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CONTENTS

Explainable AI for Cybersecurity Applications: A Review Article on Techniques, Deployments, and Usability Challenges	3
Nipuna Thalpage	
Factors Influence Artificial Intelligence Decision-making Quality...	11
Kingsley Ofosu-Ampong, Alexander Asmah, John Amoako, Nicholas Commey	
Cryptocurrency as Newer Form of Digital Asset	21
Tatiana Antipova	
Decoding Language in the Digital Age: A Model of Computational Discourse Analysis	35
Zahra Roozafzai	
Digital Technologies in Differentiation of Migrane-Like Headaches ...	54
Natalia Starikova, Iulia Jhelnina, Tatiana Baidina, Julia Karakulova, Tatiana Trushnikova	
Prevalence of anxiety and depressive disorders among labor migrants ...	61
Irina Shikina, Ekaterina Piterskaya, David Davidov, Aleksandra Moskvicheva, Denis Altunin	

Factors Influence Artificial Intelligence Decision-making Quality

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Abstract. Organizations are increasingly seeking ways to harness the power of artificial intelligence (AI) to enhance decision-making and build trust in the outcomes. While AI plays a significant role in shaping organizational thinking, concerns have been raised about the quality of its decisions—a topic that has received limited attention in the literature. This study aims to identify the key factors that influence the quality of AI-driven decision-making within organizational contexts. The study found that high-velocity data streams can overwhelm processing systems, often leading to incomplete analyses that distort the underlying reality. Additionally, when data is collected for different purposes or under varying contextual conditions, its relevance and reliability for AI-driven decision-making are significantly reduced. Without mechanisms to account for these contextual nuances, AI systems become prone to generating inaccurate or misleading outcomes. The findings highlight the critical need for robust processes to track, document, and communicate changes in data collection methods—particularly in environments where data is sourced from multiple, independent actors. Ultimately, the study concludes that the quality of AI decision-making is not solely a function of algorithmic sophistication but rather the result of a complex interplay between organizational, technical, and human factors.

Keywords: Artificial intelligence, decision-making quality, AI influence.

1. Introduction

Artificial Intelligence (AI) is rapidly reshaping how decisions are made across sectors, offering the potential for enhanced speed, consistency, and precision in solving complex problems. From personalized healthcare recommendations to predictive maintenance in manufacturing and policy targeting in public administration, AI-driven systems are increasingly relied upon to support or even automate critical decisions [1]. Yet, despite its widespread adoption and promise, there remains a fundamental question at the heart of AI's application: *What determines the quality of AI-driven decision-making?* While AI algorithms are often praised for their computational sophistication and ability to process vast volumes of data, high-quality decision-making is not solely a function of computational power or data availability [2]. In practice, the accuracy, fairness, relevance, and contextual soundness of AI decisions are influenced by a complex array of technical, organizational, and human factors [3]. These include how data is selected and labeled, the transparency and interpretability of model outputs, the governance structures surrounding AI deployment, and the capacity of end-users to understand and act upon AI-generated insights [4].

Unlike traditional decision support systems, AI operates in dynamic environments where decision quality is tightly coupled with the training data, learning algorithms, model assumptions, and feedback mechanisms embedded within the system [5]. For example, a recommendation algorithm in a retail setting may excel in short-term sales optimization but perform poorly when customer trust or long-term

loyalty is considered—revealing a gap between what is optimized and what truly constitutes a "high-quality" decision.

Moreover, the deployment of AI often involves cross-functional collaboration across data scientists, domain experts, IT teams, and decision-makers. Misalignment among these actors—such as differing priorities, levels of expertise, or interpretations of model results—can undermine the effectiveness of AI systems [6]. In some cases, organizational silos or insufficient feedback loops may result in decisions that are technically sound but contextually inappropriate or ethically questionable [7].

