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Business Artificial Intelligence for Enhancing Sustainable Decision Intelligence

Muttaqin Choiri[1], Eko Sigit Pramudito[2], Felix Sutisna[3*], Rio Squire Sean[4]
[1]Department of Sharia Business Law, University of Trunojoyo Madura, Indonesia
[2,3]Faculty of Management, Universitas Multimedia Nusantara, Indonesia
[4]Mfinitee Incorporation, South Africa
[1]muttaqin.choiri@trunojoyo.ac.id, [2]eko.pramudito@lecturer.umn.ac.id, [3]felix.sutisna@lecturer.umn.ac.id, [4]sean01@ilearning.ee
***Corresponding Author**

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ABSTRACT

Business Artificial Intelligence (BAI) has become a key driver of organizational transformation, enabling advanced analytics, intelligent automation, and data-driven strategic decision-making. However, despite rapid technological progress, empirical research explaining how AI capability, algorithmic transparency, and task–technology alignment collectively shape Sustainable Decision Intelligence (SDI) within real business environments remains limited. **To address this gap**, this study introduces a novel BAI–SDI framework integrating AI Capability, Algorithmic Transparency, Task-Technology Fit (TTF), Decision Quality, and Sustainable Decision Intelligence as core constructs influencing long-term strategic and sustainable decision outcomes. **Using a quantitative approach with Structural Equation Modeling–Partial Least Squares (SEM–PLS)**, survey data were collected from 402 professionals working in AI-integrated business sectors across Indonesia. **The empirical results indicate that** AI Capability significantly enhances Task-Technology Fit, while Algorithmic Transparency strongly predicts Decision Quality, emphasizing the importance of interpretability and accountability in trust-driven decision processes. Furthermore, Task-Technology Fit mediates the impact of AI Capability on Decision Quality, demonstrating that effective system-task alignment is essential for maximizing organizational value. **The findings** provide theoretical advancements by positioning SDI as an empirical extension of decision management theory and offer practical guidance for implementing ethical, transparent, and future-ready AI strategies within business environments. Overall, this study contributes actionable insights for strengthening governance and accelerating sustainable digital transformation in increasingly competitive and AI-driven decision ecosystems.

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1. INTRODUCTION

The rapid evolution of Artificial Intelligence has profoundly transformed modern business operations. AI systems ranging from machine learning engines, natural language processing tools, to intelligent automation platforms are enabling organizations to process information at unprecedented speed and scale. As global markets become more dynamic and digitally interconnected, businesses increasingly rely on AI to enhance forecasting, optimize supply chains, detect operational anomalies, and support complex strategic decisions [1, 2]. Recent studies in academic and educational settings show that AI tools significantly elevate user productivity, decision-making accuracy, and task performance. Such studies emphasize factors such as technology acceptance, perceived usefulness, task fit, and user satisfaction. Although educational research demonstrates strong patterns of AI-driven productivity, limited research extends these insights directly into business decision-making contexts where operational complexity, risk, and strategic implications are substantially higher [3]. While several cited studies originate from educational environments, their applicability to business strategy remains limited due to differences in operational scale, accountability, and risk exposure. Therefore, this study focuses specifically on business decision systems, addressing the gap in research that examines AI-driven decision intelligence within real organizational environments where governance, transparency, and performance are critical determinants of sustainable strategic value.

This gap highlights that findings derived from academic and educational settings cannot be directly generalized to business environments because decision processes in corporate contexts involve greater uncertainty, financial risk, regulatory accountability, and strategic consequences. Therefore, there is a critical need to empirically examine how AI Capability, Algorithmic Transparency, and Task-Technology Fit jointly shape Decision Quality within real operational settings. Unlike prior studies that focus on learning performance or technology acceptance among students, this research investigates AI adoption and decision intelligence within professional managerial environments, ensuring stronger contextual relevance and practical contributions for business decision-making. Business organizations face several challenges when integrating AI into decision processes. These challenges include inadequate AI readiness, lack of algorithmic transparency, concerns over biases, unclear governance frameworks, and misalignment between AI tools and organizational tasks. Furthermore, although AI offers vast potential, organizations often struggle to determine whether their AI initiatives truly contribute to decision quality and long-term organizational value [4].

