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ARTIFICIAL INTELLIGENCE-DRIVEN DIGITAL TRANSFORMATION MODELS FOR ENHANCING ORGANIZATIONAL COMMUNICATION AND DECISION-MAKING EFFICIENCY

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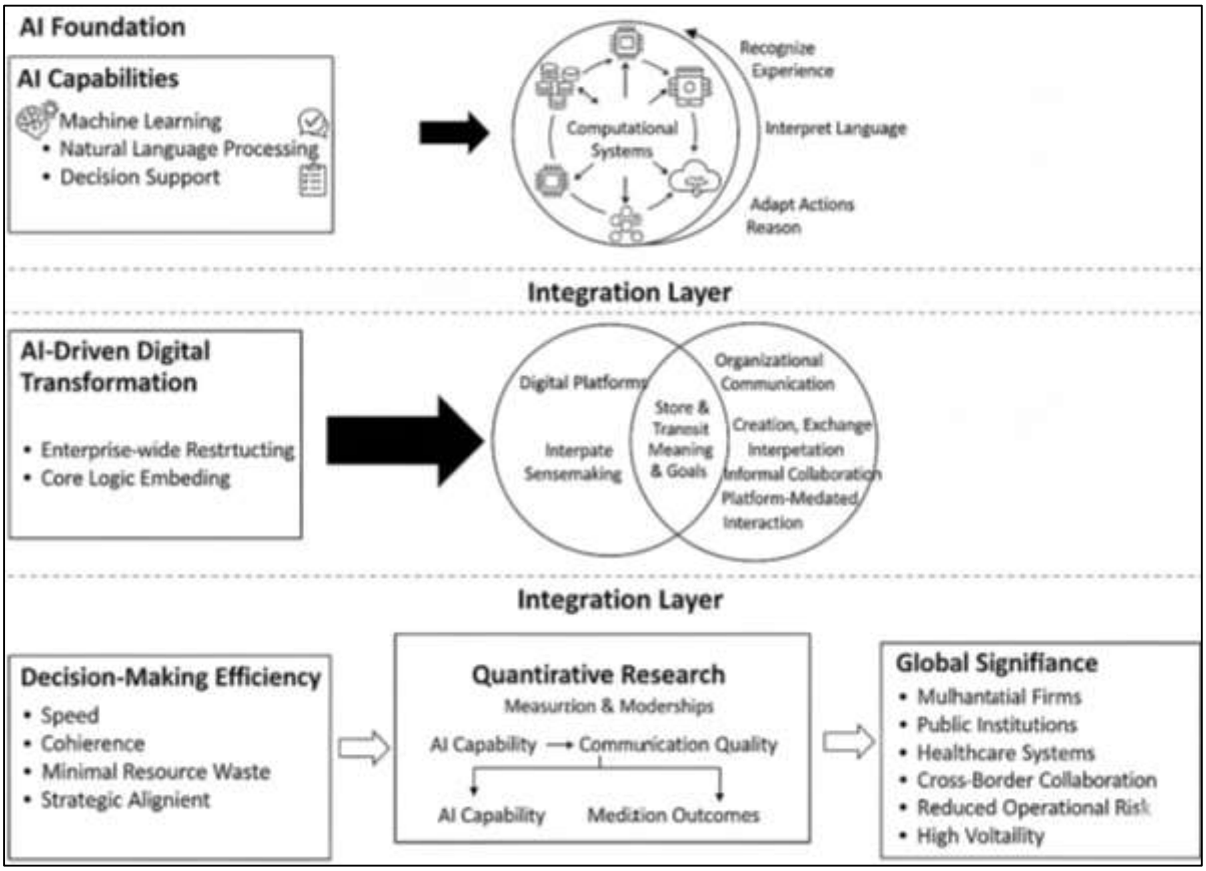
Abstract
This quantitative study investigated how artificial intelligence (AI) capability and digital transformation (DT) maturity influenced organizational communication quality and decision-making efficiency, with communication quality tested as a mediator and DT maturity as a moderator. The literature review synthesized evidence from 68 prior quantitative papers to refine construct definitions, measurement logic, and empirical pathways. A cross-sectional survey was conducted with 412 respondents from AI-adopting organizations across multiple sectors. Descriptive results indicated moderate-to-high levels of AI capability (M = 3.71, SD = 0.64) and DT maturity (M = 3.62, SD = 0.61). Communication quality recorded the highest mean (M = 3.84, SD = 0.59), followed by decision-making efficiency (M = 3.68, SD = 0.62), and distributional diagnostics supported parametric modeling. Measurement quality was strong (Cronbach's a = .86–.93; CR = .88–.94; AVE = .60–.70), and CFA fit was acceptable (CFI = .95, TLI = .94, RMSEA = .05, SRMR = .04). Correlations among principal constructs were positive and significant, with no multicollinearity risk (VIFs < 2.10). Structural modeling confirmed all hypothesized direct effects: AI capability positively predicted communication quality (β = .58, p < .001) and decision-making efficiency (β = .33, p < .001), and communication quality positively predicted decision-making efficiency (β = .49, p < .001). Mediation testing showed a significant indirect effect of AI capability on decision efficiency via communication quality (β_indirect = .28, p < .001), indicating partial mediation. Moderation analysis demonstrated that DT maturity strengthened the AI-to-decision efficiency relationship (β_interaction = .14, p = .001). Overall, the findings supported an integrated mediated–moderated model explaining how AI-driven digital transformation enhances communication and decision efficiency in organizational settings.

