



**ARTIFICIAL INTELLIGENCE ADOPTION AND
ORGANIZATIONAL PERFORMANCE: THE MEDIATING ROLE
OF DECISION-MAKING QUALITY**

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Abstract:

Artificial Intelligence (AI) is becoming popularly known as a strategic enabler of organizational change, but little empirical evidence exists explaining how the adoption of AI translates into improved organizational performance. The paper will fill this gap by analyzing how the quality of decision making mediates the relationship between the use of AI and organizational performance. The paper is based on the theory of Dynamic Capabilities and the Resource-Based View, which suggests that AI is a capability that improves decision-making processes, which will subsequently lead to performance outcomes. The research design adopted was a quantitative and cross sectional research design using a data collected by the researcher on 240 respondent managers. Partial Least Squares Structural Equation Modeling (PLS-SEM) of ADANCO was used to analyze the proposed model. The findings show that the adoption of AI has a robust positive impact on the quality of the decisions and the performance of an organization. The quality of decision-making is also an important factor in the organizational performance. The mediation analysis supports the idea that the quality of decision-making is a mediator of the relationship between the AI adoption and performance, which is why it is the critical element influencing the choice of underlying mechanisms. The results are useful to the literature as they unpack the process that creates organizational value and goes beyond the direct effect models to a more subtle, process oriented viewpoint. The research also provides some practical advice, indicating that the organizations need to supplement the investments in AI with the initiatives that will improve the decision-making processes. In general, the study can give a solid idea of how and under what conditions the adoption of AI can result in excellent organizational performance.

Keywords: Artificial Intelligence, performance, viewpoint, Dynamic Capabilities, managerial expertise

INTRODUCTION

The fast proliferation of AI technologies is transforming the way organizations create insights, distribute resources and maintain a competitive edge. Since predictive analytics through to intelligent automation ([Sandhu, 2025](#)), AI has no longer been a subject of experimental implementations but a significant enabler of organizational change ([Gala & Vashishtha, 2025](#)). Companies in industries are also integrating AI into decision making expecting that the implementation of data-driven intelligence will lead to efficiency, responsiveness, and alignment of the industry. Although this usage has become quite widespread, empirical research on the problem of whether and how AI transforms into a better organizational performance remains scattered and, at times, inconclusive ([Hyiamang et al., 2025](#)).

One of the factors that have led to such mixed purposes is the propensity of the previous research to analyze the direct interconnection between the adoption of AI and the subsequent performance results, without focusing on the inner processes that result in the creation of value ([Perifanis & Kitsios, 2023](#)). The enhancement in organizational performance is not achieved by merely using advanced technologies but it is achieved when the said technologies play a significant role in influencing the decision making process. The quality of decision-making as an accurate, timely, comprehensive, and goal-oriented approach has become a critical but understudied pathway in this context ([Sedky, 2026](#)). With the ability to process large amounts of structured and unstructured data, AI systems can be used to augment human cognition, reduce biases, and facilitate evidence-based decision-making ([Vashisht et al., 2025](#)). However the level to which these capabilities are successfully converted into high quality decisions is dependent upon organizational processes, skills, and integration practices.

This gap comes as an indication of the necessity to go beyond the simplistic input-output-based approach to AI-enabled value creation and, instead, adopt a process-based view of AI-enabled value creation. Based on the reasoning of the Dynamic Capabilities Theory, one can conceptualize the adoption of AI as an organizational capability that would enable a firm to be more attuned to opportunities, exploit them through informed decision making, and restructure resources as a result ([Liu et al., 2024](#)). In such framing, the quality of decision-making can be viewed as a mediating process within the context of which the capabilities of AI can be transformed into better organizational results ([Neiroukh et al., 2024](#)). The same argument can be based on the Resource-Based View where AI is a valuable and rare resource, but the performance implications will be how effectively it is integrated into the managerial decision process ([Wamba-Taguimdje et al., 2020](#)).

Although recent studies recognize the importance of AI as a strategic tool, empirical research with explicit models describing the quality of decisions as a mediator between AI adoption and organizational performance is sparse, especially in developing and technology-transitioning environments ([Nasiru et al., 2025](#)). Most of the available literature concentrates on either the technological capabilities or the performance measures in isolation and there is a theoretical and empirical gap between the development of capabilities and the realization of outcomes ([Nasiru et al., 2025](#)). This shortcoming is particularly applicable to organizational contexts where the use of AI is still developing and managerial cognition and decision frames play a decisive role in the use of AI.