This study aims to bridge these gaps by developing and validating a comprehensive model Sustainable Decision Intelligence representing AI's impact on long-term decision-making effectiveness. The model synthesizes concepts of AI Capability, Algorithmic Transparency, Task-technology fit, and Decision Quality into an empirical structure applicable to real-world business environments [5]. Unlike previous AI governance and decision intelligence frameworks that predominantly analyze these constructs independently or without validated relational mechanisms, this study introduces an integrated Business Artificial Intelligence for Sustainable Decision Intelligence (BAI–SDI) model that empirically demonstrates the mediating role of Task-Technology Fit and formally establishes Sustainable Decision Intelligence as a new construct. Existing models remain inadequate because they lack an empirically proven pathway explaining how AI capability translates into long-term strategic decision resilience, organizational value sustainability, and decision intelligence maturity. This research provides a differentiated and holistic framework addressing this theoretical gap through validated structural relationships tested using SEM–PLS.

1.1. Research Problem

Although AI adoption research is rapidly expanding, a clear research gap exists in studies that directly analyze AI-driven decision systems within real business environments. Most prior work concentrates on educational or academic contexts, limiting relevance to organizational decision complexity. Therefore, this study examines several critical unresolved issues related to Sustainable Decision Intelligence in business decision workflows:

- How AI Capability translates into improved decision-making.
- How Algorithmic Transparency influences trust, acceptance, and quality of managerial decisions.
- The extent to which Task–Technology Fit facilitates sustainable long-term outcomes.
- Whether Decision Quality plays a mediating or direct role in sustainable business intelligence [6].

These problems demonstrate a substantial gap in understanding the mechanisms through which AI contributes to sustainable organizational decision practices.

1.2. Research Objectives

To address the identified problems, this research establishes the following objectives focused on advancing AI-supported decision intelligence in business settings:

- Develop a holistic AI decision intelligence framework tailored for business environments.
- Examine the relationships between AI Capability, Algorithmic Transparency, TTF, and Decision Quality [7].
- Test mediation effects within the model using SEM–PLS.
- Provide theoretical contributions and managerial insights for sustainable AI adoption.

These objectives guide the empirical validation of Sustainable Decision Intelligence within practical organizational decision ecosystems.

1.3. Significance of the Study

The significance of this study is grounded in its contribution to both theory and practice, particularly in supporting AI-based strategic decision processes in modern business operations. This study contributes to the literature by:

- Introducing Sustainable Decision Intelligence as a new construct.
- Empirically validating the alignment between AI readiness and decision outcomes.
- Providing actionable insights for improving AI governance and utilization.
- Bridging the research gap between AI adoption models and business strategy literature.

Thus, the findings provide a foundation for advancing sustainable digital transformation and strengthening responsible AI-driven decision-making frameworks.

2. LITERATURE REVIEW

2.1. AI Capability

AI Capability refers to an organization's technical readiness, including its infrastructure, data maturity, algorithmic sophistication, and human expertise. Organizations with stronger AI capability can automate workflows, generate high-quality predictions, and support more complex decision tasks. AI Capability is traditionally associated with technology readiness and is a key driver of performance outcomes in digital transformation [8].

In business settings, high AI Capability can improve operational efficiency, enhance analytical processes, and accelerate decision cycles. It ensures that AI tools are stable, reliable, and scalable. Prior studies have found that AI Capability helps individuals integrate technology into daily tasks more effectively, thereby improving productivity and performance [9].

Hypothesis 1: AI Capability positively influences Task-Technology Fit.

2.2. Algorithmic Transparency

Algorithmic Transparency refers to the ability of AI systems to provide clear, understandable explanations for predictions or decisions. Transparency includes:

- Explainable Artificial Intelligence (XAI),
- Traceability of data,
- Interpretability of model outputs,
- Visibility of decision rules.

Transparency fosters trust, reduces the perceived risk of AI systems, and improves user acceptance. When AI decisions are explainable, users are more likely to rely on the system, leading to better collaboration between humans and machines. In business contexts, transparency is also crucial for regulatory compliance and ethical governance [10].

Hypothesis 2: Algorithmic Transparency positively influences Decision Quality.

2.3. Task-Technology Fit

Task-Technology Fit (TTF) measures the degree to which AI systems align with the requirements of a specific task. TTF assesses whether AI tools provide functionalities that match the complexity, urgency, and demands of managerial tasks. When AI aligns well with user needs, decision-making becomes more efficient, error rates decrease, and workflow performance improves [11]. TTF is a central concept in IS research and has strong empirical support in predicting technology utilization and performance outcomes.