Keywords
Artificial Intelligence, Digital Transformation, Communication Quality, Decision Efficiency, DT Maturity

INTRODUCTION

Artificial intelligence (AI) is broadly defined as the design and deployment of computational systems capable of executing tasks that typically require human intelligence, such as recognizing patterns, learning from experience, interpreting language, reasoning with incomplete information, and adapting actions to changing environments (Saurabh et al., 2022). In organizations, AI is most often embodied through machine learning algorithms that infer relationships from structured data, natural language processing tools that parse and generate human language, and decision-support engines that recommend actions based on probabilistic evaluation of alternatives. Digital transformation refers to an enterprise-wide process of restructuring strategies, processes, and cultural routines through digital technologies so that organizations can create value in more data-intensive, interconnected, and responsive ways (Taherizadeh & Beaudry, 2023).

Figure 1: AI-Driven Digital Transformation Framework



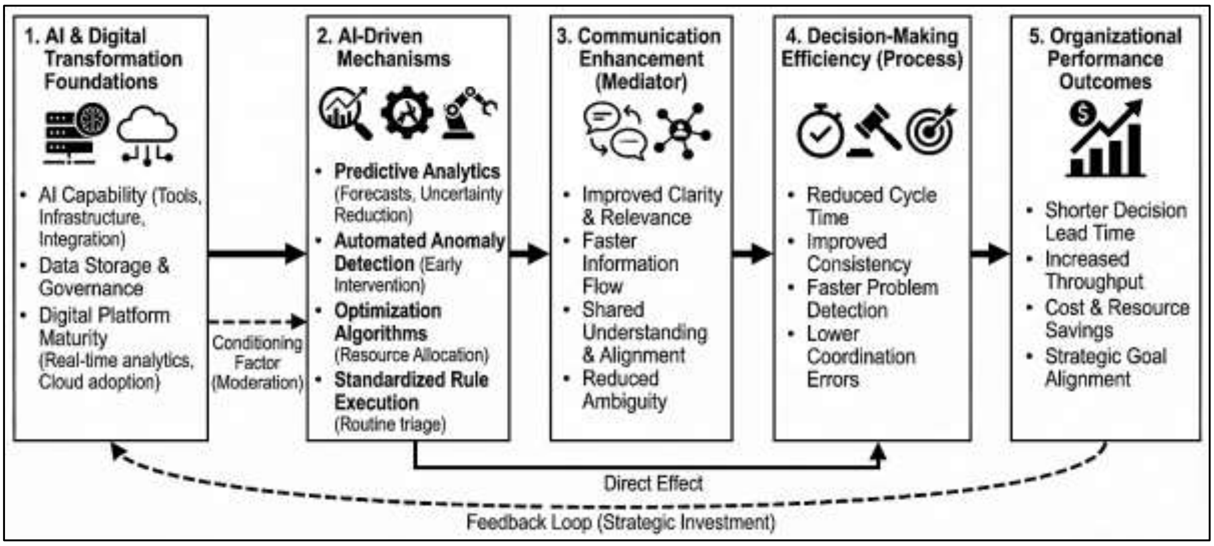
The idea of AI-driven digital transformation extends this definition by emphasizing AI not as an auxiliary tool but as a core logic embedded into transformation programs. In this framing, digital platforms do more than store and transmit information; they interpret signals, automate sensemaking, and route knowledge dynamically to relevant actors. Organizational communication is the continuous creation, exchange, and interpretation of meaning among individuals and groups who coordinate toward shared goals. It includes formal reporting, informal collaboration, platform-mediated interaction, and cross-boundary knowledge sharing. Decision-making efficiency is defined as the degree to which decisions are produced with speed, accuracy, coherence, and minimal resource waste, while remaining aligned with organizational priorities. Quantitative research on AI-driven digital transformation examines measurable relationships among AI capability, digital infrastructure use, communication quality, and decision outcomes. These relationships matter internationally because organizations increasingly operate in networks characterized by rapid information exchange, distributed teams, multilingual stakeholders, and high volatility in markets and public environments (Yablonsky, 2022). Communication delays or distortions can amplify operational risk, while inefficient decision cycles can erode competitiveness, service quality, and institutional legitimacy. AI-driven transformation models therefore function as structured explanations of how intelligent systems interact with human workflows and digital infrastructures to reshape communication accuracy, coordination latency, and decision performance. Such models are essential for quantitative inquiry because they specify constructs, expected causal pathways, and measurable indicators that can be tested across industries, regions, and organizational sizes (Brem et al., 2021).

