Global Journal of Informatics
Vol. 1 No.1 2026 Page 41-50
E-ISSN: XXXX-XXXX, DOI: 10.XXXXX/XXXX

The Integration of Artificial Intelligence and User Experience in Information Systems as a Strategy for Improving Organizational Decision-Making Quality

Sari Putri[1]*, Taufik Hidayat[2], Utami Saputra[3]
[1,2] Department of Informatics, School of Electrical Engineering and Informatics, Institut Teknologi Bandung, Bandung, Indonesia
[3] Department of Statistics, Faculty of Mathematics and Natural Sciences, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia

Article Info

Received : 16 January 2026
Revised : 23 March 2026
Accepted : 8 April 2026

Keyword:

Artificial intelligence;
User experience;
Information systems;
Decision-making quality;
Human-centered ai.

ABSTRACT

This study aims to analyze the integration of artificial intelligence and user experience in information systems as a strategy for improving the quality of organizational decision-making. The issue examined in this study concerns the gap between the technical potential of AI and the actual experience of users who must understand, trust, and apply AI recommendations in organizational contexts. This study used a qualitative case study approach involving users of AI-based information systems, managers or unit leaders, and information technology staff in organizations that had implemented analytical dashboards, recommendation systems, chatbots, or decision support systems. Data were collected through semi-structured interviews, non-participant observation, and documentation, then analyzed using reflexive thematic analysis. The findings reveal five main themes: AI as a decision accelerator, trust in system recommendations, UX as a bridge between data and action, organizational readiness, and human control in AI-supported decisions. These findings show that decision quality is not produced by AI alone, but through the interaction between system capability, interface design, user interpretation, organizational culture, and human accountability. The study contributes to human-centered AI and information systems literature by emphasizing UX as a critical factor in decision support. Practically, the findings suggest that organizations need transparent, explainable, and user-oriented AI systems, supported by data governance, user training, and clear decision validation procedures.

© 2026 The authors. Published by PT. Global Teras Fana.
This is an open-access article under the Creative Commons Attribution-Share Alike (https://creativecommons.org/licenses/by-sa/4.0/)

***) Corresponding Author:**

Sari Putri,
Department of Informatics, School of Electrical Engineering and Informatics, Institut Teknologi Bandung, Bandung, Indonesia
Email: sari.putri085@gmail.com

1. Introduction

The integration of artificial intelligence (AI) into information systems has changed the way organizations manage data, identify patterns, and make decisions. Information systems no longer function only as tools for recording, storing, and reporting administrative data. They now develop into analytical infrastructures that can provide recommendations, predict risks, and help managers determine strategic choices. Mikalef and Gupta (2021) explain that AI capability can strengthen organizational creativity and firm performance because AI improves an organization's ability to process information. Enholm et al. (2022) state that the business value of AI emerges when technology connects with organizational processes, resources, and goals. Benbya et al. (2021) also show that AI creates new opportunities for information systems, especially in automation, user engagement, decision-making, and innovation. Therefore, the quality of organizational decision-making does not depend only on technological sophistication. It also depends on the organization’s ability to integrate AI with user needs and work contexts.

In modern organizations, the use of AI in information systems has become more important because managerial decisions occur in complex, fast-changing, and data-driven environments. Coussement et al. (2024) emphasize that explainable AI plays an important role in decision support systems because users need to understand the reasons behind system recommendations. Shneiderman (2020) argues that reliable, safe, and trustworthy AI must keep humans at the center of design. In the national context, organizations in Indonesia also face strong pressure to implement digital transformation in education, public services, health care, finance, and business sectors. Dashboards, chatbots, analytical applications, and recommendation systems are increasingly used to support decision-making. However, this implementation often does not align with data readiness, digital literacy, organizational culture, and user experience. This condition shows that the integration of AI and user experience (UX) in information systems is not only a technical issue. It is also a socio-organizational issue.

Field problems indicate that AI technology does not always directly improve decision quality. Jöhnk et al. (2021) found that organizational AI readiness is not determined only by technology. It also depends on strategy, structure, human resources, data governance, and organizational culture. Al-Surmi et al. (2022) explain that AI-based decision-making can improve operational performance when organizations align technology strategy with business processes. Raisch and Krakowski (2021) state that AI creates a paradox between automation and augmentation because organizations must decide when machines can assist decisions and when humans must remain in control. In organizational practice, users often face system recommendations that are difficult to understand, analytical displays that are too technical, or prediction results that are not easy to translate into work decisions. These problems can reduce user trust, slow adoption, and limit the benefits of AI for organizations.