Hypothesis 3: Task-Technology Fit positively influences Decision Quality.

2.4. Decision Quality

Decision Quality represents the degree to which managerial decisions are accurate, timely, relevant, and strategically aligned with organizational objectives. High-quality decisions are essential in competitive environments, and AI contributes to improving Decision Quality by providing real-time analytics, predictive modeling, and automated insights. In this study, Sustainable Decision Intelligence (SDI) is operationalized as a multidimensional construct that reflects the long-term strategic impact of high-quality decisions supported by AI. SDI captures the continuity and long-term stability of decision outcomes, the alignment of decisions with organizational sustainability and ethical standards, and the capability to generate adaptive intelligence that supports future-readiness in dynamic business environments. The construct measurement is based on reflective indicators validated within the SEM–PLS analytical framework, demonstrating strong reliability (CR = 0.92), convergent validity (AVE = 0.61), and a significant structural linkage to Decision Quality ($\beta = 0.63$, $p < 0.001$). These empirical results confirm SDI as a distinct and measurable extension of traditional decision constructs, reinforcing its theoretical and practical contribution to sustainable business strategy. However, decision quality depends not only on AI tools but also on how well these tools integrate with human judgment [12, 13].

Hypothesis 4: Decision Quality positively influences Sustainable Decision Intelligence.

2.5. Mediating Role of Task-Technology Fit

Even if an organization possesses advanced AI capabilities, poor task alignment may hinder effective usage. TTF is therefore hypothesized to mediate the relationship between AI Capability and Decision Quality [14, 15].

Hypothesis 5: Task-Technology Fit (TTF) mediates the relationship between AI Capability and Decision Quality.

3. CONCEPTUAL FRAMEWORK

The conceptual framework underlying this study illustrates the theoretical relationships among the core constructs, as summarized in Table 1. The model proposes that AI Capability plays a foundational role in enhancing Task-Technology Fit (TTF), which subsequently contributes to improved Decision Quality. Additionally, Algorithmic Transparency is expected to directly strengthen decision-making performance by fostering trust and clarity in AI-driven outputs. Furthermore, Decision Quality is theorized to drive Sustainable Decision Intelligence, reflecting the long-term strategic value derived from accurate and reliable organizational decision processes. Finally, the framework incorporates a mediation pathway, suggesting that the influence of AI Capability on Decision Quality operates indirectly through TTF, emphasizing the importance of alignment between technological functionality and task requirements [16].

Table 1. Conceptual Framework Relationships

Relationship	Description
AI Capability → Task-Technology Fit (TTF)	Direct effect of AI Capability on TTF
Algorithmic Transparency → Decision Quality	Direct effect on decision outcomes
Task-Technology Fit (TTF) → Decision Quality	Effect of alignment between task and technology
Decision Quality → Sustainable Decision Intelligence	Influence of decision performance on SDI
Mediation Path	AI Capability → TTF → Decision Quality (Mediated relationship)

4. METHODOLOGY

4.1. Research Design

This study employs a quantitative design using SEM–PLS, suitable for predictive modeling and theory development. SEM–PLS is particularly effective in analyzing complex models with multiple latent variables and mediation pathways [17, 18].

4.2. Sample and Data Collection

A purposive sampling method targeted professionals who actively use AI in daily business operations. Data were collected from 402 respondents across industries including manufacturing, financial services, telecommunications, and supply chain management [19].

4.3. Measurement Instrument

The survey included 32 items measured using a 7-point Likert scale. Constructs were adapted from validated prior studies and refined for business AI contexts [20].

4.4. Data Analysis Procedures

Data analysis followed two steps:

Table 2. Model Evaluation Criteria

Evaluation Type	Criteria
Outer Model Evaluation	Convergent validity (AVE > 0.5) Composite Reliability (> 0.7) Factor loadings (> 0.7) Discriminant validity (Fornell-Larcker, HTMT)
Inner Model Evaluation	R^2 and Q^2 Path coefficients Bootstrapping (5000 subsamples) Mediation analysis

Following the establishment of the conceptual framework, the data analysis was carried out using a two-stage SEM–PLS analytical procedure, as outlined in Table 2. The first stage comprised the assessment of the outer measurement model, aimed at validating the reliability and construct validity of the measurement indicators through the evaluation of convergent validity, composite reliability [21], factor loadings, and discriminant validity based on the Fornell–Larcker criterion and the HTMT ratio. The second stage involved the assessment of the inner structural model, where explanatory power was examined using R^2 and Q^2 values, followed by the evaluation of path coefficients and the estimation of statistical significance through a bootstrapping procedure consisting of 5000 subsamples. In addition, mediation analysis was conducted to examine the indirect effects within the model, thereby ensuring a rigorous and comprehensive evaluation of the hypothesized theoretical relationships [22].