Although extensive research exists on the technical development of AI models, there is a notable lack of systematic inquiry into the socio-technical ecosystem that shapes AI decision quality [7]. Questions such as how organizational processes, human judgment, and ethical norms interact with algorithmic outputs remain underexplored. As AI moves from experimental environments to mainstream decision infrastructures, understanding these factors becomes not only relevant but essential [8].

The research question underlying this study is: What are the key factors that influence the quality of AI-driven decision-making in organizational settings? It adopts a systems-oriented perspective, recognizing that AI decision outcomes are shaped not just by data and algorithms, but also by the design of workflows, the involvement of stakeholders, and the feedback dynamics within organizations. By examining these dimensions in a real-world context, this study contributes to the growing discourse on responsible, effective, and context-aware AI.

The remainder of this paper is structured as follows: Section 2 presents a review of literature on AI decision-making and quality assessment frameworks. Section 3 outlines the research methodology used in the empirical case study. Section 4 presents the findings, identifying core technical and organizational influences on AI decision quality. Finally, Section 5 discusses the implications for AI design and governance, and Section 6 concludes with recommendations for future research.

2. Literature Review on AI Decision-Making Quality: A Framework

The pursuit of high-quality AI decision-making has emerged as a critical imperative across disciplines, yet achieving this goal requires navigating complex interdependencies that extend far beyond technical model performance [10]. While traditional approaches to AI development have focused primarily on algorithmic sophistication and computational power, contemporary research reveals that decision-making quality depends on a multifaceted ecosystem of technical, organizational, and human factors that must work in concert [11].

The AI decision-making lifecycle encompasses multiple structured stages, each presenting unique opportunities to enhance or compromise overall decision quality. These stages—from initial data capturing and storage through analysis and visualization—form the technical backbone of AI systems, but their execution varies dramatically across organizational contexts [9]. The critical insight emerging from recent scholarship is that 'who performs these tasks' and how they navigate socio-technical variability fundamentally shapes the quality of resulting decisions. This complexity becomes particularly evident when considering AI's relationship with big data. While AI systems leverage the traditional dimensions of volume, velocity, and variety, they introduce additional quality imperatives including veracity, value, variability, and volatility [12, 30]. The veracity dimension—encompassing data accuracy and trustworthiness—serves as a cornerstone of decision-making quality, as compromised data integrity cascades through the entire modeling pipeline, undermining not only predictive accuracy but also fairness and user trust [13].

The Multi-Dimensional Nature of Data Quality in Decision-Making

Data quality in AI decision-making transcends simple accuracy metrics to encompass completeness, timeliness, relevance, and consistency [30]. Each dimension contributes distinctively to decision-making quality, creating a compound effect where deficiencies in any area can compromise overall outcomes. Poor data inputs create a cascade of quality degradation, leading to flawed predictions, unintended consequences, and erosion of stakeholder confidence [16]. This phenomenon reframes traditional information systems challenges through the lens of algorithmic accountability and ethical AI deployment. The dependency on historical and externally sourced datasets introduces additional quality considerations, as AI systems must navigate temporal drift, selection bias, and representativeness issues that directly impact decision validity. Organizations must therefore develop sophisticated data governance practices that account for these quality dimensions throughout the AI lifecycle.

Organizational Readiness and Decision-Making Capacity

Effective AI decision-making quality depends critically on organizational maturity and institutional readiness [17]. Technical infrastructure alone proves insufficient; organizations must cultivate multi-level capabilities including algorithmic expertise, governance frameworks, risk mitigation strategies, and cross-functional collaboration. The success of advanced techniques such as deep learning and reinforcement learning hinges on domain-specific integration, requiring bespoke model tuning, continuous monitoring, and adaptive learning mechanisms that demand substantial organizational investment [29]. This organizational dimension of decision-making quality highlights the importance of institutional context in shaping AI outcomes. Organizations with deeper AI integration possess the resources and expertise necessary to maintain decision-making quality over time, while those with limited capabilities may struggle to achieve consistent results [18].

