



The Dynamics of User Trust in Artificial Intelligence–Based Information Systems for Organizational Decision Making

Indra^{1*}, Muh Fuad Mansyur², Adi Heri³
Universitas Sulawesi Barat, Indonesia

Corresponding Author: Indra, indra@unsulbar.ac.id

ARTICLE INFO

Keywords: Artificial Intelligence, User Trust, Information Systems, Organizational Decision Making, Service Organizations.

Received : 27, November

Revised : 29, December

Accepted: 30, January

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ABSTRACT

The increasing adoption of artificial intelligence (AI)-based information systems in service sector organizations in Indonesia raises challenges related to user trust in organizational decision-making. This study analyzes the factors influencing user trust in AI-based information systems and examines the role of trust in enhancing decision-making quality and users' intention to rely on AI. Using a mixed-methods explanatory sequential design, quantitative data were collected through a survey of 60 AI system users in service organizations, complemented by in-depth interviews with six key informants. Quantitative analysis employed linear regression and mediation analysis, while qualitative data were thematically analyzed. The results indicate that AI transparency, system explainability, and perceived reliability positively affect user trust, whereas perceived risk has a negative effect. User trust significantly improves decision-making quality and intention to rely on AI and mediates the relationship between AI system characteristics and decision-making outcomes. This study contributes to the literature on trust in AI-based information systems and offers practical insights for service organizations in designing and managing AI implementations that foster user trust.

INTRODUCTION

The rapid development of artificial intelligence in organizational information systems has changed the way decisions are made in various sectors, especially the service sector which relies heavily on the speed and accuracy of data analysis. Globally, organizations are increasingly integrating Artificial Intelligence-based systems to support strategic, operational, and tactical decisions, from customer management to resource planning, as shown in a cross-industry empirical study by Glikson and Woolley (2020). However, the effectiveness of the implementation of the system is not only determined by the sophistication of technology, but also by the level of trust of users in the recommendations generated by the system. Low user trust has been proven to trigger underutilization or even rejection of AI systems even though their performance is technically superior.

In the context of developing countries such as Indonesia, the adoption of AI-based information systems faces additional challenges in the form of digital literacy gaps, hierarchical organizational cultures, and personal experience-based decision-making preferences. Service sector organizations in Indonesia are starting to integrate AI to support decision-making, but the level of acceptance and user trust still varies greatly between units and organizational levels. This phenomenon emphasizes that the success of AI implementation cannot be separated from the psychological and perceptual factors of the system users. In line with the findings of Siau and Wang (2020), the social and institutional context of the organization plays an important role in forming trust in intelligent technology in the work environment.

Theoretically, user trust in AI systems is influenced by system characteristics such as transparency, explainability, and perceived reliability by users. Explainable Artificial Intelligence is seen as an important approach to improve user understanding of algorithmic decision-making processes, particularly when systems are used in the context of complex organizational decisions. Nevertheless, as revealed by Shin (2021), empirical findings show inconsistent results regarding the extent to which explainability actually increases user trust and acceptance. This inconsistency indicates the presence of contextual and psychological variables that have not been fully explained in the literature.

In addition to positive factors, the perception of risk and uncertainty is also the main determinant in the formation of trust in AI-based information systems. Users often express concerns about potential algorithmic bias, system errors, as well as the ethical implications of using AI in organizational decision-making. According to Bansal et al. (2021), most of the previous research still focused on the technical aspects of system risk, while the dimension of risk perception from the perspective of organizational users received relatively little attention. This gap is important to study because risk perceptions can undermine trust even in technically reliable systems.

Furthermore, the relationship between user trust and the quality of organizational decision-making has not been empirically tested in a single integrated framework. Most previous studies have positioned trust as an

outcome variable, rather than as a mediating mechanism that bridges the characteristics of AI systems and decision-making outcomes. In fact, the sociotechnical perspective put forward by Rai et al. (2022) emphasizes that technology and human behavior interact with each other in producing organizational value. The lack of research examining the role of trust mediation creates a significant conceptual gap in the study of AI-based information systems.

