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Integrating Explainable Artificial Intelligence and Human-Centered Design into Information Systems to Improve Data-Driven Decision-Making

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ABSTRACT

This study aims to explore how Explainable Artificial Intelligence and Human-Centered Design can be integrated into information systems to improve data-driven decision-making. The study addresses the growing use of AI-supported information systems and the problem of limited user understanding, trust, and accountability in interpreting AI recommendations. A qualitative case study design was used to examine user experiences in three organizations in Indonesia that had implemented data-based information systems, analytics platforms, or AI-supported decision tools. Data were collected through semi-structured interviews, limited participant observation, and documentation involving information system users, unit managers, data analysts, system developers, and organizational decision-makers. The data were analyzed using reflexive thematic analysis. The findings reveal five main themes: the importance of understandable AI explanations, the role of trust and human judgment, the influence of user-centered interface design, organizational barriers related to data quality and culture, and the need for accountability in AI-supported decisions. These findings show that AI recommendations become valuable when users can interpret, verify, and adapt them to organizational contexts. The study contributes to information systems literature by strengthening a socio-technical understanding of XAI and Human-Centered Design. It also offers practical implications for designing transparent, usable, and accountable AI-supported information systems. Future research can examine different sectors or test the relationship between explanation quality, trust, usability, and decision performance.

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1. Introduction

Digital transformation has changed how organizations collect, process, and use information for decision-making. Information systems no longer function only as administrative tools. They now operate as analytical platforms that support prediction, risk identification, service improvement, and strategic planning. In this context, Artificial Intelligence has become an important part of modern information systems because it can process large volumes of data and generate recommendations for organizational decisions. Collins et al. (2021) explain that AI research in information systems has grown because organizations need stronger knowledge about how AI supports managerial and operational practices. However, the use of AI in decision-making also creates a new challenge. Users often receive system recommendations without fully understanding how the system produces them. This condition makes Explainable Artificial Intelligence important because XAI helps users understand the logic, basis, and limits of AI-generated recommendations.

The main issue in AI-supported information systems lies in transparency and interpretability. Many AI models work with complex computational processes that users cannot easily understand. Barredo Arrieta et al. (2020) describe this problem as a major challenge in the development of responsible AI because a technically accurate model may still fail when users cannot interpret its output. Rai (2020) argues that XAI can move AI systems from a black-box condition toward a more transparent form of decision support. This issue matters because organizational decisions require more than technical accuracy. Decisions also require trust, accountability, contextual relevance, and human judgment. Schemmer et al. (2023) show that explanations can influence appropriate reliance, meaning the ability of users to accept correct AI recommendations and reject incorrect ones. Therefore, XAI should not only explain algorithms. It should also help users make better, safer, and more responsible decisions.

Empirical studies show that data-driven decision-making often faces practical barriers in real organizational settings. These barriers include poor data quality, limited user understanding, weak governance, organizational culture, and unclear accountability. Sayogo et al. (2024) found that local governments in Indonesia face several obstacles in implementing data-driven decision-making, including inconsistent data quality, limited regulation, hierarchical culture, and low awareness of data use. Zaitsava et al. (2022) also show that data-driven decision-making is not driven only by data because cognition, intuition, experience, and bias continue to influence how people interpret information. This means that AI-supported decision-making must be studied as a socio-technical process. Kaur et al. (2020) found that even data scientists may experience difficulty in using interpretability tools correctly. This finding indicates that explainability is not only a technical matter. It is also related to user experience, work routines, organizational context, and human interpretation.

From a theoretical perspective, the integration of XAI and Human-Centered Design can be understood through a socio-technical view of information systems. This perspective sees technology, users, organizational structures, work culture, and decision practices as connected elements. Shneiderman (2020) states that human-centered AI must balance human control and computer automation to create systems that are reliable, safe, and trustworthy. Langer et al. (2021) explain that different stakeholders need different forms of explanation because they have different goals, knowledge, and responsibilities. Human-Centered Design is therefore important because it places user needs, user limitations, and real work practices at the center of system development. Brasse et al. (2023) also note that XAI research in information systems still needs stronger attention to organizational settings and human behavior. This shows that the design of explainable systems must consider not only model performance, but also the way users understand, question, and use AI recommendations.

Previous studies have contributed important knowledge about XAI methods, algorithmic transparency, and AI evaluation. However, several gaps remain. Many studies still focus on technical explanations, model performance, and system accuracy. Fewer studies explore how users experience, interpret, and use AI explanations in real organizational decision-making. Kim et al. (2024) argue that human-centered XAI evaluation should consider explanation quality, user interaction, and the contribution of explanations to user performance. Rong et al. (2024) also emphasize that user studies in XAI still need more attention to trust, understanding, usability, and human-AI collaboration. This gap is relevant for qualitative research because the integration of XAI and Human-Centered Design cannot be fully understood through numerical measurement alone. It requires an in-depth understanding of user experience, meaning-making, interpretation, and decision practices.