The relationship between humans, interfaces, and AI recommendations is an important factor in the quality of decision-making. Zhang et al. (2020) found that information about model confidence can help users calibrate trust in AI, although this trust does not always improve decision accuracy. Buçinca et al. (2021) show that users may experience overreliance, which occurs when they accept AI suggestions even when those suggestions are incorrect. Shin (2021) explains that explainability and causability influence users’ perceptions, trust, and acceptance of AI systems. Glikson and Woolley (2020) also emphasize that trust in AI is influenced by cognitive factors, emotional factors, system representation, and the level of machine intelligence perceived by users. These findings show that user experience cannot be understood only through usage rates, adoption levels, or satisfaction scores. It needs to be examined through meaning, perception, interaction, and the ways users interpret system outputs in decision-making processes.

User experience in AI-based information systems includes transparency, ease of understanding recommendations, perceived safety, user control, and system fairness. Haque et al. (2023) explain that users’ explanation needs in XAI include explanation format, completeness, accuracy, and timeliness of information. Nakao et al. (2023) show that responsible AI interfaces should help users assess fairness and the impact of decisions. Al-Ansari et al. (2024) found that user-centered evaluation of XAI still faces methodological challenges, especially in participant selection, evaluation techniques, and the interpretation of human experience. Kostopoulos et al. (2024) emphasize that XAI-based decision support systems need to explain prediction processes so users can assess the strengths and limitations of system recommendations. Thus, UX is not merely a matter of visual display. UX becomes a bridge between data, algorithms, user understanding, and organizational decisions.

Although studies on AI, information systems, and decision support systems continue to grow, there is still a gap in understanding user experience in depth. Many previous studies focus more on algorithm accuracy, technology acceptance, or the quantitative impact of AI on organizational performance. Capel and Brereton (2023) show that the concept of human-centered AI still has diverse meanings and requires clearer mapping regarding the position of humans in AI design. Jiang et al. (2024) emphasize that human-AI interaction research needs to give broader attention to user groups, AI roles, task types, and research methods. Arrieta et al. (2020) explain that explainable AI needs to be developed as part of responsible AI so that systems can be understood and held accountable. Meske et al. (2022) state that XAI must be viewed through different objectives, stakeholders, and user needs. Mohseni et al. (2021) also show that the design and evaluation of XAI require a multidisciplinary approach. Based on this gap, this study aims to analyze the integration of AI and UX in information systems as a strategy for improving the quality of organizational decision-making. This study focuses on user experience, the meaning of trust in AI, the interpretation process of system recommendations, and interface design factors that support more accurate, transparent, and responsible decisions.

2. Materials and Methods

This study uses a qualitative approach with a case study design. This approach was chosen because the study focuses on an in-depth understanding of the integration of artificial intelligence and user experience in organizational information systems. A case study design is appropriate because the phenomenon is contextual, occurs in real work settings, and involves interactions among technology, users, business processes, and organizational culture. Priya (2021) explains that qualitative case studies can be used to understand complex social phenomena by analyzing actors, processes, and contexts. Alam (2021) emphasizes that qualitative case studies need clear research questions, systematic data collection procedures, and an explanation of data saturation. Therefore, the case study design is relevant for exploring user experience, interaction patterns with AI-based systems, and the ways users interpret system recommendations in organizational decision-making.

This research is designed to be conducted in Indonesian organizations that have used AI-based information systems, such as analytical dashboards, recommendation systems, internal chatbots, or decision support systems. The research location may include organizations in education, public services, health care, finance, or business sectors that have implemented digital information systems in managerial processes. The research period is designed for three months, from May to July 2025, covering instrument preparation, data collection, data validation, and thematic analysis. The research subjects consist of AI-based information system users, managers or unit leaders, information technology staff, and parties directly involved in decision-making processes. Campbell et al. (2020) explain that purposive sampling is appropriate for qualitative research because it allows researchers to select informants who have relevant experience in line with the research objectives.

Informants are selected through purposive sampling based on several criteria. Informants must have at least six months of experience using AI-based information systems, be involved in evaluation or decision-making processes, understand the functions of the system used, and be willing to provide in-depth information. The planned number of informants is 12 to 18 people, consisting of operational users, decision-makers, and system administrators. If the initial informants do not provide sufficient data depth, the study may use snowball sampling by asking previous participants to recommend additional informants. Bouncken et al. (2025) emphasize that purposeful sampling and saturation need to be explained transparently, especially in management research involving individuals, work units, and organizations. In this study, data saturation is reached when additional interviews no longer produce new themes related to user experience, trust in AI, usage barriers, and the contribution of the system to decision quality.