To fill this gap, the current research formulates and empirically tests a mediation model that is used to relate AI adoption to organizational performance via decision-making quality. Applying survey data (240 respondents) and analyzing the model using Partial Least Squares Structural Equation Modeling (PLS-SEM) with ADANCO, the study aims at providing strong evidence on both the direct and indirect effects. In this way, it adds to the ever-growing body of literature on AI and its impact on organizational performance in three ways.

First, it contributes to theoretical knowledge as it combines technology adoption with decision process views, which brings a more subtle explanation of the role that AI can play in creating organizational value. Second, it empirically confirms the quality of decision-making as a central mechanism, thus, responding to the calls of unpacking of the black box between digital capability and firm performance. Third, it offers practical advice to managers by noting that investments in AI should be complemented with organizational practices that can improve the quality of decisions, instead of basing it on the level of technological sophistication.

In this light, the study is answering a very crucial question, not only is there an improvement by AI in terms of performance, but what and how are the ways such improvements are made possible.

LITERATURE REVIEW

The adoption of Artificial Intelligence and Organizational Performance

The relationship between the implementation of the AI and the performance of the organizations has been starting to receive an increasing scholarly attention and interest, particularly in the areas of information systems and strategy management. AI adoption refers to the extent to which organizations deploy and integrate AI-driven tools, such as machine learning algorithms, predictive analytics, and intelligent automation, into their core business processes ([Nasiru et al., 2025](#)). Such technologies will likely improve efficiency, lower costs of operations and help the firms to react quickly to the market dynamics ([Domini et al., 2023](#)). In accordance with the existing literature, AI is used to improve performance by optimizing processes, the possibility to provide real-time information, and innovation capabilities ([Rinatovich, 2023](#)). Those companies that utilize AI are more likely to be associated with better customer relations, improved productivity, and better financial results compared to those companies that do not use AI. In theory, the Resource-Based View indicates that AI can be an excellent and hard-to-replicate strategic resource that can give a competitive edge in the long term when well utilized ([Javed et al., 2026](#)).

Simultaneously, the empirical results do not have uniform consistency. In some studies, the benefits of AI adoption depend on the complementary organizational capabilities, including data governance, employee skills, and managerial expertise ([Schouten & Metzinger, 2021](#)). This implies that AI in itself may not yield better performance but instead its effect will be based on its integration into organizational practices and decision making. Considering the opportunities of AI to increase efficiency and strategic performance, the hypothesis below is suggested:

H1: The implementation of Artificial Intelligence has a powerful positive effect on the work of an organization.

Adoption of Artificial Intelligence and quality of decision-making

The use of AI technologies is radically changing the methods of making decisions in organizations. The traditional decision-making process could be described as relying heavily on managerial intuition and small datasets and the systems that are enabled by AI could process vast amounts of data to provide data-driven insights ([Seremeti & Anastasiadou, 2025](#)). This has far reaching implications to the quality of the decision making that encompasses the aspects such as accuracy, timeliness, rationality and comprehensiveness ([Ahuja, 2024](#)). The quality of the decisions made by AI systems can be improved with reducing the number of cognitive biases, identifying the latent tendencies within the data, and delivering predictive skills that can facilitate proactive strategies ([Rich & Gureckis, 2019](#)). To give an illustration, machine learning models could assist the managers in estimating the demand, streamlin

supply chains, and identify new risks (Zein, 2025). The capabilities enable the organizations to move out towards reactive to proactive decision-making approaches.

According to the Dynamic Capabilities Theory, AI will increase the ability of a firm to sense and interpret the alterations in the environment thereby improving decision processes (Rais et al., 2026). By successfully incorporating AI into their operations, organizations are then better placed to achieve informed and timely decisions to meet strategic goals (Giachino et al., 2024). However, the quality of data, the degree to which users trust the AI systems and preparedness of an organization determine the level of the positive change in the quality of decision-making. Such advantages are subject to reduction due to ineffective implementation or the inflexibility of AI tools and managerial requirements. To defend this argument the hypothesis will look as follows:

H2: There is a strong positive influence of the adoption of Artificial Intelligence on the quality of decisions.