The global significance of AI-driven digital transformation arises from the scale and complexity of contemporary organizational ecosystems. Multinational firms coordinate supply chains that span continents; public institutions manage population-level services through digital portals; healthcare systems rely on coordinated diagnostic and administrative flows; universities and research bodies collaborate across borders; humanitarian organizations operate across jurisdictions under crisis conditions. In each setting, the capacity to communicate clearly across hierarchical and geographic boundaries and to convert information into timely decisions becomes a fundamental performance driver (Rajagopal et al., 2022). Digital transformation expands the reach and speed of communication via cloud platforms, enterprise resource systems, collaborative tools, and mobile infrastructures. AI deepens this transformation by enabling automated translation, semantic search, anomaly detection, predictive forecasting, and conversational interfaces that allow stakeholders to access or disseminate knowledge with less friction. AI-supported communication systems can filter noise, highlight urgent issues, and tailor messages to user roles, thereby increasing interpretive alignment. In decision environments, AI can compress cycles of data gathering, option evaluation, and risk estimation, generating recommendations that managers can validate. Efficiency gains become visible through measurable outcomes such as reduced reporting time, improved response rates, fewer coordination errors, shorter process lead times, and higher consistency across comparable decisions. The international context emphasizes additional pressures: cultural variation affects message interpretation, regulatory environments require auditable decisions, and remote or hybrid work reduces opportunities for informal clarification (Pappas et al., 2023). AI-driven digital transformation models provide a structured way to represent these realities by linking technological capability with organizational performance through communication and decision pathways. These models matter because they help organizations allocate investment across data systems, analytics, and human skill development while maintaining accountability. Quantitative approaches allow researchers to examine whether AI capability predicts communication clarity, whether platform integration mediates decision speed, and whether governance quality moderates these effects. International relevance also emerges from unequal digital maturity across economies (Frick et al., 2021). Some environments feature advanced data infrastructures and high AI readiness; others struggle with fragmented systems, low data quality, or limited analytical talent. AI-driven transformation models help compare such contexts by identifying essential components that enable measurable improvements, such as data governance, interoperability, and user trust. By focusing on quantifiable relationships, researchers can generate evidence that is portable across sectors and nations without relying on single-case narratives (Frick et al., 2021).