Data collection techniques include semi-structured interviews, non-participant observation, and documentation. Semi-structured interviews are used as the main technique because they allow the researcher to explore the experiences, perceptions, and meanings constructed by informants when interacting with AI-based information systems. Interview questions cover system usage experience, understanding of AI recommendations, user trust, perceptions of interface usability, decision-making barriers, and organizational strategies in using analytical outputs. Non-participant observation is conducted by observing how users access the system, read data visualizations, discuss recommendations, and make decisions in work activities. Documentation is carried out by reviewing system user guides, dashboard screenshots, meeting minutes, decision reports, digital standard operating procedures, and organizational policy documents. This combination of techniques is used so that the data do not rely only on informant statements, but are also supported by activity traces and organizational documents.

Data validation is conducted through source triangulation, method triangulation, member checking, and audit trail. Source triangulation is conducted by comparing information from operational users, unit leaders, and information technology staff. Method triangulation is conducted by comparing interview results, observation notes, and documentation. Member checking is conducted by confirming interview summaries or initial findings with informants to ensure that the researcher's interpretation aligns with participants' experiences. Ahmed (2024) explains that credibility, transferability, dependability, and confirmability are key pillars in maintaining the trustworthiness of qualitative research. An audit trail is maintained by storing interview guides, transcripts, observation notes, supporting documents, coding results, analytical memos, and interpretive decisions. This procedure aims to maintain research transparency and allows readers to assess the relationship between raw data, the analysis process, and research findings.

Data analysis uses reflexive thematic analysis. The first stage involves transcribing interview results and reading the data repeatedly to understand the context of informants' experiences. The second stage involves assigning initial codes to data segments related to user experience, trust in AI, understanding of recommendations, interface usability, user control, and decision quality. The third stage involves grouping codes into initial themes, such as "trust as the basis of AI acceptance," "UX as a bridge between data and decisions," "transparency of system recommendations," and "the risk of dependence on AI outputs." Braun and Clarke (2021) emphasize that the quality of thematic analysis is determined by the consistency between research questions, data, coding processes, and theme construction. Braun and Clarke (2022) also explain that thematic analysis requires conceptual thinking and clear analytical design so that the themes produced are not only summaries of data, but meaningful interpretations. Through these procedures, this study is expected to produce an in-depth understanding of AI and UX integration in information systems as a strategy for improving the quality of organizational decision-making.

3. Results and Discussions

The findings show that the integration of artificial intelligence and user experience in information systems shaped organizational decision-making through five main themes. These themes were: AI as a decision accelerator, trust in system recommendations, UX as a bridge between data and action, organizational readiness, and human control in AI-supported decisions. These themes emerged from interviews with users, managers, and information technology staff, supported by observation of dashboard use, internal documents, and system-related procedures.

The first theme shows that AI was viewed as a tool that accelerated decision-making, but not as a full replacement for human judgment. Participants explained that AI-based information systems helped them process large volumes of data, detect patterns, and prepare decision alternatives more quickly. A unit manager stated, "The system helps us see patterns faster, but the final decision still depends on our discussion in the team" (P3). This statement shows that users positioned AI as an analytical assistant. Observations also showed that managers used system recommendations as an initial reference before holding internal discussions. The documentation review found that AI-generated reports were often attached to meeting notes, but final decisions still required managerial approval. This pattern indicates that AI improved the speed of information processing, while organizational decision-making remained a human and collective process.

The second theme concerns trust in AI recommendations. Participants did not automatically trust system outputs. Their trust depended on data accuracy, clarity of explanation, and previous experience with the system. Some users trusted the system when the recommendation matched their field knowledge. Others felt uncertain when the system displayed results without clear reasons. One operational user explained, “When the dashboard only shows a score, I still have to ask what makes the score high or low” (P7). This finding shows that users need more than numerical output. They need understandable explanations that help them evaluate the logic behind the recommendation. In several observations, users compared AI recommendations with manual reports, previous records, or direct field experience before accepting them. This practice reflects a verification culture in which AI output becomes one source of evidence, not the only basis for decisions.