The Quality of Decision-Making and the Organizational Performance.

The quality of decision making is core in the outcome of the organizational success. The quality of the decisions is normally regarded in terms of alignment with the strategic objectives, dependence on the correct information and efficacy of the decision in terms of the resolution of the organizational issues (Sedky, 2026). Such types of decisions directly impact the performance of the operational performance, the outcomes of innovation and the overall performance of the firm (Li, 2023). Strategic management studies have shown that an organization that has an excellent decision making process is likely to perform better than its competitors as it is better equipped to efficiently allocate its resources and respond to the uncertainties in the environment (Cohen & May, 2025). Effective decision-making can be effective, aiding in enhancing coordination among functions, reducing errors and enhancing long-term value creation (Panpatte & Takale, 2023).

Within the context of the AI-based organizations, the quality of decision-making is even more prominent. The ultimate impact of the these tools on the performance, however, depends on the manner in which the managers interpret and apply the tools (Manjula, 2025). Quality decisions will mean that AI-generated insights will be converted into actionable strategies (Shukla, 2024), thus closing the gap between the capabilities of technology and the results of organizations. Based on this, the hypothesis below is suggested:

H3: The quality of decision-making has a significant, positive effect on the organizational performance.

Mediation of the quality of Decision-Making

Although AI adoption is set to impact the organizational performance, its impact is not expected to be completely direct. It is more of a process in which AI capabilities compliment internal processes that subsequently help in the performance outcomes (Nasiru et al., 2025). One of such important mechanisms is quality of decision making. As per the mediation perspective, AI improves the quality of any decisions since it provides data-driven insights, which, in turn, lead to the increase in the quality of the results of any particular organizations (Massab et al., 2025). This can be aligned with the Resource-Based View and the Dynamic Capabilities Theory wherein resources and capabilities are the determinants of performance through the intermediate processes and not necessarily through direct means (Neiroukh et al., 2024).

Empirical research in the related areas, including business analytics and digital transformation, suggests that the advantages of advanced technologies are achieved when they help to

improve managerial cognitions and decision efficacies (El Namaki, 2023). This emphasizes the need to consider decision-making quality as an intervening variable as opposed to considering it as a periphery variable (Nabot, 2023). Including the quality of decision making in the model, this research will cover the “black box” between the adoption and performance of AI, which will provide a more detailed understanding of how the technological investments translate to tangible outcomes. Therefore, the hypothesis below is put forward:

H4: The quality of decision making mediates between the adoption of Artificial Intelligence and the performance of the organization.

METHODOLOGY

The research design used in this study is quantitative and cross-sectional in nature to investigate the relationships between Artificial Intelligence (AI) adoption, quality of decision-making and organizational performance. A sample of 240 respondent managerial was used to collect data using a structured questionnaire that was administered online. A purposive sampling technique was used in order to make sure that the participants had the relevant experience in the field of AI-enabled decision processes. Multi-item scales based on well-established work were used to measure all constructs with reasonable modifications based on the context. Indicators were used to operationalize the adoption of Artificial Intelligence, which included the scale of AI adoption, data-driven decision-making, the use of predictive analytics, and the automation of organizational processes. These items are based on the previous research on the use of AI and big data capability, which capture technological adoption and intensity of analysis (Mikalef et al., 2019; Wamba et al., 2020; Gupta and George, 2016). The quality of decision-making was assessed with the help of the items which captured the quality of decision-making: the accuracy of the decision-making process, the timeliness of the latter, its rationality, and its effectiveness. These are based on the classical and modern literature on decision-making, where the quality of decisions is conceptualized in terms of how much decisions are informed, systematic and aligned with the organizational aims and objectives (Dean and Sharfman, 1996; Elbanna and Child, 2007; Nutt, 2008). The subjective performance indicators were used to measure the organization performance improvement in the areas of efficiency, productivity and total effectiveness as compared to the competitors. Subjective performance measures have been widely and validated in management research where objective data are hard to come by (Venkatraman and Ramanujam, 1986; Delaney and Huselid, 1996; Richard et al., 2009). The answers were noted on the five-point Likert scale between the stronger disagree and stronger agree. The operationalization of AI adoption was in terms of the level of integration of AI in organizational processes, quality of decisions captured the effectiveness and rationality of decisions, and organizational performance was determined using subjective performance measures.