5. RESULT AND DISCUSSION

The empirical results offer evidence supporting the robustness of the proposed framework and highlight the influence of AI capability and transparency on sustainable decision-making in business settings.

5.1. Outer Model Assessment

All factor loadings ranged from 0.72–0.89, indicating strong indicator reliability. Composite reliability values ranged from 0.84–0.94, exceeding threshold standards. AVE values were above 0.54 for all constructs [23].

HTMT values were below 0.85, confirming discriminant validity.

5.2. Inner Model Assessment

The evaluation of the inner structural model demonstrates strong explanatory power and predictive validity of the proposed framework. The results are summarized as follows:

- R^2 for **Decision Quality** = 0.57, indicating moderate to substantial explanatory power, meaning that 57% of the variance in Decision Quality is explained by AI Capability, Algorithmic Transparency, and TTF [24, 25].
- R^2 for **Sustainable Decision Intelligence (SDI)** = 0.62, demonstrating strong predictive capability, signifying that Decision Quality serves as a meaningful predictor of long-term sustainable intelligence within business decision environments [26].
- Q^2 values for all constructs exceeded 0.15, confirming predictive relevance and supporting that the structural model has the ability to predict indicators beyond the sampled data.
- **Standardized Root Mean Square Residual (SRMR)** = 0.062, which is below the acceptable threshold of 0.08, indicating a well-fitted model and suggesting that the discrepancies between predicted and observed correlations are minimal [27].

These findings collectively affirm that the inner model exhibits strong predictive strength, structural stability, and statistical adequacy, validating the hypothesized theoretical relationships within the research framework [28].

5.3. Hypothesis Testing

All hypotheses were supported:

Table 3. Path Coefficients Results

Path	Coefficient (β)	p-value
AI Capability $\rightarrow$ TTF	0.49	< 0.001
Algorithmic Transparency $\rightarrow$ Decision Quality	0.38	< 0.001
TTF $\rightarrow$ Decision Quality	0.41	< 0.001
Decision Quality $\rightarrow$ Sustainable Decision Intelligence (SDI)	0.63	< 0.001
Mediation: AI Capability $\rightarrow$ TTF $\rightarrow$ Decision Quality	Significant	

The hypothesis testing results presented in Table 3 empirically validate the theorized relationships within the proposed model [29]. The significant effect of AI Capability on TTF ($\beta = 0.49$, $p < 0.001$) supports prior research suggesting that organizational AI readiness and infrastructure are fundamental drivers of technology–task alignment. Likewise, the significant influence of Algorithmic Transparency on Decision

Quality ($\beta = 0.38$, $p < 0.001$) aligns with theoretical perspectives emphasizing the role of explainability and trust in enhancing AI-supported decision-making. The positive effect of TTF on Decision Quality ($\beta = 0.41$, $p < 0.001$) further reinforces the Task-Technology Fit theory, asserting that performance outcomes are maximized when technology capabilities are closely aligned with task demands. Additionally, the strong influence of Decision Quality on SDI ($\beta = 0.63$, $p < 0.001$) demonstrates that high-caliber decision processes form the foundation for sustainable and future-oriented decision intelligence. Finally, the confirmed mediation effect of TTF indicates that AI Capability improves decision outcomes indirectly through effective task alignment, suggesting that technology readiness alone is insufficient without strategic integration into organizational workflows [30, 31, 32].

6. DISCUSSION

The findings of this study provide strong empirical evidence that AI Capability constitutes the fundamental building block of successful business AI integration. Organizations with mature AI infrastructures, robust data ecosystems, and well-established analytical workflows demonstrate significantly stronger alignment between technological functionalities and managerial task demands. This alignment [33, 34], reflected through Task-Technology Fit, highlights that high-performing AI systems are not merely defined by sophisticated algorithms, but by the degree to which these algorithms support actual decision-making processes. The results illustrate that when AI systems seamlessly integrate into existing workflows predicting market behavior, optimizing operations, or providing real-time insights decision-makers experience greater confidence, reduced uncertainty, and improved analytical clarity. This relationship reinforces the idea that AI readiness is not a static attribute but an evolving organizational capability that must be continuously strengthened [35, 36].