AI capabilities alter organizational communication by reshaping how information is generated, routed, interpreted, and archived. Traditional communication systems depend on human attention to draft messages, interpret meaning, and coordinate follow-up actions. AI introduces computational mediation that can detect relevance, summarize content, suggest responses, and personalize communications based on context (Wamba-Taguimdje et al., 2020). In internal environments, AI-driven tools can analyze large message streams, identify repeated questions, and recommend standardized answers, reducing ambiguity. Semantic search and intelligent document retrieval allow employees to locate accurate information faster, which increases shared understanding and reduces redundant communication. Natural language processing enables automated summarization of meetings, extraction of action items, and classification of messages by priority. These functions can be operationalized through measurable indicators such as response timeliness, message clarity ratings, reduction in repeated queries, or increased retrieval success. AI also supports communication across functions by standardizing data definitions and ensuring that different departments interpret key metrics consistently. For example, when AI harmonizes customer or operational datasets, cross-functional reporting becomes more coherent because stakeholders work from a shared informational base. In distributed organizations, AI can translate messages, detect tone mismatches, and flag potential misunderstandings, enabling smoother collaboration across languages and cultural norms (Gölzer & Fritzsche, 2017). Communication quality in AI-driven transformation models is not merely about speed; it includes interpretive accuracy, alignment of meaning, and reduction of misinformation. When systems automatically validate inputs against data rules, they prevent incorrect or conflicting messages from circulating. AI-based recommendation systems can route updates to the most relevant recipients, limiting overload and increasing attention to critical information. These features also influence informal communication. Chatbots in enterprise platforms can provide instant support, enabling employees to clarify procedural issues without waiting for human intermediaries. The quantitative study of these effects typically treats AI capability as an independent construct measured through adoption intensity, functional breadth, or maturity of AI applications. Communication outcomes can be measured through survey scales of perceived clarity, network analysis of interaction patterns, or operational metrics such as reduced escalation frequency (Gobble, 2018). AI-driven digital transformation models hypothesize that AI capability improves communication by lowering friction in knowledge exchange, increasing accuracy, and enabling more synchronized coordination. A rigorous quantitative introduction therefore needs to frame communication improvements as measurable mediators linking AI capability to decision outcomes, setting up testable pathways rather than abstract claims (Huang et al., 2021).

Decision-making efficiency improves when organizations can move from raw data to validated action with minimal delay, error, and resource expenditure. AI-driven digital transformation contributes to this efficiency through several mechanisms that are observable and measurable. First, predictive analytics transforms historical and real-time data into forecasts that narrow decision uncertainty (Böhmer & Schinnenburg, 2023). This reduces time spent on manual scenario building and allows decision makers to focus on evaluating the most plausible alternatives. Second, automated anomaly detection highlights deviations in operations, finance, compliance, or customer behavior, enabling earlier intervention. Third, optimization algorithms provide ranked solutions under constraints, supporting resource allocation that satisfies multiple objectives simultaneously. Fourth, AI can standardize routine decision rules, ensuring consistent handling of high-volume cases such as credit approvals, inventory replenishment, scheduling, or service triage. These mechanisms reduce human cognitive load and compress deliberation cycles. In transformation models, these efficiency gains are typically expressed through outcomes such as shorter decision lead time, improved decision accuracy, reduced variance across equivalent decisions, increased throughput, or stronger alignment between decisions and performance indicators (Baptista et al., 2020). AI does not replace managerial judgment in complex settings; instead, it expands the informational base and provides structured recommendations that managers can interpret. This is particularly relevant for decisions occurring under information overload, where human actors struggle to process all signals. AI filters and prioritizes information, decreasing the likelihood that critical cues are missed. Digital transformation provides the infrastructural condition for these mechanisms: integrated databases, real-time dashboards, workflow automation, and cloud-based collaboration allow AI outputs to flow directly into decision routines. Quantitative studies examine these relationships by measuring AI application maturity, data integration level, and decision efficiency metrics. In many models, communication quality serves as a precursor to decision efficiency because decisions depend on accurate, timely, and shared understanding of information. When AI enhances communication, it indirectly enhances decision-making efficiency by improving the quality of inputs entering decision cycles (Cantú-Ortiz et al., 2020). A quantitative introduction should therefore position decision efficiency as a dependent construct influenced by both direct AI mechanisms and indirect communication improvements. This framing supports hypotheses about mediation, moderation, and cross-level effects, allowing empirical testing of how AI-driven transformation reshapes decision performance across teams and organizational units.

