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A Human-Centered Approach to the Implementation of Artificial Intelligence for Data-Driven Decision Optimization in Digital Transformation

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ABSTRACT

This study aims to explore a human-centered approach to the implementation of artificial intelligence for data-driven decision optimization in digital transformation. The study addresses the growing use of AI, data analytics, dashboards, and decision support systems in organizations, while highlighting the need to understand how humans interpret, trust, and negotiate AI recommendations in real decision-making processes. This research used a qualitative case study design involving 18 to 24 organizational actors, including leaders, digital transformation managers, information technology staff, data analysts, operational decision-makers, and direct users of AI systems. Data were collected through semi-structured interviews, limited participant observation, and document analysis. The data were analyzed using reflexive thematic analysis. The findings reveal five main themes: AI as a decision support instrument rather than a human replacement, trust and transparency in AI recommendations, human competence and adaptation, organizational culture toward data-driven decisions, and ethical control in AI-supported decision-making. These findings show that AI can improve decision quality when supported by human interpretation, data literacy, participatory culture, and clear accountability mechanisms. The study contributes to human-centered AI and digital transformation literature by emphasizing that successful AI implementation requires technical capability, human readiness, and ethical governance. The findings also suggest that organizations should strengthen explainability, user training, data governance, and human oversight in AI-supported decision-making.

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1. Introduction

Digital transformation has changed how organizations manage data, design work processes, and make strategic decisions. At the global level, digital transformation no longer refers only to the use of digital tools. It now involves changes in business models, organizational structures, work cultures, and decision-making capabilities. Verhoef et al. (2021) explain that digital transformation affects customer value, operational structures, and organizational strategy across functions. Kraus et al. (2022) also argue that business and management research increasingly views digital transformation as a complex organizational change process. In this context, artificial intelligence has become one of the key technologies that encourages organizations to use data more systematically. AI helps organizations identify patterns, accelerate analysis, predict risks, and produce decision recommendations. However, this process does not always run smoothly because successful digital transformation depends on human readiness, data culture, governance, and the ability of organizations to balance technology with human judgment.

In the national context, organizations in Indonesia have started to integrate AI, data analytics, digital dashboards, and decision support systems across public services, education, healthcare, finance, digital business, and micro, small, and medium enterprises. These changes appear in the growing use of data-based systems for performance evaluation, customer mapping, operational prediction, and internal policy formulation. Purnomo et al. (2024) found that digital transformation among Indonesian MSMEs creates opportunities for efficiency and market access, but it also faces barriers related to digital literacy, human resource readiness, and consistency in technology adoption. This finding shows that digital transformation in Indonesia does not only involve technical issues. It also involves social, behavioral, and institutional challenges. Dwivedi et al. (2021) state that AI creates major opportunities for business and public services, but it also raises challenges related to ethics, policy, trust, accountability, and human competence. Therefore, the implementation of AI in decision-making needs to be studied as a socio-technical phenomenon that connects systems, humans, data, and organizational structures.

Field realities show that many organizations already own digital systems and operational data, but they still struggle to convert data into accurate, fast, and accountable decisions. Some organizations use analytical dashboards, yet users continue to rely heavily on personal intuition when making decisions. Some managers accept system recommendations, but they still feel uncertain because they do not understand how the system produces predictions. This condition relates to transparency, interpretability, user competence, and trust in the system. Hradecky et al. (2022) show that organizational readiness to adopt AI depends on technological, organizational, and environmental factors. Mikalef and Gupta (2021) explain that AI capability can improve organizational creativity and performance when organizations manage data, technology, human skills, and organizational resources in an integrated way. Thus, data-driven decision optimization does not depend only on algorithmic sophistication. It also requires human understanding, management support, data quality, and a work culture that accepts evidence as the basis for decision-making.