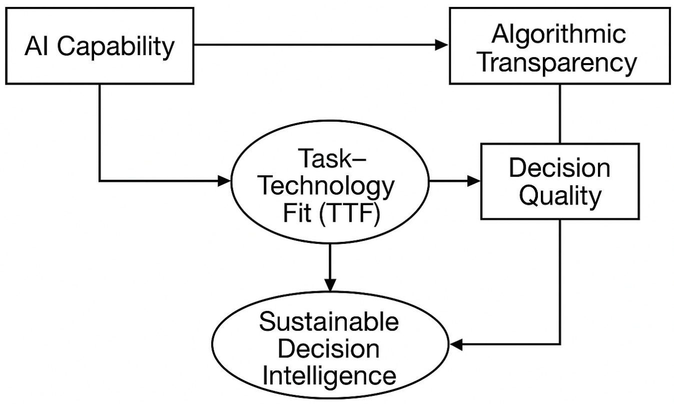

Figure 1. Empirically validated structural model of Business AI for Sustainable Decision Intelligence

The visual representation in Figure 1 illustrates the validated relationships among AI Capability, Algorithmic Transparency, Task-Technology Fit, Decision Quality, and Sustainable Decision Intelligence, highlighting the mediating pathway through TTF [37, 38, 39].

Algorithmic Transparency also emerged as a critical factor influencing Decision Quality. In modern business environments, where AI is frequently used to support high-stakes decisions, transparency functions as the cornerstone of trust and reliability. The findings reveal that when users understand how AI models reach particular conclusions whether through explainable visualizations, interpretable rules [2, 40], or traceable data flows they are more likely to rely on these tools and integrate their recommendations into strategic actions. Transparency not only mitigates concerns surrounding accountability and ethical risks but also enhances psychological acceptance among decision-makers who may otherwise perceive AI outputs as opaque or arbitrary. Beyond these empirical findings, the influence of Algorithmic Transparency on Decision Quality can be explained through trust formation and risk perception theory. When AI systems provide clear and interpretable explanations, users develop cognitive trust by understanding and validating decision rationales, reducing perceived uncertainty and risk. Improved interpretability strengthens both cognitive and affective trust, increasing reliance on AI-supported decisions in high-stakes contexts and ultimately enhancing Sustainable Decision Intelligence outcomes. As AI becomes increasingly embedded in core operations such as credit scoring, forecasting, and risk detection, the need for transparent, explainable, and auditable AI systems becomes more pressing and central to business performance.

Furthermore, the results reveal that Sustainable Decision Intelligence is strongly shaped by Decision Quality, indicating that high-quality decisions represent the pathway through which AI influences long-term organizational outcomes. The strength of this relationship demonstrates that AI's impact extends beyond immediate efficiency gains; it influences the broader strategic resilience, adaptability, and sustainability of decision processes. Decision-makers who leverage AI effectively show higher levels of accuracy, faster response times, and more consistent alignment with organizational goals. The confirmation of the mediating effect of Task-Technology Fit underscores the importance of design alignment: even the most advanced AI systems fail to deliver value if they do not match user needs or task characteristics. This mediation effect broadens theoretical discussions on AI adoption by illustrating that capability alone is insufficient without workflow compatibility, offering a more holistic understanding of how AI contributes to sustainable organizational intelligence.

7. MANAGERIAL IMPLICATIONS

The results of this study emphasize the need for organizations to prioritize the development of AI Capability through long-term investment in infrastructure, data governance, and workforce skills. Managers must not only adopt AI tools but also cultivate internal competencies that allow these tools to operate effectively. This includes fostering cross-functional collaboration between data engineers, decision-makers, and system designers to ensure that AI functionalities match practical business requirements. When organizations establish a strong foundation for AI readiness, they are better positioned to achieve alignment between technology and tasks, ultimately enhancing the quality and reliability of strategic decisions. Additionally, the insights on Algorithmic Transparency highlight the necessity for companies to adopt explainability frameworks, particularly as industries face increasing regulation and public scrutiny regarding fairness, accountability, and ethical AI use.