Based on this background, this study aims to explore how Explainable Artificial Intelligence and Human-Centered Design can be integrated into information systems to improve data-driven decision-making. The study focuses on user experiences in understanding AI explanations, assessing trust in system recommendations, and using AI-supported information in organizational decision-making. This research is expected to contribute theoretically to information systems studies by strengthening the socio-technical understanding of XAI, Human-Centered Design, and data-driven decision-making. It also offers practical contributions for system developers, managers, and policymakers who need transparent, contextual, user-friendly, and accountable information systems. The study places humans as active decision-makers, not passive recipients of automated recommendations.

2. Materials and Methods

This study uses a qualitative approach with a case study design. The case study design is selected because the research aims to understand processes, experiences, and meanings that emerge when users interact with information systems supported by Explainable Artificial Intelligence and Human-Centered Design. The study does not aim to test statistical relationships between variables. It aims to explore how users understand AI explanations, build trust in system recommendations, and use data in organizational decision-making. Ehsan and Riedl (2020) explain that human-centered XAI should be understood as a socio-technical approach because AI explanations are always connected to people, values, relationships, and use contexts. Therefore, a qualitative case study is suitable for examining the interaction between technology, users, and organizational decision processes.

The research will be conducted in three organizations in Indonesia that have used data-based information systems, analytics platforms, or AI-supported decision tools. The research sites may include public service organizations, higher education institutions, health service organizations, or digital business units that use dashboards, decision support systems, or recommendation features. The study will be carried out for three months, from February to April 2026. This period includes research preparation, access to research sites, data collection, data validation, and data analysis. The multi-site case design is used to capture variations in user experiences across different organizational settings while maintaining depth in each case.

The research participants will include information system users, unit managers, data analysts, system developers, and decision-makers who directly use organizational data. Participants will be selected through purposive sampling because the study requires informants who have direct knowledge and experience related to the research topic. Campbell et al. (2020) explain that purposive sampling helps researchers select participants who fit the purpose and depth of qualitative inquiry. The inclusion criteria are as follows. First, participants must have used data-based or AI-supported information systems for at least six months. Second, they must be involved in reading, interpreting, validating, or using system outputs for work-related decisions. Third, they must understand the data flow, system purpose, and practical problems in system use. Fourth, they must be willing to participate in interviews and data validation. The estimated number of participants is 15 to 25 people. The final number will depend on data saturation, as Hennink and Kaiser (2022) state that saturation in qualitative research depends on topic complexity, participant diversity, and the depth of information obtained.

Data will be collected through semi-structured interviews, limited participant observation, documentation, and triangulation. Semi-structured interviews will explore user experiences in understanding AI recommendations, assessing explanation clarity, comparing system recommendations with human judgment, and dealing with uncertainty in analytical outputs. Limited participant observation will be conducted by observing how users open dashboards, read data visualizations, discuss system recommendations, and use information during work activities or meetings. Documentation will include user manuals, standard operating procedures, analytical reports, meeting notes, internal policies, and screenshots of system features when permitted by the organization. Liao et al. (2020) show that users often need practical explanations about why an AI system gives a particular recommendation and how they should respond to it. Schoonderwoerd et al. (2021) also emphasize that human-centered XAI design should begin with domain analysis, user needs, and evaluation of human-system interaction.

Data validity will be maintained through source triangulation, method triangulation, member checking, and audit trail. Source triangulation will compare information from system users, managers, data analysts, system developers, and organizational documents. Method triangulation will compare interview data, observation notes, and documentation. Member checking will be conducted by sending interview summaries or preliminary findings to selected participants to ensure that the researcher's interpretation matches their experiences. An audit trail will be created by documenting research decisions, interview transcripts, coding notes, analytical memos, category development, theme revisions, and researcher reflections. Ahmed (2024) explains that credibility, transferability, dependability, and confirmability are important pillars of trustworthiness in qualitative research. These procedures will help ensure that the research process is transparent, traceable, and open to limited replication.

Data analysis will use reflexive thematic analysis. The first stage involves transcribing interview data verbatim and reading all data repeatedly. The second stage involves open coding to identify statements related to user understanding, trust in AI systems, explanation clarity, human control, data bias, interface design, and decision-making practices. The third stage involves grouping codes into initial categories, such as explanation needs, visualization quality, negotiation between AI recommendations and human judgment, organizational barriers, and the role of user-centered design. The fourth stage involves developing main themes that answer the research focus. Braun and Clarke (2021) state that reflexive thematic analysis requires consistency, reflexivity, and a clear connection between data, codes, themes, and interpretation. The final findings will be presented as thematic narratives supported by participant quotations, contextual descriptions, and theoretical interpretation related to XAI, Human-Centered Design, and data-driven decision-making.