The suggested model was examined with the help of Partial Least Squares Structural Equation Modeling (PLS-SEM) using ADANCO. The analysis was done in two steps, the first step was to assess the measurement model (reliability and validity) and the second step was to test the structural model (testing the hypothesis). Cronbach alpha, composite reliability, average variance extracted (AVE), and HTMT ratios were used to evaluate reliability, convergent and discriminant validity, respectively. The 5,000 resamples bootstrapping was used to test the significance of path coefficients and mediation effects. The common method bias was resolved by procedural remedies and statistical tests such as the single-factor test of Harman. Ethical considerations were observed by making participation voluntary and anonymity of respondents.

4. RESULTS ANALYSIS

The partial least squares structural equation modeling (PLS-SEM) in ADANCO was used to perform the empirical analysis with bootstrapping (5,000 resamples). The assessment was done in two steps; the measurement model and the structural model.

4.1 Measurement Model Assessment

Construct Reliability

The DijkstraHenselers rho (rhoA) and Joreskogs rho (rhoC) were used in examining the internal consistency reliability. Cronbach alpha (alpha) was used in the examination of the internal consistency reliability. Table 4.1 shows that all the constructs are above the recommended measure of 0.70 which indicates a high degree of reliability. In most cases, the values are below the upper bound of 0.95-0.97 which does not indicate any concern of redundancy.

Table 4.1: Construct Reliability

Construct	ρ_A	ρ_C	Cronbach's α	AVE
Artificial Intelligence Adoption (AIA)	0.9621	0.9616	0.9615	0.8068
Organizational Performance (OP)	0.9487	0.9482	0.9482	0.7534
Decision-Making Quality (DMQ)	0.9535	0.9528	0.9528	0.7711

These findings corroborate the fact that the measurement items are always reflective of their respective latent constructs.

Convergent Validity

The measurement of convergent validity was conducted with the help of the Average Variance Extracted (AVE). All of the AVE values presented in Table 4.1 will be above the threshold of 0.50, which confirms that each of the constructs will explain more than half of the variance of the indicators of the construct. This means that there is high convergence between the measurement indicators.

Discriminant Validity

Both the HTMT criterion and FornellLarcker criterion were used to evaluate discriminant validity. As Table 4.3 demonstrates, all the values of the constructs are less than the conservative value of 0.90, which suggests that the constructs are empirically different.

Table 4.2: Discriminant Validity (HTMT)

Construct	AIA	OP	DMQ
AIA	—	—	—
OP	0.8018	—	—
DMQ	0.7484	0.8457	—

Similarly Table 4.3 emphasizes the FornellLarcker Criterion, the square root of AVE (diagonal elements) is greater than inter-construct correlations which also confirms the discriminant validity. Combined with the findings, the results provide a sufficient level of discriminant validity.

Table 4.3: Fornell–Larcker Criterion

Construct	AIA	OP	DMQ
AIA	0.8068		
OP	0.6433	0.7534	
DMQ	0.5627	0.7166	0.7711

4.2 Structural Model Assessment

Model Fit: The assessment of the model fit was done using SRMR, d_ ULS and d_ G. The SRMR value (0.0197) is far below the threshold of 0.08. The values of the discrepancy are smaller than the corresponding values of HI95 and HI99, which indicates that there is no significant model misspecification. Such values facilitate a model fit that is acceptable.

Structural Model Results: The relationships in the hypotheses were tested based on bootstrapping procedures. The findings have been summarized in Table 4.5. The results show that Artificial Intelligence Adoption has a positive and statistically significant impact on Organizational Performance ($\beta = 0.3819, p < 0.001$), which supports H1. AIA also has a strong positive effect on Decision-Making Quality ($\beta = 0.7501, p = 0.001$), helping to prove H 2. In turn, Decision-Making Quality has a significant impact on Organizational Performance ($\beta = 0.5600, p < 0.001$), in favor of H3.

Table 4.4: Results of Structural Model (Direct Effects)

Hypothesis	Path	β	t-value	p-value	Decision
H1	AIA \rightarrow OP	0.3819	7.2871	0.000	Supported
H2	AIA \rightarrow DMQ	0.7501	22.3967	0.000	Supported
H3	DMQ \rightarrow OP	0.5600	10.4258	0.000	Supported

Figure 4.1 shows a visual representation of the structural model that includes path coefficients that are standardized.