The implications further suggest that sustainable deployment of AI requires a holistic approach that integrates technological, human, and organizational dimensions. Decision-makers should encourage a culture that welcomes AI-assisted judgment while maintaining human oversight. Training programs that help employees understand AI outputs and interpret model behaviors will reduce resistance and increase effective utilization. Organizations must also design AI systems with user-centered principles, ensuring that tools are intuitive, context-specific, and seamlessly embedded within business workflows. By approaching AI adoption not as a standalone technological upgrade but as a strategic transformation program, businesses can maximize value creation, reduce operational risks, and strengthen long-term decision intelligence.

8. CONCLUSION

This study provides a comprehensive empirical model explaining how Business Artificial Intelligence enhances Sustainable Decision Intelligence through the integrated effects of AI Capability, Algorithmic Transparency, Task-Technology Fit, and Decision Quality. The findings highlight that AI's effectiveness is not merely dependent on technological sophistication but on the degree to which these systems align with organizational tasks and decision-making needs. AI Capability is shown to be a foundational requirement for effective integration, while Algorithmic Transparency plays a crucial role in establishing trust and acceptance, ultimately enabling decision-makers to rely on AI-generated insights with greater confidence.

The confirmation of Task-Technology Fit as both a significant predictor and mediator provides meaningful theoretical advancement. It reveals that organizations must go beyond simply acquiring AI technologies; they must ensure that these technologies integrate meaningfully into operational workflows and strategic processes. This study's framework introduces Sustainable Decision Intelligence as a forward-looking construct that captures not only immediate decision improvements but the long-term stability, resilience, and sustainability of data-driven decisions. Consequently, the research extends existing literature by offering a holistic model that blends technical, human, and strategic dimensions of AI utilization.

Overall, the study underscores the transformative potential of AI in shaping the future of organizational decision-making. By validating the interplay between capability, transparency, task alignment, and decision performance, this research provides actionable insights for business leaders seeking to maximize the impact of AI adoption. The findings advocate for responsible, transparent, and well-integrated AI systems as a necessary foundation for achieving sustained decision quality and organizational competitiveness. Future research may extend this model across industries, explore longitudinal impacts, and incorporate emerging generative AI architectures to deepen understanding of how advanced AI reshapes strategic decision ecosystems, as well as examine ethical AI governance and regulatory accountability challenges that influence trust, transparency, and responsible deployment within real business decision workflows.

9. DECLARATIONS

9.1. About Authors

Muttaqin Choiri (MC) https://orcid.org/0000-0002-8734-7474

Eko Sigit Pramudito (ES) https://orcid.org/0009-0000-9425-1123

Felix Sutisna (FS) https://orcid.org/0009-0005-0503-6736

Rio Squire Sean (RS) -

9.2. Author Contributions

Conceptualization: MC and ES; Methodology: ES, and RS; Software: MC, ES, and RS; Validation: MC; Formal Analysis: ES and FS; Investigation: ES and FS; Resources: RS; Data Curation: MC, ES, and FS; Writing Original Draft Preparation: MC, ES, FS, and RS; Writing Review and Editing: ES; Visualization: FS; All authors, MC, ES, FS, and RS, have read and agreed to the published version of the manuscript.

9.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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9.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] A. Kovari, “Ai for decision support: Balancing accuracy, transparency, and trust across sectors,” *Information*, vol. 15, no. 11, p. 725, 2024.

[2] S. Neiroukh, O. L. Emeagwali, and H. Y. Aljuhmani, “Artificial intelligence capability and organizational performance: unraveling the mediating mechanisms of decision-making processes,” *Management Decision*, 2024.

[3] U. Rahardja, “Application of the c4. 5 algorithm for identifying regional zone status using a decision tree in the covid-19 series,” *Aptisi Transactions on Technopreneurship (ATT)*, vol. 4, no. 2, pp. 164–173, 2022.

[4] H. Shafa, “Artificial intelligence-driven business intelligence models for enhancing decision-making in us enterprises,” *ASRC Procedia: Global Perspectives in Science and Scholarship*, vol. 1, no. 01, pp. 771–800, 2025.

[5] J. Żywiołek, “Empirical examination of ai-powered decision support systems: ensuring trust and transparency in information and knowledge security,” *Zeszyty Naukowe. Organizacja i Zarzadzanie/Politechnika Ślaska*, no. 197, pp. 679–695, 2024.