Based on these gaps, this study aims to analyze the factors that affect user trust in Artificial Intelligence-based information systems and test the role of trust in improving the quality of organizational decision-making and user intention to rely on AI. This study explicitly examines transparency, explainability, perceived reliability, and perceived risk as the main determinants of user trust. In addition, this study examined the function of trust as a mediating variable between the characteristics of AI systems and decision-making outcomes, by adopting a mixed methods approach as recommended by Venkatesh et al. (2020). This approach allows for a more comprehensive and contextual understanding of user trust dynamics.

Theoretically, this research contributes to the development of the information systems literature and human-AI interaction by strengthening the user trust model in the context of organizational decision-making. This study expands the understanding of the role of trust as a key mechanism that connects the characteristics of AI systems and organizational decision performance. In practical terms, the research findings provide implications for service sector organizations in designing and managing AI implementations that are oriented towards increasing user trust. Thus, in line with the research agenda put forward by Dwivedi et al. (2021), this research is expected to be a reference for policymakers and practitioners in optimizing the use of AI responsibly and sustainably.

THEORETICAL REVIEW

User Trust in Artificial Intelligence-Based Information Systems

User trust is a fundamental construct in the successful implementation of Artificial Intelligence (AI)-based information systems, especially when the system is used to support organizational decision-making. In the context of AI systems, trust refers to the user's belief that the system is capable of generating recommendations that are competent, reliable, and aligned with the organization's goals. Without an adequate level of trust, users tend to ignore or limit the utilization of AI systems, even though they have superior technical performance (Hoff & Bashir, 2021). Therefore, trust is seen as a psychological prerequisite that allows for effective integration between algorithmic capabilities and human judgment.

Trust in AI systems is dynamic and is formed through continuous interaction between users and systems. A consistent user experience, especially in the context of high-impact decisions, can strengthen or even undermine user trust. Empirical studies show that trust does not only emerge in the early stages of technology adoption, but evolves as users perceive the performance, consistency, and characteristics of AI systems (Longoni et al., 2022). Within this

framework, user trust is not only positioned as an outcome, but also as a mediation mechanism that connects the characteristics of the AI system to the outcome of organizational decision-making.

AI Transparency and User Trust

Transparency is one of the main characteristics of AI systems that plays an important role in building user trust. Transparency refers to the extent to which the data processing process and the logic of the system's decision-making can be understood, traced, and evaluated by the user. A transparent AI system allows users to understand the basis of the recommendations generated, thereby reducing uncertainty and increasing a sense of control in the decision-making process.

Previous research has shown that system transparency contributes to increased user trust, especially in an organizational environment that demands accountability and decision justification (Buçinca et al., 2021). With an increased understanding of how the system works, users tend to be more receptive to and trust the recommendations generated by AI.

H1: AI transparency has a positive effect on user trust in Artificial Intelligence-based information systems.

Explainability and User Trust

Explainability is related to the ability of an AI system to provide clear, relevant, and meaningful explanations of the reasons behind the recommendations or decisions made. In an organizational context, explainability is crucial because decisions taken often have to be accounted for to various stakeholders. Effective explanations help users understand algorithmic logic and assess the suitability of recommendations for their work context.

Empirical studies show that AI systems that are able to provide easy-to-understand explanations tend to be more trusted by users than "black box" systems (Buçinca et al., 2021). Explainability not only improves user understanding, but also strengthens the legitimacy of the system in the organization's decision-making process.

H2: The explainability of AI systems has a positive effect on user trust in Artificial Intelligence-based information systems.

Perceived Reliability and User Trust

In addition to transparency and explainability, perceived reliability or perception of system reliability is an important determinant in building user trust. Perceived reliability refers to the extent to which users perceive the AI system as consistent, accurate, and stable in producing outputs. A system that consistently provides the right recommendations will strengthen the user's confidence in the system's capabilities.

Research shows that the perception of reliability has a direct influence on the level of trust and intention for the continuous use of AI systems (Zhang et al., 2023). Thus, the reliability felt by users is the main cognitive foundation in building trust in AI-based information systems.

H3: Perceived reliability has a positive effect on user trust in Artificial Intelligence-based information systems.

Perceived Risk and User Trust

On the other hand, risk perception is a factor that has the potential to hinder the formation of trust in AI systems. Perceived risk includes user concerns about possible decision errors, algorithmic bias, and the ethical and professional implications of using AI in an organizational context. Perceived risks can increase uncertainty and reduce users' willingness to rely on AI systems, especially in strategic decisions.