Figure 2: AI-Driven Digital Transformation Efficiency Framework



AI-driven digital transformation models generally specify interconnected components that can be operationalized for quantitative analysis (Ng et al., 2023). The first component is technological capability, which includes AI tools, computing infrastructure, data storage, and integration platforms. This capability is often measured through adoption breadth, system interoperability, automation depth, and analytical sophistication. The second component is data governance, referring to policies and controls over data quality, access, security, and lifecycle management. Governance matters because AI performance relies on reliable, consistent, and ethically managed datasets. The third component is process redesign, involving the reengineering of workflows so that AI outputs are embedded into routine operations rather than appended as optional reports. This includes automation of handoffs, alignment of decision checkpoints with AI analytics, and digitalization of communication channels. The fourth component is human capability, encompassing employee digital literacy, analytical skills, and willingness to collaborate with AI systems (Rowe, 2018). Human capability is measurable through training intensity, skill assessments, and perceived ease of use. The fifth component is leadership and strategic alignment, capturing how top management frames transformation goals, allocates resources, and sets accountability structures. Strategic alignment ensures that AI adoption targets communication and decision bottlenecks that matter for performance. The sixth component is organizational culture, which shapes trust in AI, openness to experimentation, and norms of knowledge sharing. Culture is often treated as a moderator affecting the strength of relationships between AI capability and outcomes. In communication-focused models, digital platforms act as the connective tissue linking these components: they allow AI to ingest data from processes, generate insights, and communicate them to humans at the right moment. Quantitative research benefits from such models because each component can be turned into measurable constructs, enabling path analysis or structural equation modeling (Martínez-Peláez et al., 2023). Researchers can examine which components most strongly predict communication quality, and whether communication quality explains improvements in decision efficiency. These models also allow multi-level analysis, where AI capability at the organizational level affects team communication networks, which then influence individual decision behavior. A detailed introduction must clarify these model components and their presumed relationships so that the subsequent empirical sections have a coherent theoretical basis grounded in observable variables (Malar et al., 2019).

The objective of this quantitative study is to examine how artificial intelligence–driven digital transformation models influence organizational communication and decision-making efficiency in measurable and explainable ways. Specifically, the study seeks to identify the extent to which AI capability within an organization predicts improvements in communication quality, including clarity, timeliness, relevance, and shared understanding among employees and teams. At the same time, the study aims to determine whether AI capability is associated with higher decision-making efficiency, operationalized through indicators such as reduced decision cycle time, improved consistency of choices, faster problem detection, and lower coordination errors during implementation. A central objective is to test an integrated pathway in which organizational communication quality functions as a mediating mechanism between AI-driven digital transformation and decision-making efficiency, meaning that AI-enabled transformation may improve decisions partly because it enhances how information is exchanged, interpreted, and aligned across the organization. In addition, the study intends to assess the role of digital transformation maturity as a conditioning factor that strengthens or weakens the effects of AI on communication and decisions, recognizing that AI tools operate differently in highly integrated digital environments compared with fragmented ones. Another objective is to compare these relationships across different organizational contexts—such as sector type, size, and structural complexity—by analyzing whether the magnitude of AI's impact varies according to organizational characteristics. The study also aims to produce a validated measurement framework by translating the constructs of AI capability, digital transformation maturity, communication quality, and decision-making efficiency into observable survey and operational indicators suitable for statistical modeling. Through regression-based and structural modeling approaches, the research objective is to quantify both direct effects (AI capability → decision efficiency) and indirect effects (AI capability → communication quality → decision efficiency), establishing how much variance in organizational outcomes can be attributed to AI-driven transformation inputs. Ultimately, the study aims to provide statistically grounded evidence on whether and how AI-centered transformation models serve as effective organizational designs for improving the speed and quality of internal communication and managerial decision processes in data-intensive work environments.