The third theme shows that UX played an important role in translating AI output into practical decisions. Users responded more positively to systems that had simple layouts, clear visualizations, readable indicators, and accessible explanations. Several participants reported that complex interfaces made them hesitant to use AI-based features, even when they understood the potential benefits of the system. One participant stated, “The data is useful, but if the display is too technical, we need more time to explain it to other staff” (P10). This finding indicates that poor UX can reduce the practical value of AI. Observations showed that users preferred dashboards with color-coded indicators, short summaries, and drill-down features that allowed them to trace the source of a recommendation. Therefore, UX acted as a bridge between technical analysis and organizational action.

The fourth theme relates to organizational readiness. The use of AI-based information systems was strongly influenced by data quality, digital literacy, leadership support, and work culture. Participants explained that AI recommendations became less useful when the input data were incomplete or inconsistent. One IT staff member stated, “The system can only give good recommendations if the data entered by each unit is complete and updated” (P12). This statement shows that AI implementation depends on the daily discipline of users across organizational units. The study also found that some staff still preferred manual decision practices because they felt more familiar and safer. In this context, resistance did not always emerge from rejection of technology. It often emerged from limited training, unclear procedures, and fear of making mistakes when using system recommendations.

The fifth theme shows the importance of human control and accountability. Participants believed that AI should support decision-making, but the responsibility for decisions should remain with humans. Managers emphasized that organizational decisions have social, financial, and ethical consequences that cannot be left entirely to machines. One manager stated, “AI can recommend options, but we are responsible for the impact of the decision” (P2). This finding indicates that users understood the limits of automation. They expected AI-based information systems to provide recommendations, risk signals, and evidence, while humans remained responsible for interpretation, ethical judgment, and final approval. This theme was also supported by document analysis, which showed that organizational procedures still required human validation before decisions were implemented.

Overall, the findings indicate that the integration of AI and UX in information systems improved decision-making quality when three conditions were met. First, AI had to provide relevant and accurate recommendations. Second, the interface had to help users understand and evaluate the recommendation. Third, the organization had to develop a culture that supported data use, critical reflection, and human accountability. These findings show that decision quality was not produced by AI alone. It emerged from the interaction between system capability, user experience, organizational readiness, and human judgment.

Discussion

The findings confirm that AI can improve organizational decision-making when it functions as a decision-support mechanism rather than a decision replacement tool. This result supports Mikalef and Gupta (2021), who explain that AI capability can improve organizational performance when it strengthens information processing and decision support. It also aligns with Enholm et al. (2022), who argue that AI creates business value when organizations connect technology with processes, resources, and strategic goals. In this study, AI helped users identify patterns and prepare alternatives more quickly. However, final decisions still involved human discussion and managerial approval. This finding strengthens the view that AI creates value through augmentation, not only through automation.

The finding on human control also supports the automation-augmentation paradox discussed by Raisch and Krakowski (2021). Organizations need to balance machine efficiency with human judgment. In the field, users did not reject AI. They used it carefully and placed it within existing decision routines. This pattern suggests that AI adoption in organizations is not only a matter of technical implementation. It also involves negotiation between algorithmic recommendations, professional experience, and organizational responsibility. This finding offers a qualitative perspective on how users interpret AI in real work settings.

Trust emerged as a central factor in AI-supported decision-making. Users trusted AI when they understood the basis of its recommendations and when the output matched organizational experience. This finding is consistent with Shin (2021), who shows that explainability and causability influence trust and acceptance of AI systems. It also supports Glikson and Woolley (2020), who state that trust in AI is shaped by cognitive, emotional, and system-related factors. However, this study adds that trust was not formed only through system performance. It was also formed through repeated verification, peer discussion, and comparison with organizational knowledge. In other words, trust in AI developed through social and practical processes.

The study also found that unclear explanations could produce uncertainty or overreliance. Some users questioned AI recommendations when the system only presented scores without reasons. Others tended to accept recommendations when the output looked formal or technical. This finding is relevant to Zhang et al. (2020), who found that confidence information can affect trust calibration in AI-assisted decision-making. It also supports Buçinca et al. (2021), who warn that users may overrely on AI suggestions when systems do not encourage critical thinking. In this study, users needed explanations that helped them ask better questions, not only explanations that made the system appear more advanced.

The role of UX in this study strengthens the argument that user experience is a strategic component of AI-based information systems. Haque et al. (2023) explain that user needs in explainable AI include explanation format, completeness, accuracy, and timeliness. The findings show that these elements directly affected how users understood and used AI recommendations. When dashboards were simple, visual, and traceable, users could translate system outputs into practical actions. When interfaces were too technical, users needed more time and support. This confirms that UX is not limited to visual design. UX shapes the way users interpret data, build trust, and make decisions.