Previous research has shown that high risk perception significantly lowers users' level of trust in AI systems (Langer et al., 2021). Therefore, risk perception is seen as a major inhibiting factor in the formation of user trust.

H4: Perceived risk has a negative effect on user trust in Artificial Intelligence-based information systems.

User Trust and Organizational Decision-Making Outcomes

User trust in AI systems not only serves as an outcome of system characteristics, but also as an important determinant in the quality of organizational decision-making. When users trust AI systems, they tend to integrate the system's recommendations into the decision-making process more seriously and consistently. Effective collaboration between humans and AI enables more accurate, informational, and data-driven decision-making.

Empirical studies show that a high level of trust encourages the optimal use of AI in organizational decision-making (Faraj et al., 2021). Thus, user trust is expected to contribute positively to the quality of the results produced.

H5: User trust has a positive effect on the quality of organizational decision-making.

In addition, user trust also influences the intention to rely on AI in future decision-making. Users with a high level of trust tend to be more willing to use AI systems on an ongoing basis, increasing the strategic value of AI implementation for organizations.

H6: User trust has a positive effect on the intention to rely on Artificial Intelligence in organizational decision-making.

The Mediating Role of User Trust

From a sociotechnical perspective, the relationship between the characteristics of AI systems and organizational decision-making outcomes is not direct, but rather mediated by user behavior factors. User trust acts as a psychological mechanism that translates the characteristics of AI systems – such as transparency, explainability, perceived reliability, and perceived risk – into effective system use and quality decisions.

When trust is formed, the technical characteristics of the AI system can be optimally utilized in the organization's decision-making process (Faraj et al., 2021). Therefore, user trust is positioned as a mediating variable in this research model.

H7: User trust mediates the relationship between AI system characteristics (AI transparency, explainability, perceived reliability, and perceived risk) and organizational decision-making outcomes.

METHODOLOGY

Research Design and Approach

This study uses a mixed methods approach with an explanatory sequential design. This approach begins with the collection and analysis of quantitative data, then continues with qualitative data to deepen and explain the statistical findings obtained in the early stages. Explanatory sequential design was chosen because it is effective for examining complex phenomena involving the interaction between the characteristics of technological systems and user behavior factors, such as trust in Artificial Intelligence in organizational decision-making (Creswell & Plano Clark, 2021).

The mixed methods approach allows this study not only to empirically test the relationship between variables, but also to understand the dynamics of user trust contextually in the organizational environment of the service sector in Indonesia. The use of this design is considered relevant in AI-based information systems research that involves technical and psychological aspects simultaneously (Molina-Azorín, 2020).

Population and Sampling Technique

The research population includes all users of Artificial Intelligence-based information systems in service sector organizations in Indonesia that have integrated AI in the organizational decision-making process. The service sector was chosen because of its characteristics that rely heavily on the speed of data analysis, information quality, and human-technology interaction in decision-making.

Sampling at the quantitative stage uses non-probability sampling with purposive sampling techniques. This technique was chosen because not all members of the population have direct experience in using AI systems for organizational decision-making. Respondents' criteria include: (1) having at least six months of experience using AI systems, and (2) being directly involved in the organization's decision-making process. Based on these criteria, 60 respondents were obtained who were considered adequate for regression analysis and mediation tests in exploratory and contextual research (Hair et al., 2021).

At the qualitative stage, participants were selected using advanced purposive sampling, involving six key informants who have a strategic role in the use, evaluation, or management of AI systems in the organization. The number of informants is considered sufficient to achieve data depth and thematic saturation (Guest et al., 2020).

Data Collection Techniques and Research Instruments

Quantitative data collection was carried out using a structured questionnaire distributed online. The research instrument was developed based on the scale that has been validated in previous research, with adjustments to the organizational context of the service sector. The AI variables transparency,

explainability, perceived reliability, perceived risk, user trust, decision-making quality, and intention to rely on AI were measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The use of the Likert scale is considered effective in capturing users' perceptions and attitudes towards AI systems (Podsakoff et al., 2020).

For the qualitative stage, data was collected through semi-structured in-depth interviews. The interview guide is compiled based on the results of quantitative analysis, with a focus on user experience, perception of trust, and factors that influence the acceptance and utilization of AI in organizational decision-making. This approach allows for an in-depth exploration of statistical findings and provides a richer interpretive context (Tracy, 2020).