Human-AI Collaboration and Decision Quality

The human-AI interface represents a critical determinant of decision-making quality, where interpretability, trust, and user experience converge to influence outcomes [19, 31]. As AI systems increasingly function as decision aids rather than autonomous agents, the quality of human-AI collaboration becomes paramount. Decision-makers must possess the capability to interpret, validate, and when necessary, override algorithmic recommendations. The growing complexity and opacity of AI models creates an interpretability gap that directly threatens decision-making quality [20]. When decision-makers lack the cognitive or technical resources to understand model outputs, they cannot effectively validate recommendations or recognize potential errors. This challenge has catalyzed the development of Explainable AI (XAI) as a critical component of decision-making quality assurance [22].

Collaborative Processes and Quality Assurance

Organizational dynamics and team interactions profoundly influence AI decision-making quality. Research demonstrates that cross-functional collaboration between data scientists, domain experts, designers, and end-users enhances contextual understanding and reduces implementation gaps that can compromise

decision quality [15]. Conversely, siloed operations and misaligned mental models lead to AI system misapplication and suboptimal outcomes. Quality assurance in AI decision-making therefore requires robust governance structures, ethical deliberation processes, effective communication practices, and feedback loops that ensure alignment across the development and deployment lifecycle [21]. These collaborative processes serve as quality gates that help maintain decision integrity.

A Systems Approach to Decision-Making Quality

The quality of AI decision-making emerges from the complex interplay of multiple interconnected factors [14, 29]:

Data Foundations: *Input data quality and representativeness establish the baseline for all subsequent decision-making processes, requiring comprehensive attention to accuracy, completeness, and bias mitigation.*

Technical Robustness: *Model explainability and robustness ensure that AI systems can provide reliable, interpretable outputs that support high-quality human decision-making.*

Organizational Capabilities: *Domain integration and institutional readiness determine whether organizations can effectively implement and maintain AI systems that consistently deliver quality decisions.*

Human Factors: *User interpretability, trust, and oversight capabilities shape how effectively humans can collaborate with AI systems to achieve optimal outcomes.*

Governance Structures: *Collaborative processes and ethical frameworks provide the institutional scaffolding necessary to maintain decision-making quality over time.*

As AI systems become embedded in increasingly high-stakes decisions across domains such as healthcare, finance, criminal justice, and environmental policy, ensuring decision-making quality demands a comprehensive socio-technical systems approach[22]. This approach must account for the interdependence between technical design choices, institutional contexts, and human values to promote reliable, transparent, and equitable AI deployment. Future advances in AI decision-making quality will require continued research and practice that bridges technical innovation with organizational development and human-centered design [23]. Only through this integrated approach can we realize AI's potential to enhance decision-making while mitigating the risks of poor implementation and unintended consequences.

From the literature analysis, there is a recognition that AI decision-making quality is not merely a technical challenge but a complex socio-technical undertaking that requires sustained attention to the full ecosystem of factors that influence outcomes [24]. Success in this endeavor will determine whether AI fulfills its promise as a tool for improving human decision-making or becomes a source of new risks of information overload with lack of due diligence and inequities.

3. Methodology

Participants were 10 information systems (IS) experts who responded affirmatively to an invitation issued by this author through their IS lead. A url for the interview questionnaire used in this study was emailed to all participants and also forwarded to their Whatsapp platform by the lead. Among them, 70% (n=7) were males and the mean age was 38.3 (SD=8.83) years. The mean length of IS experience among the participants was 8.36 (SD=8.29) years. Nearly all the participants were IS/IT consultants advising on enterprise systems, digital transformation, and IT strategy (95%) and the mean years of AI service experience was 5.23 (SD=4.04).

Most of the IS experts (90%, n=169) hold at least a master's degree (e.g., MIS, MSc in IS, MBA with IS concentration).