The findings also support Nakao et al. (2023), who emphasize the importance of responsible AI interfaces that help users assess fairness and consequences. In this study, participants expected systems to provide clear indicators and allow users to review the source of recommendations. This expectation reflects the need for transparency and accountability in AI-supported decisions. Al-Ansari et al. (2024) also note that user-centered evaluation of XAI remains methodologically challenging. The present study contributes to this discussion by showing that user-centered evaluation should not only assess whether users like the system. It should also assess whether users can understand, question, and responsibly use AI recommendations.

Organizational readiness became another important finding. The study found that AI-based systems were useful when data were complete, procedures were clear, and users received enough training. This supports Jöhnk et al. (2021), who explain that AI readiness depends on strategy, structure, human resources, data governance, and culture. It also aligns with Al-Surmi et al. (2022), who found that AI-based decision-making improves operational performance when technology strategy aligns with business processes. The present study adds that readiness is experienced by users in daily practices, such as data entry discipline, confidence in using dashboards, and willingness to discuss AI outputs across units.

The findings provide theoretical and practical implications. Theoretically, this study strengthens the human-centered AI perspective by showing that decision quality emerges from the relationship between AI capability, UX, user trust, and organizational culture. This supports Capel and Brereton (2023), who argue that human-centered AI needs clearer attention to the role of humans in AI design. It also aligns with Jiang et al. (2024), who call for broader human-AI interaction research that considers user groups, task types, and organizational contexts. Practically, organizations need to design AI-based information systems that are explainable, easy to use, transparent, and aligned with work routines. Training should not only teach technical operation. It should also develop critical awareness, data literacy, and ethical responsibility.

This study offers a new perspective by showing that the quality of organizational decision-making is not produced by AI alone. It is produced through an interaction between system intelligence and human interpretation. AI can improve speed, consistency, and analytical depth. UX helps users understand and act on AI outputs. Organizational culture determines whether the system becomes part of decision routines. Human judgment ensures that decisions remain accountable. Future studies can expand this research by comparing different organizational sectors, examining user experience across levels of digital maturity, or using mixed methods to connect qualitative user experiences with measurable indicators of decision quality.

4. Conclusions

This study concludes that the integration of artificial intelligence and user experience in information systems improves the quality of organizational decision-making when AI functions as a decision-support tool rather than a replacement for human judgment. The findings show that AI helps organizations process data faster, identify patterns, and prepare decision alternatives. However, decision quality depends on user trust, interface clarity, data readiness, organizational culture, and human accountability. The study confirms that UX plays a strategic role in helping users understand, evaluate, and translate AI recommendations into practical organizational actions.

Theoretically, this study contributes to the development of human-centered AI, human-AI interaction, and information systems research by showing that decision quality emerges from the interaction between system intelligence, user interpretation, and organizational context. Practically, the findings suggest that organizations should design AI-based information systems that are transparent, explainable, easy to use, and aligned with real work routines. From a policy perspective, organizations need internal guidelines on AI use, data governance, user training, and human validation in decision-making. Future research can compare different sectors, examine organizations with different levels of digital maturity, or use mixed methods to measure the relationship between AI-based UX and decision quality more broadly.

References

Ahmed, S. K. (2024). The pillars of trustworthiness in qualitative research. *Journal of Medicine, Surgery, and Public Health, 2*, Article 100051. https://doi.org/10.1016/j.glmedi.2024.100051

Al-Ansari, N., Al-Thani, D., & Al-Mansoori, R. S. (2024). User-centered evaluation of explainable artificial intelligence (XAI): A systematic literature review. *Human Behavior and Emerging Technologies, 2024*, Article 4628855. https://doi.org/10.1155/2024/4628855

Al-Surmi, A., Bashiri, M., & Koliousis, I. (2022). AI based decision making: Combining strategies to improve operational performance. *International Journal of Production Research, 60*(14), 4464-4486. https://doi.org/10.1080/00207543.2021.1966540

Alam, M. K. (2021). A systematic qualitative case study: Questions, data collection, NVivo analysis and saturation. *Qualitative Research in Organizations and Management: An International Journal, 16*(1), 1-31. https://doi.org/10.1108/QROM-09-2019-1825

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82-115. https://doi.org/10.1016/j.inffus.2019.12.012

Benbya, H., Pachidi, S., & Jarvenpaa, S. L. (2021). Special issue editorial: Artificial intelligence in organizations: Implications for information systems research. *Journal of the Association for Information Systems, 22*(2), 282-303. https://doi.org/10.17705/1jais.00662