A human-centered AI approach becomes important because organizations cannot position AI as a complete replacement for humans in all decision-making processes. Shneiderman (2020) emphasizes that reliable, safe, and trustworthy AI must still provide space for human control. Sigfrids et al. (2023) explain that human-centricity in AI governance should function as a systemic principle that considers human values, social responsibility, transparency, and user participation. This view aligns with the automation-augmentation paradox proposed by Raisch and Krakowski (2021). AI can automate parts of work, but it can also strengthen human ability to analyze complex situations. In organizational practice, this paradox appears when users must choose whether to follow AI recommendations or maintain professional judgment based on experience. This situation shows that AI implementation does not only concern efficiency. It also concerns authority, responsibility, and the meaning of work.

Previous studies have explained the relationship between AI, organizations, and performance. Enholm et al. (2022) state that AI can create business value through automation, data-based insight, and better decision-making. Davenport et al. (2020) show that AI can transform how organizations understand customers and design marketing decisions. Glikson and Woolley (2020) also show that human trust in AI depends on system transparency, task characteristics, and the way users interact with intelligent systems. However, performance-oriented studies often do not fully explore human experience as the core of AI use. Lebovitz et al. (2022) found that professionals may face dilemmas when using opaque AI systems for critical judgments. Kellogg et al. (2020) show that workplace algorithms can create new forms of control through recording, evaluation, recommendation, and restriction of human action. Anthony et al. (2023) later emphasize that human-AI relations should be understood as a work system that shapes and is shaped by organizational practice. These studies open space for qualitative research that examines experience, meaning, negotiation, and adaptation in AI-supported digital transformation.

Based on this background, this study focuses on a human-centered approach to the implementation of artificial intelligence for data-driven decision optimization in digital transformation. The study examines user experience, perceptions of AI recommendations, organizational adaptation, the relationship between human intuition and analytical output, and mechanisms of decision oversight. This research aims to explore how organizational actors understand, use, and negotiate the role of AI in data-driven decision-making. Theoretically, this study contributes to the development of human-centered AI, digital transformation, and socio-technical perspectives in organizational studies. Practically, this study provides insights for organizations that seek to design AI implementation in a more ethical, transparent, participatory, and human-oriented way. Through a qualitative approach, this study explains processes that quantitative measurement may not fully capture, especially how humans create meaning, build trust, and maintain responsibility in AI-supported decisions.

2. Materials and Methods

This study uses a qualitative approach with a case study design. The case study design fits the research objective because this study seeks to understand the implementation of AI in a real organizational context. This approach allows the researcher to examine experiences, meanings, practices, and social dynamics that emerge when organizations use AI to support data-driven decision optimization. Busetto et al. (2020) explain that qualitative research helps answer questions about processes, contexts, and reasons behind a phenomenon. Lim (2025) also states that qualitative research provides space to understand social phenomena through participant experience and contextual interpretation. In this study, the case study design helps explore how organizational actors understand AI functions, assess data-based recommendations, manage risks, and adjust work processes during digital transformation. This approach is suitable because AI implementation cannot be separated from organizational culture, data quality, decision structures, and human readiness.

This study will be conducted in Indonesian organizations that have used AI, data analytics, predictive dashboards, or decision support systems in decision-making processes. The research location may include organizations in the service sector, education, healthcare, public service, digital business, or data-driven companies that have implemented digital transformation programs. The research will take place over three months, from February to April 2026. The research stages include location identification, research permission, participant selection, data collection, transcription, data validation, thematic analysis, and report writing. The research sites will be selected purposively because the study needs organizations with direct experience in using AI. This selection helps ensure that the data come from actual work practices rather than only conceptual views. Hradecky et al. (2022) show that AI adoption readiness relates to internal organizational factors, human competence, and environmental support. For this reason, the organizational context becomes a key element in understanding the success and barriers of AI implementation.