A self-report interview guide was used for this study. In addition to providing their demographic information, participants responded to questions on data source quality, governance mechanism, organisational structure, AI data dynamics, collaboration, technological infrastructure and cultural adaptation. All items were presented in English. The items used in this study were adapted from published sources [14].

4. Results

From the qualitative analysis AI decision-making quality is shaped by a complex network of interrelated factors that evolve over time and across organizational contexts. A deep dive into the interview-based evidence reveals that the journey to embedding AI in decision-making is not linear but iterative, involving organizational adaptation, technological refinement, and shifts in governance [1]. The findings of this study, while not longitudinal in design, offer longitudinal insights through retrospective examination of the interviews, highlighting the dynamic and evolving nature of AI adoption within the organizational setting.

Initially, AI and Big Data Analytics (BDA) adoption began with ad hoc practices driven by curiosity or immediate operational needs. These early efforts were often isolated and lacked the structure necessary for high-quality decision-making. As the use of AI and BDA matured, the organization experienced a shift toward formalization and institutionalization. This shift involved structural changes such as the creation of a dedicated department separate from operational units, aimed at maximizing the potential of AI applications. The separation of AI functions from traditional operations allowed for more agile experimentation, rapid capability development, and the targeted recruitment of staff with relevant AI expertise [4].

A central insight highlighted by one participant is that the quality of AI decision-making is inextricably tied to the quality and governance of data—AI's foundational input. Data quality emerges as a critical determinant, as poor data leads to flawed algorithmic outputs. This reveals that different stages of the data value chain—from collection and cleansing to aggregation and analysis—introduce potential risks that can degrade AI decision outcomes [25]. These include errors due to noise, inconsistencies in naming conventions, differences in data granularity, and lack of contextual information. For AI systems to function optimally, there must be clear understanding and agreement on the context in which the data was gathered, how it will be processed, and how it should be interpreted.

Governance—both relational and contractual—was found plays a pivotal role in supporting AI-driven decision-making. Initially, relational governance dominated, with informal agreements and trust-based interactions facilitating data access and sharing. Over time, as the AI initiatives scaled and became integral to core decision-making, formal governance mechanisms gained importance [26]. Contracts and service-level agreements (SLAs) were introduced to standardize data quality, clarify responsibilities, and ensure the consistency and timeliness of data supply. These governance mechanisms were essential in institutionalizing AI use and mitigating risks associated with fragmented data ownership and inconsistent data standards.

Another major factor influencing AI decision-making quality is the capability of the workforce. The interview with the IS experts show that AI decision-making is not solely a technical challenge but also a human one. Skilled personnel are needed not only to build and maintain AI models but also to interpret the results and integrate them into decision-making processes. The shortage of individuals with the necessary blend of domain expertise, technical proficiency, and communication skills posed a significant barrier. As stated by a participant, skills gap is addressed, in part, by

forming partnerships with external AI firms and hiring specialists outside traditional public-sector recruitment channels. However, even with expert intervention, the integration of AI into established decision-making frameworks required a cultural shift within the organization, including the retraining of staff and the reengineering of processes [29].

Table 1. Factors influencing AI decision-making quality

Identified factors	Description
Data Quality	Fundamental to AI accuracy; poor-quality data (e.g., noisy, inconsistent, or context-lacking) leads to flawed outputs. Attention needed across the data lifecycle: collection, cleansing, aggregation, analysis.
Governance Mechanisms	Transition from informal (relational) to formal (contractual) governance ensured data quality, standardized responsibilities, and enabled scalable AI use.
Workforce Capability	AI decision-making requires skilled personnel with both domain knowledge and technical proficiency. Skills gaps were addressed through partnerships and strategic hiring, but internal cultural shifts were also necessary.
Organizational Structure	Separation of AI functions from core operations enabled agility, experimentation, and focused expertise development. Structural adaptation was key for institutionalizing AI.
Technological Infrastructure	Initial limitations required manual effort; later, flexible infrastructure improved system integration, speed, and real-time decision-making.
Algorithmic Suitability	Choosing the right AI models and tools was challenging, requiring domain understanding and iterative experimentation to match analytical tools with decision needs.
Data Dynamics (Velocity, Variability, Veracity)	Fast-changing and heterogeneous data can overwhelm systems or distort outcomes. Contextual mismatches or misaligned data purposes reduce reliability.
Human Judgment	Experienced decision-makers were crucial in interpreting and integrating AI outputs appropriately. AI augments rather than replaces human judgment.
Collaboration	Effective communication and co-creation among data providers, analysts, AI developers, and end-users ensured relevance, understanding, and actionable insights.
Cultural Adaptation	Adoption required rethinking workflows, retraining staff, and shifting organizational culture to embrace data-driven decision-making.