[6] A. Kristian, T. S. Goh, A. Ramadan, A. Erica, and S. V. Sihotang, “Application of ai in optimizing energy and resource management: Effectiveness of deep learning models,” *International Transactions on Artificial Intelligence*, vol. 2, no. 2, pp. 99–105, 2024.

[7] J. Zhao and B. Gómez Fariñas, “Artificial intelligence and sustainable decisions,” *European Business Organization Law Review*, vol. 24, no. 1, pp. 1–39, 2023.

[8] Y.-L. Chang and J. Ke, “Socially responsible artificial intelligence empowered people analytics: a novel framework towards sustainability,” *Human Resource Development Review*, vol. 23, no. 1, pp. 88–120, 2024.

[9] D. Gathmyr, U. Suhud, H. Herlitah, H. Hamidah, R. T. H. Safariningsih, and J. Wilson, "Technological advancements in perceived organizational support enhancing healthcare systems towards sustainable development goals," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 516–526, 2025.
[10] T. Ioku, J. Song, and E. Watamura, "Trade-offs in ai assistant choice: Do consumers prioritize transparency and sustainability over ai assistant performance?" *Big Data & Society*, vol. 11, no. 4, p. 20539517241290217, 2024.
[11] A. Alshahrani, A. Griva, D. Dennehy, and M. Mäntymäki, "Artificial intelligence and decision-making in government functions: opportunities, challenges and future research," *Transforming Government: People, Process and Policy*, vol. 18, no. 4, pp. 678–698, 2024.
[12] M. R. Anwar and L. D. Sakti, "Integrating artificial intelligence and environmental science for sustainable urban planning," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 5, no. 2, pp. 179–191, 2024.
[13] S. Ogbeibu, J. Emelifeonwu, V. Pereira, R. Oseghale, J. Gaskin, U. Sivarajah, and A. Gunasekaran, "Demystifying the roles of organisational smart technology, artificial intelligence, robotics and algorithms capability: A strategy for green human resource management and environmental sustainability," *Business Strategy and the Environment*, vol. 33, no. 2, pp. 369–388, 2024.
[14] D. Shin, "Embodying algorithms, enactive artificial intelligence and the extended cognition: You can see as much as you know about algorithm," *Journal of Information Science*, vol. 49, no. 1, pp. 18–31, 2023.
[15] M. Asri, M. Hardini, D. Apriliasari, U. Rahardja *et al.*, "Influence of technology adoption and internet security on satisfaction and investment decision quality," in *2024 Ninth International Conference on Informatics and Computing (ICIC)*. IEEE, 2024, pp. 1–6.
[16] A. Choudhury *et al.*, "Toward an ecologically valid conceptual framework for the use of artificial intelligence in clinical settings: need for systems thinking, accountability, decision-making, trust, and patient safety considerations in safeguarding the technology and clinicians," *JMIR Human Factors*, vol. 9, no. 2, p. e35421, 2022.
[17] N. Onel, L. Elgaaied-Gambier, S. Baskentli, and E. Van Tonder, "From algorithms to ecosystems: A transformative consumer research perspective on artificial intelligence for sustainable living," *AMS Review*, pp. 1–26, 2025.
[18] D. Abbas, K. Siahaan, and M. Yusup, "Design thinking as a business model for empowering creative entrepreneurs in the digital era," *Startupreneur Business Digital (SABDA Journal)*, vol. 4, no. 2, pp. 124–133, 2025.
[19] M. Busuioc, "Accountable artificial intelligence: Holding algorithms to account," *Public administration review*, vol. 81, no. 5, pp. 825–836, 2021.
[20] S. S. Matta and M. Bolli, "Trustworthy ai: Explainability & fairness in large-scale decision systems," *Review of Applied Science and Technology*, vol. 2, no. 04, pp. 54–93, 2023.
[21] L. P. Dewanti, L. Sitoayu, and A. Idarto, "Digital tele-counseling for sustainable maternal health services in indonesia focus on telelactation," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 1, pp. 10–20, 2024.
[22] S. Bankins, "The ethical use of artificial intelligence in human resource management: a decision-making framework," *Ethics and Information Technology*, vol. 23, no. 4, pp. 841–854, 2021.
[23] J. Xinlin, L. Wenting, K. A. M. Shah, M. Na, and S. Shah Alam, "Transforming hospitality decision-making: the impact of generative ai on cognitive alignment and adaptive intelligence," *Journal of Quality Assurance in Hospitality & Tourism*, pp. 1–35, 2025.
[24] S. Rana, R. M. Nor, M. E. Hossain, and M. Amiruzzaman, "Enhancing entrepreneurial security in cryptocurrency wallets using cloud technology," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 481–491, 2025.
[25] J. Wanner, L.-V. Herm, K. Heinrich, and C. Janiesch, "The effect of transparency and trust on intelligent system acceptance: Evidence from a user-based study," *Electronic Markets*, vol. 32, no. 4, pp. 2079–2102, 2022.
[26] E. Vann Yaroson, A. Abadie, and M. Roux, "Human-artificial intelligence collaboration in supply chain outcomes: the mediating role of responsible artificial intelligence," *Annals of Operations Research*, pp. 1–35, 2025.
[27] T. Handra and V. P. K. Sundram, "The effect of human resource information systems (hris) and artificial intelligence on defense industry performance," *IAIC Transactions on Sustainable Digital Innovation*