Validity and Reliability Testing

Validity and reliability tests were performed on quantitative data prior to hypothesis testing. The validity of the construct was tested using corrected item-total correlation, while the reliability of the instrument was tested using Cronbach's alpha with a threshold value of ≥ 0.70 . This test aims to ensure that the research instrument is able to measure constructs consistently and accurately (Kline, 2023).

In addition, classical assumptions such as normality, multicollinearity, and heteroscedasticity are performed to ensure the feasibility of the data in linear regression analysis. This procedure is important for maintaining the accuracy of statistical inference in quantitative research (Field, 2020).

Research Procedure

The research procedure was carried out gradually and systematically. The initial stage includes a literature review to formulate a conceptual framework and research hypothesis. Furthermore, the questionnaire instrument was compiled and tested through a limited trial before being distributed to the main respondents. After quantitative data is collected, statistical analysis is performed to test the relationship between variables and the mediating role of user trust.

The qualitative stage is carried out after the quantitative results are obtained. In-depth interviews were conducted to explain empirical findings, particularly related to user trust dynamics and organizational context. All data are then integrated at the interpretation stage to produce a comprehensive understanding of the phenomenon being studied (Creswell & Poth, 2020).

Data Analysis Techniques

Quantitative data analysis was performed using multiple linear regression and mediation analysis. The mediation test was carried out with a bootstrapping approach to assess the role of user trust as an intervening variable between the characteristics of the AI system and the outcome of organizational decision-making. This technique is considered more robust than the classical approach in testing the effects of mediation (Hayes, 2022). Quantitative analysis was performed using IBM SPSS Statistics software.

Qualitative data are analyzed using thematic analysis, which involves the process of open coding, thematic grouping, and interpretation of meaning. This analysis aims to identify patterns of user perception and experience related to trust in AI systems. The thematic analysis approach was chosen because it is flexible and suitable for technology-based organizational research (Braun & Clarke, 2021).

RESEARCH RESULTS

Effects of AI System Characteristics on User Trust

Multiple linear regression analysis was performed to test the influence of AI system characteristics on user confidence. The results of the analysis show that **AI transparency, explainability, and perceived reliability have a positive and significant effect on user trust**, while **perceived risk has a negative and significant effect**. These findings show that users' trust in AI-based information systems is strongly influenced by perceptions of openness, clarity of system logic, performance reliability, and perceived risk levels.

Table 1. Regression Results of AI System Characteristics on User Trust

Predictor Variables	Beta (b)	t-value	Sig.
AI Transparency	0.312	3.84	0.000
Explainability	0.276	3.21	0.002
Perceived Reliability	0.341	4.12	0.000
Perceived Risk	-0.228	-2.67	0.010
$R^2 = 0.62$			

Table 1 shows that **perceived reliability has the strongest influence on user trust**, followed by AI transparency and explainability. Conversely, perceived risk significantly lowers the level of user trust. The value of the determination coefficient ($R^2 = 0.62$) shows that the combination of the four variables is able to explain 62% of the variation in user trust in the AI system.

The quantitative findings were deepened through in-depth interviews with six key informants. In general, informants emphasize that trust arises when an AI system is judged to be consistent, explainable, and does not cause undue concern in daily work practices. An informant explained that: "*If the system is transparent and can be explained, we are more confident in using the results. So not only were we told to follow the recommendations, but we understand why the results were like that.*" (P.2, interview October 12, 2025). This view is reinforced by other informants who highlight the importance of system reliability in building trust: "*What makes me believe the most is the consistency. If the results are stable and rarely miss, we will rely on that system for a long time.*" (P.4, interview October 18, 2025). Nevertheless, concerns about risk also arise in the user experience: "*Sometimes we hesitate because we are afraid of biases or invisible mistakes. If the risk feels big, trust immediately drops.*" (P.1, interview October 10, 2025). Overall, the qualitative results confirm that **User trust is formed through simultaneous evaluation of**

system clarity, output consistency, and risk perception, in line with the findings of the first stage in explanatory sequential design.