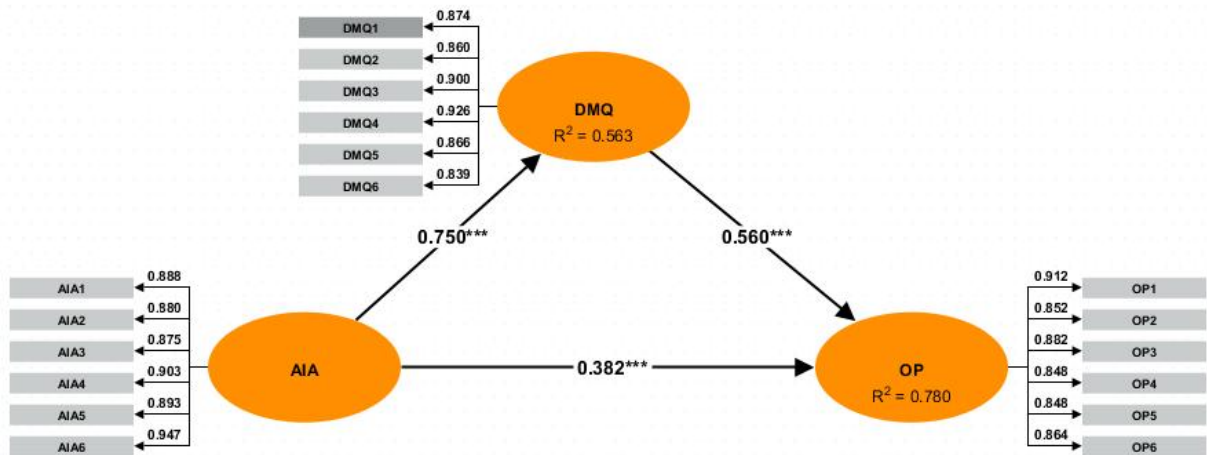


Figure 4.1: Structural Model containing Path Coefficients.

Coefficient of Determination (R^2): R^2 were used to measure the explanatory power of the model. The results indicate that AIA accounts the 56.3% of the variance in Decision-Making Quality and AIA and DMQ jointly explain 78.0% of variance in the Organizational Performance. The values of these values show that they have high predictive accuracy.

Mediation Analysis: Decision-Making Quality was used to test the mediating role of its bootstrapped test. Table 4.5 shows the indirect and total effects. The mediating effect is positive and statistically significant, which confirms that the mediating role is played by the Decision-Making Quality between AI adoption and organizational performance. The confidence interval does not include the value of zero (see bootstrap quantiles), which further supports the strength of the mediation effect.

Table 4.5: Mediation Analysis

Effect Type	Path	β	t-value	p-value	Result
Indirect Effect	AIA \rightarrow DMQ \rightarrow	0.4201	9.7274	0.000	Significant

	OP				
Direct Effect	AIA → OP	0.3819	7.2871	0.000	Significant
Total Effect	AIA → OP	0.8020	30.9134	0.000	Significant

The mediation can be defined as partial mediation since both direct and indirect effects are significant. This confirms H4 and demonstrates that the adoption of AI has both a direct and an indirect impact on performance, as well as an impact on performance via a positive effect on the quality of decisions made. The findings depict a steady trend. The use of Artificial Intelligence can improve the performance of organizations directly and at the same time improve the quality of decisions. The power of the indirect pathway underscores the pivotal position of decision processes in the conversion of the technological adoption into concrete performance outcomes.

DISCUSSION AND IMPLICATIONS

The empirical results are rather conducive to the proposed model, with all the hypothesized relationships found to be significant, which is why the adoption of Artificial Intelligence (AI) can be translated into the enhancement of the organizational performance. The fact that the use of AI is correlated with the performance of the organization supports the idea that AI-enabled capabilities can help organizations to gain efficiency, innovate, and develop competitive advantages. Companies that integrate AI into their work and strategic processes are better placed to apply information that is data-driven, streamline the process and respond to the changing environment (Nasiru et al., 2025). Meanwhile, the findings point to the fact that the impact of AI is not merely technological, but one based on the organizational processes.