The study will select participants through purposive sampling. The participant criteria include direct involvement in AI use or data-based systems, at least six months of experience in digital transformation processes, the ability to explain changes in work processes, and willingness to participate voluntarily in interviews. The main informants will include organizational leaders, digital transformation managers, information technology staff, data analysts, operational decision-makers, and direct users of AI systems. The study will involve approximately 18 to 24 participants. The final number will depend on the richness of information and the achievement of data saturation. Hennink and Kaiser (2022) explain that saturation in qualitative research can occur with a relatively limited number of participants when the research objective is clear and the participant group is specific. Sebele-Mpofu (2020) argues that saturation should refer to the adequacy of meaning, not only to the number of participants. If the initial participants do not provide sufficient variation in experience, the researcher will use snowball sampling by asking relevant informants to recommend other participants. This technique will help identify individuals involved in data management, dashboard monitoring, validation of AI recommendations, or strategic decision-making.

Data will be collected through semi-structured interviews, limited participant observation, and document study. Semi-structured interviews will explore participant experiences related to AI adoption, changes in work processes, trust in system recommendations, barriers to data use, risks of bias, and decision oversight mechanisms. Each interview will last approximately 45 to 75 minutes and will be recorded after the participant gives consent. Lobe et al. (2020) explain that qualitative interviews can be conducted face-to-face or online as long as the researcher maintains interaction depth, data confidentiality, and participant comfort. Limited participant observation will be conducted in activities related to AI use, such as data-based evaluation meetings, dashboard monitoring, recommendation simulations, or analytical report interpretation. Document study will examine digital transformation guidelines, standard operating procedures, performance reports, training materials, data governance policies, and other relevant internal documents. Method triangulation will compare interview data, observation notes, and documents so that the findings do not rely on a single data source. Campbell et al. (2020) also show that purposive sampling and clear case selection help strengthen the relevance of qualitative data when the research focuses on a specific phenomenon.

Data validation will use source triangulation, method triangulation, member checking, audit trail, and peer discussion. Source triangulation will compare information from leaders, data analysts, technology staff, and system users. Method triangulation will compare interview data, observation notes, and documents. Member checking will be conducted by sending interview summaries or early interpretations to key informants to confirm meaning accuracy. The audit trail will include research notes, interview transcripts, analytical memos, coding guidelines, category changes, and theme development decisions. O'Connor and Joffe (2020) explain that transparency in the coding process can improve the traceability of qualitative analysis. Johnson et al. (2020) state that qualitative rigor can be strengthened through credibility, dependability, confirmability, and transferability. These steps help ensure that the interpretation remains consistent with participant experience and the organizational context studied.

Data analysis will use reflexive thematic analysis. The analysis will begin with repeated reading of transcripts to understand the overall narrative of each participant. After that, the researcher will conduct initial coding of statements related to AI use experience, trust in systems, data quality, changes in human roles, tension between intuition and algorithmic recommendations, and decision optimization practices. Codes with similar meanings will be grouped into initial categories, such as human readiness, system transparency, decision control, data bias, evidence-based work culture, and AI governance. These categories will then be developed into main themes that explain the dynamics of human-centered AI implementation. Kiger and Varpio (2020) explain that thematic analysis helps researchers identify and interpret patterns of meaning in qualitative data. Braun and Clarke (2021) emphasize that the quality of thematic analysis depends on reflective depth and the connection between themes and research questions. Naeem et al. (2023) also explain that thematic analysis needs to follow clear stages so that each theme has a strong conceptual basis. In the final stage, the themes will be compared with theories of human-centered AI, digital transformation, and human-AI relations to produce findings that are relevant both theoretically and practically.

3. Results and Discussions

The thematic analysis generated five main themes that explain how organizations implement artificial intelligence for data-driven decision optimization during digital transformation. These themes include: AI as a decision support instrument, trust and transparency in AI recommendations, human competence and adaptation, organizational culture toward data-driven decisions, and ethical control in AI-supported decision-making. These themes emerged from semi-structured interviews, limited observations of data-based decision activities, and document analysis of digital transformation guidelines, internal reports, dashboard procedures, and AI-related operational policies.