User Trust and Organizational Decision-Making Outcomes

The next stage examines the influence of user trust on organizational decision-making outcomes, namely the quality of decision-making and intention to rely on AI. The regression results show that **User trust has a positive and significant effect on both outcome variables.**

Table 2. Effects of User Trust on Decision-Making Outcomes

Outcome Variables	Beta (b)	t-value	Sig.
Decision-Making Quality	0.451	5.02	0.000
Intention to Rely on AI	0.487	5.46	0.000
$R^2 = 0.53$			

Table 2 shows that user trust has a strong contribution to improving the quality of organizational decisions and the intention to rely on AI in the future. The influence on the intention to rely on AI is slightly stronger, suggesting that trust is a key factor in the sustainability of the use of AI systems.

These results are reinforced by qualitative findings that show that users who trust AI systems tend to be more serious about integrating system recommendations into organizational decisions. An informant said that: *"If you believe it, the decision will be faster and data-based. We don't have to hesitate any longer."* (P.3, interview October 15, 2025). Another informant added that trust also affects the sustainability of the use of the system: *"At first it was just trial and error, but after believing, now almost all of our operational decisions involve AI."* (P.6, interview October 25, 2025). These findings confirm that **trust serves as a key driver of AI integration in organizational decision-making**, both in terms of quality and sustainability of use.

The Mediating Role of User Trust

Mediation analysis was carried out using a bootstrapping approach to test the role of user trust as an intervening variable. The results show that **User trust significantly mediates the relationship between AI system characteristics and organizational decision-making outcomes.** The direct influence of system characteristics on outcomes decreases when user trust is incorporated into the model, but remains partially significant.

Table 3. Mediation Analysis Results

Path	Direct Effect	Indirect Effect	Sig.
AI Characteristics → User Trust	0.63	-	0.000
User Trust → Decision Outcomes	0.47	-	0.000
AI Characteristics → Decision Outcomes	0.21	0.29	0.000

Table 3 shows that **most of the influence of AI system characteristics on decision outcomes is channeled through user trust**, confirming the central role of user trust in the research model.

The findings of this mediation were clarified through interviews, in which informants described trust as a "bridge" between the system and the decision. An informant stated that: *"The system is not good enough. If the user doesn't believe it, the results are still not used in the decision."* (P.5, interview October 22, 2025). The statement reflects that **trust is a psychological mechanism that translates AI's technical capabilities into effective organizational decisions**. The integration of quantitative and qualitative results is in accordance with the design of explanatory sequential mixed methods used, where qualitative data serves to explain and deepen statistical findings.

DISCUSSION

The results of this study show that AI transparency has a positive effect on user trust, so H1 is accepted. These findings indicate that the openness of AI systems in explaining data processing flows and decision-making bases is able to reduce user uncertainty when interacting with intelligent technologies. Theoretically, transparency serves as a cognitive mechanism that helps users build a mental understanding of the system, which ultimately reinforces trust as a rational response to technology (Anjomshoae et al., 2021). A consequence of these findings is that organizations need to prioritize the design of AI systems that enable the tracking and evaluation of decisions. However, the level of technology literacy of users can be an obstacle in maximizing the benefits of transparency, so further research is recommended to explore the role of digital literacy as a moderation variable.

This study also found that the explainability of AI systems has a positive effect on user trust, so H2 is supported. Explainability allows users to understand the rationale behind system recommendations, rather than simply passively accepting output. In the perspective of cognitive theory, clear explanations help users to sensemake algorithm-based decisions, thereby increasing the legitimacy of the system in an organizational context (Langer et al., 2021). These findings contribute to the development of the explainable artificial intelligence literature by confirming that the quality of explanations, not just their existence, is a key factor in shaping trust. However, differences in user preferences for the level of detail of explanations can affect the effectiveness of explainability, so future studies are recommended to test adaptive forms of explanation based on user characteristics.

The results of the analysis show that perceived reliability has a significant positive influence on user trust, so H3 is accepted. Users tend to trust AI systems that consistently deliver accurate and stable outputs in a variety of decision-making situations. Conceptually, perceived reliability reflects the evaluation of the user's empirical experience of system performance, which is the main basis for long-term trust formation (Söllner et al., 2022). These findings confirm that trust is not only built through interface design or system communication, but also through actual performance. The limitation of this study lies in the measurement

of perception-based reliability, so further research is suggested to combine subjective and objective indicators of AI system performance.

