Learning Models*. 2025. doi: 10.2174/9789815305548125010004.
- [22] V. N. Orobinskaya, T. N. Mishina, A. P. Mazurenko, and V. V. Mishin, "Problems of Interpretability and Transparency of Decisions Made by AI," in *Proceedings - 2024 6th International Conference on Control Systems, Mathematical Modeling, Automation and Energy Efficiency, SUMMA 2024*, 2024, pp. 667–671. doi: 10.1109/SUMMA64428.2024.10803745.
- [23] M. A. Shakir *et al.*, "Developing Interpretable Models for Complex Decision-Making," in *Conference of Open Innovation Association, FRUCT*, 2024, pp. 66 – 75. doi: 10.23919/FRUCT64283.2024.10749922.
- [24] H.-F. Cheng *et al.*, "Explaining decision-making algorithms through UI: Strategies to help non-expert stakeholders," in *Conference on Human Factors in Computing Systems - Proceedings*, 2019. doi: 10.1145/3290605.3300789.
- [25] H. Li and Z. Sun, "Is Algorithmic Accessibility Sufficient? The Pivotal Role of Accessibility and Accountability in Shaping Trust in Automated Decision-Making," *Governance*, vol. 38, no. 4, 2025, doi: 10.1111/gove.70067.
- [26] R. Yang, S. Li, Y. Qi, J. Liu, Q. He, and H. Zhao, "Unveiling users' algorithm trust: The role of task objectivity, time pressure, and cognitive load," *Comput. Hum. Behav. Reports*, vol. 18, 2025, doi: 10.1016/j.chbr.2025.100667.
- [27] J. Zhou, S. Z. Arshad, S. Luo, and F. Chen, "Effects of uncertainty and cognitive load on user trust in predictive decision making," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10516 LNCS, pp. 23 – 39, 2017, doi: 10.1007/978-3-319-68059-0_2.
- [28] M. Singh, S. Ghai, and R. Sharma, *The relationship between humanity versus artificial intelligence trust and personality and locus of control*. 2024. doi: 10.4018/979-8-3693-2849-1.ch016.
- [29] H. Rumapea, D. R. Manalu, and Y. Y. P. Rumapea, "Interpretable Deep Learning for Enhanced AI Trust and Clarity," *J. Artif. Intell. Technol.*, vol. 5, pp. 345 – 353, 2025, doi: 10.37965/jait.2025.0748.
- [30] H. R. Putranti, R. Retnowati, A. A. Sihombing, and D. Danang, "Performance assessment through work gamification: Investigating engagement," *South African J. Bus. Manag.*, vol. 55, no. 1, pp. 1–12, 2024.
- [31] I. Englishtina, H. R. D. Putranti, D. Danang, and A. A. B. Pujiati, "SITENAR CERYA as an innovation in English language learning at SMP Stella Matutina Salatiga: Merging technology and folktales," *REKA ELKOMIKA J. Pengabd. Kpd. Masy.*, vol. 5, no. 3, pp. 241–250, 2024.
- [32] H. R. D. Putranti, D. Danang, T. M. F. B. Da Silva, and A. A. B. Pujiati, "Integrating hands-on and virtual learning for environmental sustainability: Eco enzyme soap making at Stella Matutina," *REKA ELKOMIKA J. Pengabd. Kpd. Masy.*, vol. 6, no. 1, pp. 88–97, 2025.