The strong correlation between the use of AI and the quality of the decision-making process is a testimony to the transformative potential of AI in changing the way of thinking and making decisions among managers. By processing large amounts of data, identifying trends and making predictive forecasts, AI systems allow organizations to make decisions that are more accurate, timely and comprehensive (Kini et al., 2025). This confirms the perspective that AI is a cognitive enhancement tool and not a substitute to human judgment that enhances managerial abilities and minimizes biases in decision-making. The results also confirm that the quality of decisions has the direct and positive impact on organizational performance as the high quality of decisions is the core of the effective resource allocation, strategic alignment and problem-solving.

One of the main contributions of the study is that it has determined the mediating role of decision-making quality in the relationship between AI adoption and organizational performance. The findings show that the adoption of AI has both direct and indirect effects on the performance through the improvement of the decision-making process, which unpacks the underlying mechanism by which AI creates value. This fills a very critical gap in the previous studies, which have tended to assume that AI adoption and performance are directly related but are missing the discussion of the processes that occur between the two. As explained within the framework of Dynamic Capabilities Theory, AI improves the ability of a firm to sense and interpret the signals in the environment, and the quality of the decisions taken reflects the ability of a firm to capture opportunities and exploit them successfully (Giachino et al., 2024). Likewise, according to the Resource-Based View, AI is a good and useful resource whose contribution to the performance would be determined by its successful integration into organizational routines and decision frameworks. The results altogether imply that AI proves to be more valuable to organizations when it is integrated into decision-making systems that give greater importance to the data-driven and analytically-based judgments.

There are a number of relevant theoretical implications of the study. It contributes to the body of literature by incorporating the technology adoption and decision-making perspectives into a single framework and showing that the outcomes of organizational performance are influenced not just by the existence of advanced technologies but also by the processes involved in utilizing advanced technologies. The study addresses calls to lift the lid on the black box between digital capability and firm performance. The addition of the Dynamic Capabilities Theory and the Resource-Based View, further enhance the theoretical foundation by connecting AI adoption with resource-based benefits as well as process-based capabilities to further extend their application in the context of emerging digital technologies.

In managerial perspective, the findings highlight the fact that the advantages of AI implementation cannot be achieved by the implementation of technologies alone. To promote data-driven decision-making, organizations need to work on improving the quality of their decision-making by aligning AI systems with the managerial workflow, investing in employee training, and promoting a culture that values data-driven decision-making. Managers are advised to see that AI generated insights are well interpreted and translated into actionable strategies, instead of having to rely on intuition or old decision-making models. The findings also shed light on the need to develop organizational capabilities that will facilitate the introduction of AI to daily decision-making processes, including the organization of data governance, the cross-functional teamwork, and the continuous learning processes.

On a larger scale, the results have consequences to the policymakers and industry stakeholders. The adoption of AI needs not only the technological infrastructure but also the human capital and organisational preparedness development. Efforts to improve digital skills, promote the use of AI-based transformation, and encourage responsible use of technology can be of critical importance to help organizations fully realize the benefits of AI-driven transformation.

Although the study offers a strong empirical evidence, it as well opens up possibilities of further investigation. Further studies can explore more mediating or moderating factors (such as an organizational culture, leadership style, or technological preparedness) to build a more robust picture of AI-enabled performance. Longitudinal designs may assist in gaining a more profound understanding of how the impact of AI adoption changes over time and help to create a firmer causal interpretations.

CONCLUSION

The authors are interested in this study to investigate how adoption of Artificial Intelligence (AI) affects the performance of organisations that have an underlying mechanism of action, which is the quality of decision making. The results show that the adoption of AI does not only affect performance directly in a positive way but also has a positive impact on the quality of decisions, which consequently leads to better organizational performance. This two-way process highlights the point that the actual value of AI is that it can help improve managerial decision making processes and not so much as a stand-alone technological solution. The study provides a better account of how the AI capabilities are converted into performance improvements by putting the quality of decision making as a primary mediator. These results confirm the relevance of both Dynamic Capabilities Theory and Resource-Based View to the concept of AI-enabled transformation in which the resources and capabilities generate value when effectively integrated into the organizational processes. Collectively, the analysis offers both theoretical elucidation and practical guidance in the idea that organizations aiming to make the most out of AI should look at enhancing the quality of decisions that are facilitated by such technologies.

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