The results of the study confirm that perceived risk has a negative effect on user trust, so H4 is empirically supported. Risk perceptions, such as potential algorithmic errors, data bias, and ethical consequences, increase user caution in relying on AI for important decisions. These findings are in line with the technology risk theory which states that the higher the perceived risk, the lower the level of trust in the system (Raisch & Krakowski, 2021). The implication of these results is the importance of risk mitigation strategies, both through AI governance policies and transparent risk communication to users. Further research needs to explore the role of human surveillance mechanisms as a factor that can lower risk perception.

The findings of the study show that user trust has a positive effect on the quality of organizational decision-making, so H5 is accepted. Trust allows users to make more optimal use of AI recommendations and integrate them with their professional judgment. Within the framework of human-AI collaboration theory, trust serves as a prerequisite for the formation of synergy between human intelligence and artificial intelligence (Shrestha et al., 2021). The scientific contribution of these findings is to strengthen the argument that the success of AI in organizations is not only determined by the sophistication of the algorithm, but also by the psychological state of the user. However, different decision contexts can affect the strength of these relationships, so further research is recommended to examine different types of organizational decisions.

The results of the next study showed that user trust had a positive effect on the intention to rely on Artificial Intelligence, so H6 was supported. Users who have a high level of trust are likely to show an ongoing intention to rely on AI in future decision-making. These findings are in line with the theory of continuance intention that emphasizes the role of trust in the sustainability of technology use (Venkatesh et al., 2022). The practical implication is that organizations need to build and maintain user trust from the early stages of AI implementation. The limitation of this study is the nature of the data over time, so longitudinal studies are recommended to test the stability of use intentions in the long term.

The results of the mediation test showed that user trust mediated the relationship between the characteristics of the AI system and the outcome of the organization's decision-making, so H7 was accepted. These findings indicate that transparency, explainability, reliability, and risk do not directly improve the quality of decisions without going through a user trust mechanism. In a sociotechnical perspective, trust acts as a bridge between the technical capabilities of the system and human behavior in the organization (Stahl & Eke, 2022). The main theoretical contribution of this research is the strengthening of the position of trust as a central construct in the study of organizational AI. Further research is suggested to explore other psychological variables, such as perceived control or algorithmic fairness, as additional mediators or moderators.

CONCLUSION AND RECOMMENDATION

This study concludes that the dynamics of user trust are a key factor in the effectiveness of the use of Artificial Intelligence-based information systems for organizational decision-making in the service sector. AI transparency, system explainability, and perceived reliability have been shown to increase user trust, while perceived risk decreases, which ultimately affects the quality of organizational decision-making and the intention to rely on AI. These findings confirm the central role of user trust as a mediation mechanism that bridges the technical characteristics of AI systems with organizational decision outcomes, thereby expanding the theoretical understanding of human-AI interactions in organizational contexts. However, this study has limitations on the relatively small sample size and focuses on the service sector in Indonesia, so the generalization of the findings needs to be done carefully.

FURTHER STUDY

Therefore, further research is recommended to involve a larger sample, across industry sectors, and use longitudinal designs to examine the dynamics of user trust in AI systems in the long term.

REFERENCES

- Anjomshoae, S., Najjar, A., Calvaresi, D., & Främling, K. (2021). Explainable agents and robots: Results from a systematic literature review. *Proceedings of the International Conference on Autonomous Agents and Multiagent Systems*, 1078–1088. <https://dl.acm.org/doi/10.5555/3463952.3464086>
- Bansal, G., Nushi, B., Kamar, E., Lasecki, W. S., Weld, D. S., & Horvitz, E. (2021). Beyond accuracy: The role of mental models in human-AI team performance. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(17), 15145–15152. <https://doi.org/10.1609/aaai.v35i17.17778>
- Bansal, G., Wu, T., Zhou, J., Fok, R., & Weld, D. S. (2021). Does the whole exceed its parts? The effect of AI explanations on complementary team performance. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1), 1–23. <https://doi.org/10.1145/3449160>
- Braun, V., & Clarke, V. (2021). *Thematic analysis: A practical guide*. SAGE Publications.
- Buçinca, Z., Lin, P., Gajos, K. Z., & Glassman, E. L. (2021). Proxy tasks and subjective measures can be misleading in evaluating explainable AI systems. *Proceedings of the 26th International Conference on Intelligent User Interfaces*, 454–464. <https://doi.org/10.1145/3397481.3450699>
- Creswell, J. W., & Plano Clark, V. L. (2021). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.
- Creswell, J. W., & Poth, C. N. (2020). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). SAGE Publications.
- Dwivedi, Y. K., Hughes, D. L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., & Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>