AI as a Decision Support Instrument, Not a Human Replacement

The first theme shows that participants viewed AI as a tool that supports decision-making rather than a system that replaces human judgment. Most participants stated that AI helped them read large volumes of data, detect patterns, and produce faster recommendations. However, they still positioned human judgment as the final authority in decision-making. This pattern appeared clearly in managerial and operational contexts, especially when decisions involved customer behavior, institutional policy, budget allocation, or service priorities.

One participant stated, "The system gives us direction, but the final decision still depends on the manager. We use AI to see patterns, not to let the machine decide everything" (P3). Another participant explained, "AI makes the process faster because we do not need to read all reports manually. But we still need discussion because not all numbers explain the real situation in the field" (P7). These statements show that users did not reject AI. They accepted AI when it worked as an analytical assistant that strengthened human reasoning.

Observation also supported this finding. In several decision meetings, the dashboard became the starting point of discussion, but participants still debated the meaning of the data before making a decision. They asked whether the data reflected actual field conditions, whether the prediction matched recent events, and whether the recommendation could create unintended consequences. This practice shows that AI created a new decision pattern where data initiated discussion, while human judgment shaped the final interpretation.

Trust Depends on Transparency and Explainability

The second theme relates to trust. Participants trusted AI recommendations when they could understand the logic behind the output. They did not require a full technical explanation of the algorithm, but they needed simple explanations about data sources, indicators, and the reasons behind the recommendation. When the system only produced a score, ranking, or prediction without explanation, users tended to hesitate.

One participant said, "I trust the dashboard when I know where the data comes from. If the system only gives a number without explanation, I still need to check it manually" (P5). Another participant added, "Sometimes the recommendation looks correct, but we do not know why the system chooses that option. That makes us careful before using it" (P11). These views show that trust in AI did not emerge automatically from system accuracy. Trust grew when users could connect the recommendation with organizational knowledge and field experience.

Document analysis showed that some organizations already had data governance guidelines, but the guidelines focused more on data collection and reporting than on explainability. Few documents explained how users should evaluate AI recommendations or how they should respond when system outputs contradicted human experience. This gap created uncertainty in daily practice. Users wanted AI to support decisions, but they also needed a clear basis for accepting, questioning, or rejecting system recommendations.

Human Competence Shapes AI Use

The third theme shows that human competence played a central role in AI implementation. Participants who had stronger digital literacy and data interpretation skills were more confident in using AI systems. They could read dashboards, compare indicators, and ask critical questions about data quality. In contrast, participants with limited experience in data analytics tended to use AI only as a reporting tool. They did not fully use its predictive or diagnostic functions.

A data analyst explained, "The problem is not only the system. Some users still see the dashboard as a report, not as a tool for analysis. They need training to ask better questions from the data" (P2). A manager also stated, "At first, staff only waited for the system result. After several training sessions, they started to discuss why the result appeared and what action we should take" (P9). These quotations show that AI capability depends on the interaction between technology and user competence.

The findings also show that training should not only focus on technical operation. Users needed training on interpretation, risk reading, bias awareness, and ethical responsibility. Several participants said that they could operate the system, but they were unsure how to translate the results into decisions. This indicates that organizations need to build data literacy as part of digital transformation. Without this competence, AI may become a symbolic tool that looks advanced but does not improve decision quality.

Organizational Culture Influences Data-Driven Decision-Making

The fourth theme concerns organizational culture. AI implementation worked better in organizations that encouraged evidence-based discussion, cross-unit collaboration, and openness to data correction. Participants explained that AI often challenged old decision habits because some leaders and staff were used to making decisions based on personal experience, hierarchy, or routine procedures. AI introduced new evidence that sometimes confirmed existing assumptions, but it also questioned them.

One participant stated, "Before we used the dashboard, decisions often followed the opinion of senior staff. Now we can compare opinions with data, although not everyone is comfortable with that" (P4). Another participant explained, "Data helps us talk more objectively, but culture is still important. If leaders do not want to listen to data, the system will not change anything" (P13). These statements show that AI implementation requires cultural readiness, not only technical readiness.