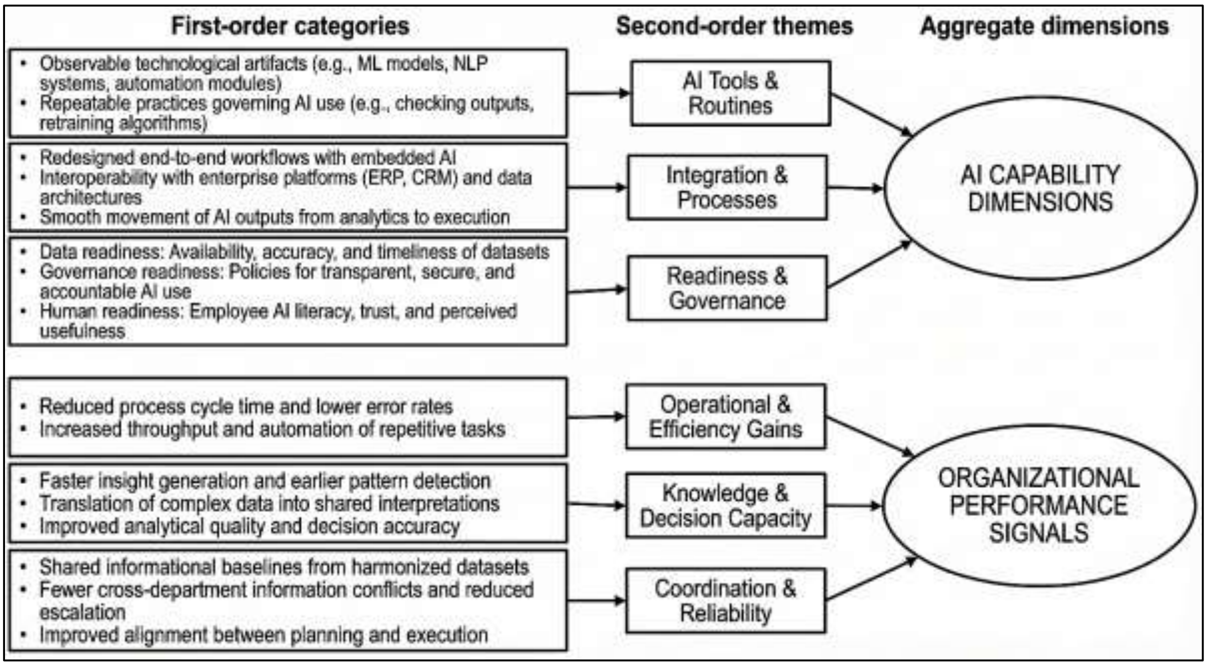
LITERATURE REVIEW

This literature review synthesizes empirical and theoretical work on artificial intelligence–driven digital transformation and its measurable effects on organizational communication and decision-making efficiency. The purpose of this section is to establish a rigorous scholarly foundation for the quantitative model by clarifying what is already known, how key constructs have been operationalized, and where empirical results converge or diverge. Because the present study tests relationships among AI capability, digital transformation maturity, organizational communication quality, and decision-making efficiency, the literature review is organized to mirror these constructs and the causal pathways linking them (Alahi et al., 2023). The section therefore begins by examining quantitative conceptions of AI capability and digital transformation models, emphasizing how researchers measure adoption intensity, functional breadth, system interoperability, and data governance readiness. It then reviews evidence on AI-enabled organizational communication, focusing on measurable outcomes such as communication timeliness, clarity, collaboration density, and knowledge-sharing effectiveness. Next, the review covers AI-based decision-making efficiency, highlighting quantitative indicators including decision cycle time, predictive accuracy, consistency of decisions, and error reduction. A dedicated part integrates the two streams by discussing studies that treat communication as a mediator or enabling mechanism for decision performance. The review also considers contextual moderators frequently tested in prior research—such as leadership alignment, organizational culture, employee analytics capability, trust in AI, and sectoral regulation—because these variables often explain why AI-driven transformation yields stronger effects in some organizations than others (Alahi et al., 2023). Throughout, the review prioritizes statistically grounded findings (e.g., regression, structural equation modeling, multilevel modeling, and panel data studies) so that the conceptual model and hypotheses of the present paper are anchored in measurable patterns rather than descriptive claims. By structuring the literature in this way, the section prepares a logically consistent basis for hypothesis development and quantitative testing in the subsequent methodology and results chapters (Walia et al., 2023).

Artificial intelligence Capability in Organizations

Artificial intelligence capability in organizations is defined in quantitative research as a structured, measurable ability to acquire, deploy, integrate, and leverage AI technologies so that they contribute to organizational goals through reliable learning, prediction, and automation (Rodgers et al., 2023). This capability is not synonymous with owning AI software or running isolated pilots; rather, it reflects an organization-level condition produced by the joint presence of technical AI assets, high-quality data environments, and the routines that embed AI outputs into day-to-day work.