3. Results and Discussions

The analysis generated five main themes that explain how users experienced the integration of Explainable Artificial Intelligence and Human-Centered Design in information systems for data-driven decision-making. These themes include: understanding AI explanations, trust and human judgment, usability of system design, organizational barriers, and accountability in AI-supported decisions. The findings show that users did not treat AI recommendations as neutral outputs. They interpreted them through work experience, organizational routines, data quality, and perceived system transparency.

The first theme concerns the role of explainability in helping users understand AI recommendations. Participants stated that AI outputs became useful when the system showed the reasons behind a recommendation, not only the final score or prediction. Several users explained that they needed simple explanations, visual indicators, and contextual notes before using system outputs for decision-making. One participant said, "I do not need to see the full algorithm, but I need to know why the system gives this recommendation and which data supports it" (P4). This finding shows that users valued explanations that connected technical output with practical work meaning. The explanation helped them reduce uncertainty and increased their ability to discuss system recommendations with colleagues.

The second theme relates to trust and human judgment. Participants did not fully accept AI recommendations without human review. They compared system outputs with field experience, organizational knowledge, and previous decision patterns. One manager explained, "The system helps us see the pattern, but the final decision still needs human judgment because the data cannot capture every situation in the field" (P8). This pattern shows that users viewed AI as a decision support tool, not as a replacement for human decision-makers. Trust emerged when users could check the logic of the system, identify the data source, and understand the limits of the recommendation. When the system gave recommendations without sufficient explanation, users became hesitant and returned to manual judgment.

The third theme focuses on Human-Centered Design and usability. Participants reported that the design of dashboards, visualizations, and explanation features shaped how they used the system. Clear layout, readable visualizations, simple language, and interactive filters made AI explanations easier to understand. A participant from the data management unit stated, "When the dashboard is too technical, users only look at the color or score. They do not understand what action should follow" (P11). This statement shows that design affects interpretation. Users needed interfaces that translated analytical results into decision-relevant information. The study also found that users preferred layered explanations. They wanted short explanations for quick decisions and deeper explanations when they needed to justify decisions to supervisors or stakeholders.

The fourth theme concerns organizational barriers in data-driven decision-making. Participants identified several barriers, including inconsistent data input, limited data literacy, hierarchical decision culture, and weak coordination between technical teams and decision-makers. Some users stated that AI recommendations became less trusted when the underlying data came from different units with different formats and standards. One participant explained, "Sometimes the system looks sophisticated, but the data behind it is incomplete. That makes users question the recommendation" (P6). This finding indicates that explainability cannot solve all decision-making problems if the organization does not manage data quality and governance properly. Users also noted that senior leaders sometimes relied more on personal experience than system-based evidence, especially when AI recommendations challenged established routines.

The fifth theme relates to accountability and human control. Participants wanted clear rules about who should be responsible when AI-supported recommendations influenced organizational decisions. They stated that the system should support transparency, but accountability must remain with human decision-makers. One participant said, "The system can give suggestions, but someone must be responsible for checking and approving the decision" (P15). This finding shows that users accepted AI more easily when the organization defined human roles, review mechanisms, and decision authority. Users also expected the system to provide traceable records, such as data sources, explanation logs, and decision histories. These features helped them justify decisions and reduce the risk of blind reliance on AI.

Overall, the results show that the integration of XAI and Human-Centered Design improved data-driven decision-making when users could understand, question, and contextualize AI recommendations. The system became more valuable when it supported human reasoning, not when it forced users to accept automated outputs. The findings also show that explainability must work together with usability, data governance, user training, and organizational accountability. Without these elements, AI-supported information systems may increase technical sophistication without improving decision quality.

Discussion

The findings support the socio-technical view of information systems. This perspective argues that technology, users, organizational structures, work culture, and decision practices influence one another. The study found that users did not evaluate AI recommendations only through technical accuracy. They also assessed the clarity of explanations, the quality of data, the relevance of outputs to real work, and the extent to which the system respected human judgment. This finding aligns with Ehsan and Riedl (2020), who argue that human-centered XAI must consider social context, values, and user interpretation. It also supports Shneiderman's (2020) view that human-centered AI should balance automation with human control.

The findings also confirm that explainability plays an important role in building appropriate trust. Users trusted AI recommendations when the system explained the reason, evidence, and limitation behind its output. This result supports Schemmer et al. (2023), who state that explanations can improve appropriate reliance on AI advice. However, the study also shows that explanation alone does not automatically create trust. Users still examined data quality, organizational relevance, and decision consequences. This finding extends previous XAI studies by showing that trust depends on the relationship between explanation, context, and accountability. In practice, users need explanations that answer real decision questions, not only technical descriptions of model behavior.