Observation of decision meetings showed that data-based discussions were more productive when leaders invited staff to explain the meaning of indicators. In contrast, discussions became less effective when AI outputs were treated as commands that should not be questioned. This finding shows that human-centered AI requires participatory decision culture. Users need room to discuss, validate, and contextualize AI outputs. When organizations fail to create this space, AI may increase compliance but reduce critical reflection.

Ethical Control and Accountability Remain Critical

The fifth theme relates to ethical control and accountability. Participants expressed concern about data bias, privacy, overdependence on automation, and unclear responsibility when AI-supported decisions produced negative outcomes. These concerns appeared strongly among participants who handled sensitive data, customer profiling, performance evaluation, or service prioritization.

One participant said, "If the system recommends one group as high risk, we need to know whether the data is fair. We cannot simply follow the label because it may affect people" (P6). Another participant noted, "When a decision uses AI, responsibility should still be clear. We

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cannot blame the system if the decision is wrong" (P15). These quotations indicate that ethical awareness became part of user experience in AI implementation.

Documents reviewed during the study showed that most organizations had general data security policies, but only a few had specific procedures for AI ethics, bias review, explainability, and human oversight. This condition created a practical gap between AI adoption and AI governance. Participants expected clearer rules about who validates system outputs, who approves final decisions, and how organizations should respond to errors or biased recommendations. This finding confirms that human-centered AI requires institutional mechanisms that protect accountability and human responsibility.

Discussion

The findings show that AI implementation in digital transformation is not only a technological process. It is a socio-technical process shaped by human judgment, organizational culture, data governance, and ethical responsibility. This finding supports the argument of Verhoef et al. (2021), who state that digital transformation changes organizational structures, processes, and strategic orientations. In this study, AI changed not only how users accessed data, but also how they discussed problems, questioned assumptions, and justified decisions.

The finding that participants treated AI as a decision support instrument aligns with the automation-augmentation paradox proposed by Raisch and Krakowski (2021). AI can automate data processing and pattern detection, but it also augments human reasoning when users interpret recommendations critically. The study adds a qualitative perspective to this debate by showing that users do not simply accept or reject automation. They negotiate the role of AI based on trust, context, experience, and perceived risk. This negotiation becomes a key feature of human-centered AI in organizational decision-making.

The findings also support Shneiderman's (2020) view that AI should remain reliable, safe, and trustworthy while allowing human control. Participants showed a strong need for final human authority, especially when AI recommendations affected people, resources, or strategic choices. This finding suggests that human-centered AI should not only focus on user interface design. It should also address decision rights, interpretive authority, and accountability structures. In this sense, human-centered AI operates at both the technical and organizational levels.

Trust emerged as a central issue in AI implementation. Participants trusted AI when they understood the data source, logic, and relevance of the recommendation. This finding is consistent with Glikson and Woolley (2020), who argue that trust in AI depends on system features, task characteristics, and interaction design. The present study adds that trust also depends on organizational explanation practices. Users did not always need complex algorithmic detail. They needed clear, usable, and context-sensitive explanations that helped them connect system output with field realities.

The study also confirms the importance of AI capability in organizational performance. Mikalef and Gupta (2021) argue that AI capability involves technological, human, and organizational resources. The findings strengthen this argument by showing that AI capability becomes meaningful only when users can interpret, question, and apply AI outputs in real decisions. Technical access to AI does not guarantee decision optimization. Organizations need human competence, data literacy, and decision routines that allow AI recommendations to become actionable knowledge.

The findings differ from studies that emphasize AI mainly as a driver of efficiency and business value. Enholm et al. (2022) explain that AI can create business value through automation, insight generation, and decision improvement. This study agrees with that view, but it shows that value creation depends on human mediation. AI recommendations did not directly become decisions. They passed through discussion, interpretation, validation, and contextual adjustment. This finding offers a more grounded view of AI value creation in organizations.

