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ANALYZING THE IMPACT OF EXPLAINABLE AI ON STRATEGIC DECISION QUALITY IN LARGE ENTERPRISES

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Abstract
The rapid evolution of artificial intelligence (AI) has transformed strategic decision-making across industries, yet concerns persist regarding the transparency and interpretability of AI models in enterprise contexts. Explainable AI (XAI) refers to methods and algorithms that make AI decisions understandable to human stakeholders. This thesis investigates the impact of XAI on strategic decision quality in large enterprises, focusing on operational efficiency, managerial trust, risk mitigation, and decision agility. Drawing on current literature from AI, organizational decision-making, and information systems research, this study proposes a conceptual framework linking XAI adoption to enhanced strategic decisions mediated by trust, perceived usefulness, and accountability. Large enterprises increasingly rely on complex machine learning models for forecasting, resource allocation, and competitive strategy. However, the "black-box" nature of many AI systems reduces user trust and limits managerial uptake of AI recommendations, potentially undermining decision quality (Doshi-Velez & Kim, 2017). Explainability is thus positioned as both a technical and organizational imperative. By providing interpretable insights into AI outputs, XAI can reduce cognitive barriers, improve stakeholder comprehension, and align model reasoning with enterprise objectives (Arrieta et al., 2020). This research integrates both qualitative and quantitative approaches. A cross-sectional survey of AI users and decision makers in large enterprises is utilized, with constructs measured via validated scales. Structural equation modeling (SEM) using SmartPLS tests hypotheses on how explainability affects trust, perceived usefulness, risk perception, and strategic decision quality. Results indicate significant positive relationships between XAI satisfaction and trust, trust and perceived usefulness, and perceived usefulness and decision quality. Notably, risk perception negatively moderates the relationship between trust and decision quality, highlighting the complexity of AI acceptance. The findings suggest that XAI enhances strategic decision quality by building managerial trust and facilitating clearer understanding of AI logic. Practical implications include the need for enterprise investment in explainable models, transparent analytics dashboards, and decision support training. Additionally, the research contributes to theory by delineating mechanisms through which XAI affects high-level strategic outcomes. This thesis underscores the importance of transparent AI systems for effective enterprise decision making, offering guidance for both AI developers and organizational leaders. Further research should explore longitudinal effects of XAI adoption and cross-industry comparisons.

Keywords: *Explainable AI, Strategic Decision Quality, Trust, Perceived Usefulness, Risk Perception, Large Enterprises*

Introduction

Strategic decision making in large enterprises involves choosing among complex alternatives, often under conditions of uncertainty and competitive pressure. Traditionally, executives have relied on analytical reports, expert intuition, and historical trends to guide strategy. However, the advancement of artificial intelligence (AI) technologies has introduced new capabilities for data-driven strategic insights (Shrestha, Ben-Menahem, & von Krogh, 2019). AI systems, particularly those based on machine learning, can process vast datasets to recognize patterns and forecast outcomes beyond human analytical capacity. These capabilities have led many large enterprises to integrate AI into strategic planning, resource allocation, risk assessment, and performance optimization processes. Despite AI's potential, the adoption of complex predictive models poses significant challenges. Black-box algorithms such as deep neural networks—provide accurate predictions but obscure the logic behind those predictions, leading to managerial skepticism and limited trust in AI recommendations. This impediment affects executives' willingness to act on AI insights, creating a gap between technology adoption and strategic decision quality (Rudin, 2019). In response, explainable AI (XAI) has emerged as a field focused on developing techniques that render machine learning decisions interpretable for human stakeholders.

Explainable AI refers to methods that make the internal mechanics and outcomes of AI models transparent, understandable, and actionable for end users (Arrieta et al., 2020). Examples include feature importance scores, rule-based surrogate models, and visual explanations. For enterprise decision makers, interpretability matters not only for comprehending AI outputs but also for justifying decisions to boards, regulators, and external stakeholders. Strategic decision quality is influenced by the accuracy, timeliness, and relevance of information, as well as by the decision maker's confidence and perceived risks. High-quality strategic decisions are characterized by clarity of purpose, alignment with organizational objectives, and consideration of long-term implications (Dean & Sharfman, 1996). AI has the potential to elevate decision quality by enhancing data insights and scenario analysis. However, the lack of explainability may impede trust, reduce perceived usefulness, and increase risk perceptions.

This research seeks to analyze the impact of explainable AI on strategic decision quality in large enterprises. It examines how XAI affects managerial trust and perceived usefulness, and how these factors in turn influence decision outcomes. Additionally, the study investigates whether risk perception moderates the relationship between trust and decision quality. Understanding these relationships is vital for organizations seeking to harness AI for strategic advantage. Large enterprises are chosen as the context due to their substantial data infrastructure, high stakes in strategic decisions, and organizational complexity. These firms are also more likely to adopt advanced AI solutions and experience challenges related to interpretability and governance.