AI capabilities have the tendency to influence decision-making quality [23]. The study highlights the challenge of selecting appropriate algorithms and tools, particularly when dealing with complex, multi-variable data. Participants indicated that analysts faced difficulties in visualizing data outputs and identifying patterns, which often necessitated iterative experimentation and deep domain understanding, which prolongs the quality process. Moreover, limitations in existing systems and infrastructure initially required extensive manual effort to process data [24]. In this regard, establishment of a flexible infrastructure enables better system integration, reducing lead times and enhancing real-time decision-making capabilities.

Concerning data, the dynamic nature of AI applications further complicates decision-making. Factors such as data velocity, variability, and veracity introduce uncertainty into the decision-making process [12]. For instance, high-velocity data streams can overwhelm processing systems, resulting in partial data analysis that misrepresents the underlying reality. Similarly, if data is collected for different

purposes or under different contextual conditions, its relevance and reliability for AI decision-making diminish. AI systems, without mechanisms to understand these contextual nuances, are vulnerable to producing erroneous or misleading outcomes. The study underscores the importance of having mechanisms in place to track, document, and communicate changes in data collection methods, especially in environments where data originates from multiple independent actors. This goes a long way to improve AI decision-making quality.

The experience and interpretive skills of decision-makers using AI outputs also influence the overall decision quality. AI systems do not replace human judgment but rather augment it [28]. The more experienced the decision-makers, the better they were at understanding the strengths and limitations of AI outputs and using them appropriately. Early adoption was characterized by both enthusiasm and uncertainty, as users grappled with legal, ethical, and operational implications of AI-generated insights. Over time, greater familiarity with AI tools and outputs led to improved confidence and more effective integration into decision-making.

A recurring theme in the interview study is the necessity of collaboration—between data providers, AI developers, analysts, and end-users [20]. Effective collaboration mitigated the risks of fragmented knowledge and facilitated the alignment of AI tools with decision-making needs. Communication was essential, not just in interpreting data but in setting shared expectations about data usage, limitations, and goals. AI systems achieved better performance when technical and domain experts co-created analytic solutions, ensuring that AI insights were relevant, interpretable, and actionable.

In conclusion, the quality of AI decision-making is shaped by a confluence of factors including data quality, governance structures, workforce capabilities, infrastructural flexibility, algorithmic suitability, and human judgment. These elements do not operate in isolation; rather, they interact in a dynamic and often reinforcing manner. As AI continues to evolve, organizations must approach its integration holistically—by not only investing in technology but also rethinking their structures, practices, and cultures to support informed and reliable AI-driven decisions.

5. Implications for Policy and Research

The dynamic and evolving landscape of artificial intelligence (AI) adoption in organizations presents important implications for business research, particularly in enhancing decision-making quality. The interview-based insights into AI implementation reveal that high-quality decision-making is not merely a function of sophisticated algorithms but is contingent on a constellation of interrelated factors—organizational, technological, human, and contextual. For the businesses, these findings underscore the need for a holistic research agenda that bridges technical innovation with organizational realities, especially in public and global governance contexts. A foundational implication is the centrality of data quality in AI decision-making. Business research must prioritize understanding how organizations can systematically ensure the integrity, consistency, and contextual relevance of data throughout its lifecycle. From data collection and cleansing to aggregation and analysis, each stage introduces risks that can distort AI outputs. Research is needed to develop scalable data governance models that are adaptive across sectors and geographies, particularly in environments where data is fragmented or originates from multiple independent actors, such as those found in many organisational-led development projects.