The results also align with Lebovitz et al. (2022), who found that professionals may struggle when they use opaque AI systems for critical judgments. In this study, opacity created hesitation among users. However, users did not always interpret opacity as a reason to reject AI. Instead, they responded by checking data sources, discussing outputs with colleagues, and comparing recommendations with field knowledge. This response shows that users develop practical strategies to manage uncertainty when AI systems are not fully explainable.

The finding on organizational culture supports the view that digital transformation requires more than technology adoption. Kraus et al. (2022) describe digital transformation as a broad organizational change process. This study shows how such change appears in everyday decision-making. AI challenged hierarchical decision habits and encouraged evidence-based discussion. However, the change depended on leadership openness and user participation. When leaders treated data as a shared basis for dialogue, AI supported learning. When leaders treated AI outputs as rigid instructions, the system reduced critical reflection.

The ethical concerns found in this study also support Sigfrids et al. (2023), who argue that human-centricity in AI governance must address values, responsibility, transparency, and social impact. Participants worried about bias, privacy, and accountability because AI-supported decisions could affect people directly. This finding shows that ethical AI cannot remain only at the policy level. Organizations need clear operational procedures for bias review, human oversight, appeal mechanisms, and responsibility assignment.

Theoretically, this study contributes to human-centered AI literature by showing that human-centered implementation involves three interconnected dimensions. The first dimension is interpretive control, where users need the ability to understand and question AI outputs. The second dimension is organizational participation, where users need space to discuss and contextualize recommendations. The third dimension is ethical accountability, where organizations need clear rules for validating and approving AI-supported decisions. These dimensions extend the discussion of human-centered AI from design principles to organizational practice.

Practically, the findings suggest that organizations should not implement AI only by purchasing systems or building dashboards. They need to prepare human competence, data governance, and decision protocols. Organizations should train users to interpret data, identify bias, and evaluate recommendations. They should also define who can approve AI-supported decisions, how users can challenge system outputs, and how errors should be reviewed. These steps can help organizations use AI as a tool for decision optimization without reducing human responsibility.

Future research can deepen this topic in several ways. First, future studies can compare human-centered AI implementation across sectors, such as healthcare, education, public service, finance, and manufacturing. Second, future research can examine how different levels of algorithmic explainability affect user trust and decision quality. Third, longitudinal studies can explore how user perceptions of AI change over time as organizations gain more experience. Fourth, mixed-method research can combine qualitative insights with quantitative measures of decision speed, accuracy, trust, and perceived accountability. These directions can strengthen understanding of how AI supports digital transformation while keeping humans at the center of decision-making.

4. Conclusions

This study concludes that the implementation of artificial intelligence for data-driven decision optimization in digital transformation depends not only on technological capability, but also on human judgment, organizational readiness, data culture, and ethical governance. The findings show that AI functions most effectively when it supports, rather than replaces, human decision-making. Participants viewed AI as a tool that helps identify patterns, accelerate analysis, and improve the accuracy of recommendations, but they still considered human interpretation essential in final decisions. Trust in AI emerged when users understood data sources, system logic, and the relevance of recommendations to real organizational conditions. Human competence, data literacy, participatory culture, and clear accountability also shaped the effectiveness of AI-supported decision-making.

Theoretically, this study contributes to human-centered AI, digital transformation, and socio-technical perspectives by showing that AI implementation requires interpretive control, organizational participation, and ethical accountability. Practically, the findings suggest that organizations should strengthen user training, data governance, explainability mechanisms, and decision protocols before relying on AI for strategic decisions. From a policy perspective, organizations need clear guidelines on human oversight, bias review, privacy protection, and responsibility in AI-supported decisions. Future studies can expand this research by comparing different organizational sectors, examining user trust over time, or combining qualitative findings with quantitative measures of decision quality, system acceptance, and accountability.

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