The findings are consistent with Liao et al. (2020), who show that users often ask practical questions when interacting with AI systems. They want to know why the system gives a recommendation, what information the system uses, and how they should act on the output. This study adds that users in organizational settings also need explanations that support communication with supervisors, colleagues, and stakeholders. Therefore, XAI should not only support individual understanding. It should also support collective decision-making. This is important in organizations where decisions often involve meetings, approval structures, and cross-unit coordination.

The study also strengthens the role of Human-Centered Design in AI-supported information systems. Participants preferred interfaces that used simple language, clear visualizations, and layered explanations. This finding aligns with Schoonderwoerd et al. (2021), who argue that human-centered XAI design should begin with domain analysis and user needs. The findings also support Kim et al. (2024), who emphasize the importance of human-centered evaluation in XAI applications. A system may have a strong model, but it can fail in practice when users cannot understand the interface or connect the explanation to their work tasks. Thus, system developers need to design AI explanations as part of the user experience, not as an additional technical feature.

The findings also reveal that data governance remains a key condition for effective data-driven decision-making. Participants questioned AI recommendations when the data behind the system looked incomplete, inconsistent, or outdated. This result supports Janssen et al. (2020), who argue that trustworthy AI requires strong data governance. It also relates to Sayogo et al. (2024), who found that local governments in Indonesia face challenges related to data quality, regulation, organizational culture, and user awareness. This study adds a qualitative explanation of how these barriers appear in user experience. Users did not reject AI because they opposed technology. They became cautious because they saw gaps between system outputs and data conditions in the organization.

The findings offer a different perspective from studies that treat AI decision-making mainly as a technical optimization problem. This study shows that users combine AI outputs with professional judgment, contextual knowledge, and organizational norms. This finding supports Zaitsava et al. (2022), who state that data-driven decision-making also involves cognition, intuition, and interpretation. AI may provide patterns and predictions, but humans still decide how to interpret and act on them. Therefore, the value of XAI lies not only in making models transparent. Its value also lies in helping users negotiate between data, experience, and responsibility.

The theoretical implication of this study is that XAI and Human-Centered Design should be understood as integrated elements in information systems research. XAI provides transparency and interpretability, while Human-Centered Design ensures that explanations match user needs, tasks, and contexts. Together, both concepts strengthen the socio-technical function of information systems. The study contributes to information systems literature by showing that data-driven decision-making depends on the interaction between explanation quality, user interpretation, interface design, data governance, and organizational accountability.

The practical implication is clear. Organizations should not adopt AI-supported information systems only by focusing on model accuracy or system automation. They must also prepare users, improve data governance, design readable dashboards, provide explanation features, and define decision responsibility. Managers need to ensure that AI recommendations remain open to review and discussion. System developers need to create explanation features that use simple language and provide different levels of detail. Policymakers and organizational leaders need to create standards for responsible AI use, including transparency, auditability, and human oversight.

Future research can expand this study by comparing different sectors, such as public administration, healthcare, education, and finance. Future studies can also examine how different user groups interpret AI explanations, including managers, technical staff, frontline workers, and policymakers. Quantitative research may test the relationship between explanation quality, trust, usability, and decision performance. Longitudinal research can also explore how user trust changes over time as organizations become more familiar with AI-supported systems. These directions can deepen understanding of how XAI and Human-Centered Design shape responsible data-driven decision-making in real organizational contexts.

4. Conclusions

This study concludes that the integration of Explainable Artificial Intelligence and Human-Centered Design in information systems strengthens data-driven decision-making when users can understand, question, and contextualize AI recommendations. The findings show that users do not rely on AI outputs automatically. They compare system recommendations with professional judgment, field experience, data quality, and organizational accountability. Five main themes emerged from the study: the need for understandable AI explanations, the role of trust and human judgment, the importance of usable system design, organizational barriers in data-driven decision-making, and the need for clear accountability in AI-supported decisions. These findings confirm that AI-supported decision-making is not only a technical process, but also a socio-technical practice shaped by users, organizational culture, governance, and decision responsibility.

Theoretically, this study contributes to information systems literature by linking XAI, Human-Centered Design, and data-driven decision-making through a socio-technical perspective. Practically, the findings suggest that organizations should not focus only on model accuracy or automation. They need to improve data governance, design readable dashboards, provide layered explanations, train users, and define human oversight mechanisms. From a policy perspective, the study highlights the need for responsible AI standards that support transparency, auditability, and accountability. Future research can expand this study across different sectors, compare user groups, or apply mixed methods to examine the relationship between explanation quality, trust, usability, and decision performance.

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