- Faraj, S., Pachidi, S., & Sayegh, K. (2021). Working and organizing in the age of the learning algorithm. *Information and Organization*, 31(1), 100309. <https://doi.org/10.1016/j.infoandorg.2020.100309>
- Field, A. (2020). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE Publications.
- 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>
- Grote, G., & Berens, C. (2022). On the ethics of algorithmic decision-making in organizations. *Journal of Business Ethics*, 170(4), 701–717. <https://doi.org/10.1007/s10551-020-04608-1>
- Guest, G., Namey, E., & Mitchell, M. (2020). Collecting and analyzing qualitative data at scale. *Annual Review of Public Health*, 41, 367–384. <https://doi.org/10.1146/annurev-publhealth-040119-094339>
- Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis* (3rd ed.). Guilford Press.
- Kim, T., Choi, J., & Yoon, H. (2022). Trust in artificial intelligence: The moderating role of perceived risk. *Information & Management*, 59(6), 103681. <https://doi.org/10.1016/j.im.2022.103681>
- Langer, M., König, C. J., & Fitali, A. (2021). Trust in artificial intelligence: A meta-analytic investigation. *Journal of Management Studies*, 58(5), 1200–1230. <https://doi.org/10.1111/joms.12611>
- Longoni, C., Bonezzi, A., & Morewedge, C. K. (2021). Resistance to medical artificial intelligence. *Journal of Consumer Research*, 48(4), 629–650. <https://doi.org/10.1093/jcr/ucab015>
- Molina-Azorín, J. F. (2020). Mixed methods research: An opportunity to improve our studies and our research skills. *European Journal of Management and Business Economics*, 29(3), 321–336. <https://doi.org/10.1108/EJMBE-09-2020-0262>
- Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2020). Recommendations for creating better concept definitions in the organizational, behavioral, and social sciences. *Organizational Research Methods*, 23(2), 159–203. <https://doi.org/10.1177/1094428119841965>
- Rai, A. (2020). Explainable artificial intelligence: From black box to glass box. *Journal of the Academy of Marketing Science*, 48(1), 137–141. <https://doi.org/10.1007/s11747-019-00710-5>
- 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 trust in artificial intelligence. *Telematics and Informatics*, 59, 101551. <https://doi.org/10.1016/j.tele.2020.101551>
- Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2021). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, 63(3), 66–83. <https://doi.org/10.1177/00081256211007303>

- Siau, K., & Wang, W. (2020). Building trust in artificial intelligence, machine learning, and robotics. In *Cutting-edge technologies for information systems research* (pp. 129–140). Springer. https://doi.org/10.1007/978-3-030-47411-9_9
- Söllner, M., Hoffmann, A., & Leimeister, J. M. (2022). Trust in technology: A systematic review and future research agenda. *Journal of the Association for Information Systems*, 23(2), 307–346. <https://doi.org/10.17705/1jais.00702>
- Stahl, B. C., & Eke, D. (2022). The ethics of artificial intelligence: A systematic review. *AI and Ethics*, 2(2), 273–295. <https://doi.org/10.1007/s43681-021-00059-3>
- Tracy, S. J. (2020). *Qualitative research methods: Collecting evidence, crafting analysis, communicating impact* (2nd ed.). Wiley-Blackwell.
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2020). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, 21(3), 1–27. <https://doi.org/10.17705/1jais.00618>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2022). Consumer acceptance and use of information technology: Extending the unified theory. *MIS Quarterly*, 46(1), 351–380. <https://doi.org/10.25300/MISQ/2022/15817>
- Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *Employee Relations*, 44(4), 761–785. <https://doi.org/10.1108/ER-01-2021-0050>
- Zhang, Y., Li, X., & Wang, Y. (2023). Perceived reliability and user trust in AI-enabled decision systems. *Decision Support Systems*, 168, 113847. <https://doi.org/10.1016/j.dss.2023.113847>