Governance structures represent another vital area. The case study illustrates a shift from informal, trust-based governance to formal contractual mechanisms (e.g., service-level agreements) as AI initiatives mature. For international organizations,

this transition holds lessons for structuring multi-stakeholder data ecosystems. Business research can inform best practices for data-sharing agreements, ethical AI oversight, and interoperability standards that align with global development goals.

Also the interview revealed that the workforce dimension warrants focused inquiry. AI systems do not operate autonomously; they require skilled professionals to develop, interpret, and apply outputs effectively [27]. Business research should explore strategies to bridge the talent gap through hybrid skill development, cross-sector partnerships, and adaptive organizational learning. For the technology firms, this means examining how to cultivate AI readiness in public institutions, especially in low- and middle-income countries, through capacity-building programs that integrate domain knowledge with digital literacy.

Another insight with profound research implications is the importance of organizational structure and culture in AI adoption. The establishment of autonomous AI units within organizations enabled agility and specialization, which improved experimentation and decision integration. Business researchers can investigate models of structural decoupling that enhance innovation without creating silos. Equally, research should address how cultural resistance to AI can be mitigated through change management, participatory design, and inclusive governance mechanisms. The interpretive role of human judgment is a recurring theme. Business research should move beyond the technical performance of AI to examine how decision-makers interact with and trust AI outputs. Understanding the cognitive, ethical, and institutional factors that shape this interaction is key to promoting effective and responsible AI adoption in complex decision environments.

Finally, the collaborative dimension of AI deployment—between data providers, analysts, developers, and end-users—emphasizes the need for interdisciplinary research. AI solutions co-developed with domain experts are more likely to be interpretable and actionable. For the organisations, this supports an approach where AI is embedded not only in technology strategy but also in human development and governance frameworks. In sum, business research must evolve to address AI decision-making quality as a multi-level, adaptive process. This calls for integrative frameworks that consider data, governance, people, and systems together—ensuring that AI-driven decisions are not only technically sound but also ethically grounded, contextually relevant, and socially beneficial.

6. Conclusion

This study highlights that AI decision-making quality is not determined solely by the sophistication of algorithms but by a complex interplay of organizational, technical, and human factors. The journey to effective AI integration is iterative and deeply contextual, shaped by evolving governance mechanisms, workforce capabilities, infrastructural readiness, and cultural adaptation. High-quality data and robust governance emerge as foundational enablers, while human judgment and collaborative practices ensure that AI outputs are interpreted and applied meaningfully.

For organizations, including global institutions, the implications are clear: successful AI adoption requires more than technical investment. It demands structural alignment, strategic talent development, clear data stewardship, and mechanisms to foster trust, learning, and collaboration across all stakeholders. Business research has a critical role to play in advancing these dimensions by offering insights into how AI can be responsibly and effectively embedded into real-world decision-making contexts. Ultimately, improving AI decision-making quality is not just a technological goal—it is a systemic and strategic endeavour that must be pursued with deliberate coordination, inclusive design, and continuous learning.

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Aims and Objectives

Published online by Institute of Cited Scientists, Cyprus, two times a year, Journal of Digital Science (JDS) is an international peer-reviewed journal which aims at the latest ideas, innovations, trends, experiences and concerns in the field of digital science covering all areas of the scholarly literature of the sciences, social sciences and arts & humanities.

The principal ambition of this periodical is the efficacious propagation of original insights and outcomes derived from human cerebral activity and exemplified in scholarly treatises through the utilisation of contemporary information and digital technology.

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