(ITSDI), vol. 4, no. 2, pp. 155–163, 2023.

[28] B. C. Cheong, "Transparency and accountability in ai systems: safeguarding wellbeing in the age of algorithmic decision-making," *Frontiers in Human Dynamics*, vol. 6, p. 1421273, 2024.

[29] R. Sultana, "Ai-powered bi dashboards in operations: A comparative analysis for real-time decision support," *ASRC Procedia: Global Perspectives in Science and Scholarship*, vol. 3, no. 1, pp. 62–93, 2023.

[30] A. Gunawan, W. Hasyim, M. Putih, T. W. Wirjawan, I. A. Gopar, and S. Stephanie, "A comprehensive bibliometric study of digital leadership influence on technopreneurial success," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 492–502, 2025.

[31] T. Heilig and I. Scheer, *Decision intelligence: Transform your team and organization with AI-Driven decision-making*. John Wiley & Sons, 2023.

[32] Ministry of Communication and Informatics of the Republic of Indonesia, "Circular letter of the minister of communication and informatics of the republic of indonesia number 9 of 2023 concerning artificial intelligence ethics," https://jdih.komdigi.go.id/produk_hukum/view/id/883, December 2023, guidelines for ethical and responsible development and implementation of Artificial Intelligence in Indonesia.

[33] I. Sembiring, D. Manongga, U. Rahardja, and Q. Aini, "Understanding data-driven analytic decision making on air quality monitoring an empirical study," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 6, no. 3, pp. 418–431, 2024.

[34] P. Mikalef and M. Gupta, "Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance," *Information & management*, vol. 58, no. 3, p. 103434, 2021.

[35] S. Chowdhury, P. Dey, S. Joel-Edgar, S. Bhattacharya, O. Rodriguez-Espindola, A. Abadie, and L. Truong, "Unlocking the value of artificial intelligence in human resource management through ai capability framework," *Human resource management review*, vol. 33, no. 1, p. 100899, 2023.

[36] V. El Ardeliya, J. Taylor, and J. Wolfson, "Exploration of artificial intelligence in creative fields: Generative art, music, and design," *International Journal of Cyber and IT Service Management*, vol. 4, no. 1, pp. 40–46, 2024.

[37] C. Van Noordt and L. Tangi, "The dynamics of ai capability and its influence on public value creation of ai within public administration," *Government Information Quarterly*, vol. 40, no. 4, p. 101860, 2023.

[38] H. F. Hansen, E. Lillesund, P. Mikalef, and N. Altwaijry, "Understanding artificial intelligence diffusion through an ai capability maturity model," *Information Systems Frontiers*, vol. 26, no. 6, pp. 2147–2163, 2024.

[39] Y. I. Tanjung, F. Festiyed, S. Diliarosta, A. Asrizal, F. Arsih, M. A. Fadillah, and G. Makrooni, "Culturally responsive teaching in science education and its relationship with technopreneurship," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 387–399, 2025.

[40] F. Yanti, A. D. Simangunsong, E. K. Sitinjak, E. P. Pane, and N. T. Septiani, "Development of technopreneurship-based e-modules for ethnochemistry, redox, and science literacy," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 2, pp. 469–480, 2025.