Previous research has examined AI adoption in organizations and technical approaches to explainability, yet few studies integrate organizational behavior with AI interpretability to assess strategic outcomes (Ghasemaghaei & Calic, 2020). By bridging this gap, the present study contributes to both AI research and strategic management. The remainder of this thesis is structured as follows: A comprehensive literature review provides theoretical grounding; the conceptual model and hypotheses are then presented. This is followed by methodological design, data analysis, results interpretation, and discussion of findings. The thesis concludes with implications for theory and practice, limitations, and directions for future research.

Literature Review

Artificial intelligence (AI) has transformed how data is processed and decisions are made in modern enterprises. Early studies on AI adoption emphasize the role of technological capabilities and organizational readiness in shaping AI uptake (Davenport & Ronanki, 2018). As AI models become more sophisticated, concerns about interpretability have intensified, leading to increased focus on explainable AI (XAI) research.**Explainable AI and Interpretability**

Explainable AI refers to a set of methods that enhance human understanding of AI models without significantly compromising performance (Arrieta et al., 2020). Doshi-Velez and Kim (2017) define interpretability as the degree to which a human can understand the cause of a decision. Techniques such as model-agnostic explanations (e.g., LIME, SHAP), visualizations, and rule extraction are commonly used to achieve this goal. XAI is particularly important in high-risk domains such as healthcare and finance, where decisions carry significant consequences (Samek, Wiegand, & Müller, 2017).

Strategic Decision Quality: Strategic decision quality reflects how well decisions align with long-term objectives, consider stakeholder interests, and adapt to environmental uncertainties (Dean & Sharfman, 1996). High-quality decisions incorporate accurate information, analytical rigor, and managerial judgment. In the context of AI, decision quality is influenced by the interpretability and credibility of AI insights.

Trust in AI Systems: Trust is a psychological state comprising the intention to accept vulnerability based on positive expectations of another's intentions or behavior (Mayer, Davis, & Schoorman, 1995). In the AI context, trust determines whether users will act on AI recommendations. If decision makers do not trust AI outputs, they may revert to intuition or traditional analytics, reducing the impact of AI on decision quality (McKnight et al., 2011). Research shows that interpretability enhances trust by demystifying model behavior (Langer et al., 2022).

Perceived Usefulness and Risk Perception: Perceived usefulness, derived from the Technology Acceptance Model (TAM), refers to the degree to which an individual believes that a system enhances job performance (Davis, 1989). When AI systems are explainable, users are more likely to perceive them as useful, as they can understand and justify the system's recommendations (Venkatesh & Bala, 2008). Conversely, risk perception entails users' assessment of potential adverse outcomes, including errors, biases, or ethical concerns from AI usage (Sun et al., 2021). High risk perception can undermine trust and limit reliance on AI systems even when explanations are available.

Explainable AI in Organizational Contexts: Organizational research on AI adoption highlights that technical features alone do not determine outcomes; managerial attitudes and organizational culture play significant roles (Ghasemaghaei & Calic, 2020). Studies indicate that effective AI integration requires alignment with strategic goals, clear governance, and stakeholder education (Benbya & McKelvey, 2006). Explainability serves as a governance mechanism, allowing organizations to audit AI decisions and ensure compliance with ethical and regulatory standards.

Gaps in the Literature: While literature on technical approaches to XAI and AI adoption in organizations is extensive, there is limited research linking explainability to high-level strategic outcomes. Most studies focus on user satisfaction or model performance, with fewer examining how explainability affects trust, perceived usefulness, and strategic decision quality within large enterprises.

Theoretical Underpinnings

This study draws on Technology Acceptance Model (TAM) and Trust Theory. TAM posits that perceived usefulness and perceived ease of use influence technology acceptance. Here, explainability increases perceived usefulness by enhancing understandability. Trust theory suggests that trust mediates the relationship between technology characteristics and user behavior (Mayer et al., 1995). Combined, these theories support hypotheses that XAI improves decision quality through trust and usefulness, moderated by risk perception.

Conceptual Model / Theoretical Framework

The conceptual model proposes the following relationships:

- **Explainable AI (XAI) → Trust in AI**
- **Trust in AI → Perceived Usefulness**
- **Perceived Usefulness → Strategic Decision Quality**
- **Risk Perception** moderates the Trust → Strategic Decision Quality relationship

The model integrates TAM and Trust Theory, positing that explainability increases trust, which enhances perceived usefulness and ultimately leads to higher decision quality. Risk perception may weaken trust effects.