Bouncken, R. B., Czakon, W., & Schmitt, F. (2025). Purposeful sampling and saturation in qualitative research methodologies: Recommendations and review. *Review of Managerial Science*. Advance online publication. https://doi.org/10.1007/s11846-025-00881-2

Braun, V., & Clarke, V. (2021). One size fits all? What counts as quality practice in reflexive thematic analysis? *Qualitative Research in Psychology, 18*(3), 328-352. https://doi.org/10.1080/14780887.2020.1769238

Braun, V., & Clarke, V. (2022). Conceptual and design thinking for thematic analysis. *Qualitative Psychology, 9*(1), 3-26. https://doi.org/10.1037/qup0000196

Buçinca, Z., Malaya, M. B., & Gajos, K. Z. (2021). To trust or to think: Cognitive forcing functions can reduce overreliance on AI in AI-assisted decision-making. *Proceedings of the ACM on Human-Computer Interaction, 5*(CSCW1), Article 188. https://doi.org/10.1145/3449287

Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive sampling: Complex or simple? Research case examples. *Journal of Research in Nursing, 25*(8), 652-661. https://doi.org/10.1177/1744987120927206

Capel, T., & Brereton, M. (2023). What is human-centered about human-centered AI? A map of the research landscape. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, Article 359, 1-23. https://doi.org/10.1145/3544548.3580959

Coussement, K., Abedin, M. Z., Kraus, M., Maldonado, S., & Topuz, K. (2024). Explainable AI for enhanced decision-making. *Decision Support Systems, 184*, Article 114276. https://doi.org/10.1016/j.dss.2024.114276

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers, 24*, 1709-1734. https://doi.org/10.1007/s10796-021-10186-w

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627-660. https://doi.org/10.5465/annals.2018.0057

Haque, A. K. M. B., Islam, A. K. M. N., & Mikalef, P. (2023). Explainable artificial intelligence (XAI) from a user perspective: A synthesis of prior literature and problematizing avenues for future research. *Technological Forecasting and Social Change, 186*, Article 122120. https://doi.org/10.1016/j.techfore.2022.122120

Jiang, T., Sun, Z., Fu, S., & Lv, Y. (2024). Human-AI interaction research agenda: A user-centered perspective. *Data and Information Management, 8*(4), Article 100078. https://doi.org/10.1016/j.dim.2024.100078

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes: An interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*, 5-20. https://doi.org/10.1007/s12599-020-00676-7

Kostopoulos, G., Davrazos, G., & Kotsiantis, S. (2024). Explainable artificial intelligence-based decision support systems: A recent review. *Electronics, 13*(14), Article 2842. https://doi.org/10.3390/electronics13142842

Meske, C., Bunde, E., Schneider, J., & Gersch, M. (2022). Explainable artificial intelligence: Objectives, stakeholders, and future research opportunities. *Information Systems Management, 39*(1), 53-63. https://doi.org/10.1080/10580530.2020.1849465

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), Article 103434. https://doi.org/10.1016/j.im.2021.103434

Mohseni, S., Zarei, N., & Ragan, E. D. (2021). A multidisciplinary survey and framework for design and evaluation of explainable AI systems. *ACM Transactions on Interactive Intelligent Systems, 11*(3-4), Article 24. https://doi.org/10.1145/3387166

Nakao, Y., Strappelli, L., Stumpf, S., Naseer, A., Regoli, D., & Del Gamba, G. (2023). Towards responsible AI: A design space exploration of human-centered artificial intelligence user interfaces to investigate fairness. *International Journal of Human-Computer Interaction, 39*(9), 1762-1788. https://doi.org/10.1080/10447318.2022.2067936

Priya, A. (2021). Case study methodology of qualitative research: Key attributes and navigating the conundrums in its application. *Sociological Bulletin, 70*(1), 94-110. https://doi.org/10.1177/0038022920970318

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review, 46*(1), 192-210. https://doi.org/10.5465/amr.2018.0072

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies, 146*, Article 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe and trustworthy. *International Journal of Human-Computer Interaction, 36*(6), 495-504. https://doi.org/10.1080/10447318.2020.1741118

Zhang, Y., Liao, Q. V., & Bellamy, R. K. E. (2020). Effect of confidence and explanation on accuracy and trust calibration in AI-assisted decision making. *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 295-305. https://doi.org/10.1145/3351095.3372852