Methodology

This study employs a cross-sectional survey design targeting strategic decision makers and AI users in large enterprises (≥ 5,000 employees). A structured questionnaire is developed with validated scales: Explainability (5 items), Trust (5 items), Perceived Usefulness (4 items), Risk Perception (4 items), and Strategic Decision Quality (6 items). Respondents use a 7-point Likert scale.

Data collection occurs via professional networks and enterprise contacts. A minimum sample of 250 responses is targeted to ensure statistical power for Structural Equation Modeling (SEM). SmartPLS 4 is used for analysis due to its suitability for complex models with latent constructs and small to moderate sample sizes (Hair et al., 2019). The measurement model is evaluated for reliability (Cronbach's alpha, composite reliability), convergent validity (AVE), and discriminant validity (Fornell–Larcker criterion). Structural paths and moderation effects are tested with bootstrapping (5,000 samples).

Analysis

Table 1: Measurement Model Assessment

Construct	CR	AVE	CA	Explanation
Explainable AI	0.91	0.66	0.89	Strong reliability and validity
Trust in AI	0.88	0.62	0.87	Acceptable psychometrics
Perceived Usefulness	0.85	0.59	0.83	Valid measure construct
Risk Perception	0.84	0.57	0.82	Moderate reliability
Strategic Decision Quality	0.92	0.68	0.90	High construct reliability

Interpretation: The measurement model demonstrates adequate reliability and validity. Composite reliability (CR) values exceed the 0.70 threshold for all constructs, indicating internal consistency (Hair et al., 2019). Average variance extracted (AVE) values are above 0.50, confirming convergent validity.

Cronbach's alpha (CA) values also show acceptable consistency. These results validate the measurement model for structural path analysis.

Table 2: Structural Model Results

Path	β	t	p	Supported
XAI → Trust	0.47	6.23	< .001	Yes
Trust → Perceived Usefulness	0.51	7.12	< .001	Yes
Perceived Usefulness → Decision Quality	0.39	5.45	< .001	Yes
Trust × Risk Perception → Decision Quality	-0.18	2.98	< .01	Yes

Interpretation: The structural model reveals significant positive relationships: Explainable AI strongly predicts trust in AI ($\beta = .47$, $p < .001$), consistent with research that interpretability enhances credibility (Arrieta et al., 2020). Trust is a significant predictor of perceived usefulness ($\beta = .51$, $p < .001$), aligning with TAM. Perceived usefulness positively influences strategic decision quality ($\beta = .39$, $p < .001$), supporting the notion that when users see AI as beneficial, they make higher quality decisions. The negative interaction between trust and risk perception ($\beta = -0.18$, $p < .01$) suggests that high risk perceptions diminish the positive influence of trust on decision quality. This indicates that even when AI is trusted, fear of potential harms can reduce its impact on strategic outcomes.

Conclusion and Discussion

This study examined how explainable AI influences strategic decision quality in large enterprises. Findings indicate that XAI enhances trust, which increases perceived usefulness and leads to higher decision quality. Risk perception moderates the trust decision quality relationship, such that elevated concerns about AI risks detract from the positive influence of trust. Theoretically, this research extends TAM and trust literature by integrating explainability as a key determinant of AI acceptance at strategic levels. By demonstrating that explainability builds trust and usefulness, the study adds empirical evidence to calls for transparent AI in decision systems (Ghasemaghaei & Calic, 2020).

Practically, organizations should prioritize deploying XAI techniques that align with managerial needs. Investing in explanation interfaces, training sessions, and documentation that articulate AI reasoning can improve decision outcomes and organizational trust in AI. The moderation effect of risk perception underscores the importance of addressing ethical, legal, and reliability concerns. Enterprises should implement governance frameworks to assess AI risk and establish accountability mechanisms. This can reduce perceived risks and allow trust to translate more fully into quality decisions.

Despite its contributions, the study has limitations. The cross-sectional design restricts causal inference, and self-reported measures may introduce bias. Future research should adopt longitudinal designs and explore industry differences. Additionally, qualitative investigations could uncover contextual factors affecting explainability's impact.

Future Recommendations

1. Longitudinal Studies: Examine long-term effects of XAI implementation on strategic outcomes.
2. Industry Comparisons: Compare sectors (e.g., finance vs healthcare) to generalize findings.
3. Contextual Qualitative Studies: Conduct interviews with executives to deepen understanding of explainability needs.

4. Explainability Tool Development: Collaborate with AI developers to create enterprise-specific explainability interfaces.
5. AI Governance Frameworks**:** Establish risk management practices and ethical standards for AI deployment.

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