Figure 3: Defining and Measuring AI Capability



Conceptually, AI capability is treated as a higher-order construct because it represents multiple interrelated dimensions that cannot be captured by a single indicator. Quantitative studies commonly emphasize three separable but connected layers. The first layer is AI tools, meaning the observable technological artifacts such as machine-learning models, language-processing systems, intelligent automation modules, and analytics platforms. These tools can be inventoried and categorized, and they represent the material base of AI adoption (Ouyang et al., 2023). The second layer is AI routines, which refer to repeatable organizational behaviors governing how AI is used, monitored, validated, and improved over time. Routines include practices such as checking model outputs, escalating exceptions, retraining algorithms, and standardizing AI-based reporting. The third layer is AI-enabled processes, defined as redesigned end-to-end workflows in which AI is structurally embedded into sensing, analyzing, communicating, and executing tasks. This process layer matters because AI becomes a true capability only when it changes how workflows, not merely how tasks are assisted. Another key concept in the literature is that AI capability functions as a socio-technical condition, meaning its effectiveness depends on alignment between technology and organizational context. For this reason, definitions of AI capability incorporate data readiness and governance readiness as essential conceptual components (Fan et al., 2021). Data readiness reflects the availability, integration, accuracy, and timeliness of datasets that allow algorithms to learn reliably. Governance readiness refers to policies and controls that ensure AI use is transparent, secure, ethical, and accountable. When these conceptual elements are combined, AI capability becomes a measurable organizational attribute that captures both the scale of intelligent technology use and the depth of its embedding into routines and processes. Such a definition provides the theoretical clarity required for statistical modeling because it specifies what should be measured, how dimensions relate, and why capability is distinct from simple digitalization or automation.

Quantitative literature operationalizes AI capability through validated multi-item dimensions that allow researchers to compare organizations consistently. A primary dimension is AI adoption intensity, reflecting how widely and frequently AI tools are used across functions, teams, and decision areas. Adoption intensity is measured through indicators such as the proportion of departments using AI applications, the frequency of AI-supported tasks, and the degree to which managers rely on AI outputs in operational or strategic activities (Hernández-Orallo, 2017). A second dimension is functional breadth, which captures the diversity of AI functions integrated into organizational workflows. Breadth indicators measure whether AI is used for multiple purposes—such as prediction, classification, recommendation, anomaly detection, automation, and language-based assistance—

rather than a single narrow task. Broader functional footprints are interpreted as evidence that AI is not peripheral but woven into organizational activity. A third dimension is AI integration maturity, describing how effectively AI systems interoperate with enterprise platforms such as ERP, BI dashboards, CRM systems, and collaboration suites (Gani et al., 2016). Integration maturity is measured through data-flow continuity, compatibility between AI models and operational systems, and the extent to which AI outputs appear in routine reporting and workflow triggers. A fourth dimension is AI data dependence and data readiness, which refers to the richness of the data environment required for AI learning. Quantitative studies use indicators related to data volume availability, update speed, variety of data sources, standardization of data definitions, and perceived data trustworthiness. Some measurement frameworks also include lifecycle management depth, which is operationalized through items about model monitoring frequency, retraining regularity, performance auditing, and the presence of specialized AI governance teams. Human and organizational readiness is frequently added as a complementary dimension, measured through employee AI literacy, training coverage, perceived usefulness of AI, and trust in AI recommendations (Wang et al., 2015). These dimensions collectively form composite indices or latent constructs in statistical models. The advantage of this multidimensional measurement approach is that it captures actual capability rather than symbolic adoption. An organization may show high adoption counts but low integration maturity, resulting in weak capability effects; conversely, moderate adoption paired with deep integration and governance can produce stronger outcomes. By specifying intensity, breadth, integration, data readiness, and human readiness, quantitative studies provide a robust basis for modeling AI capability as an explanatory variable linked to communication and decision outcomes. These dimensional structures anchor the current study's construct design by clarifying which measurable facets should be included, how they are typically scaled, and how they jointly represent AI capability in organizations (Choung et al., 2023).

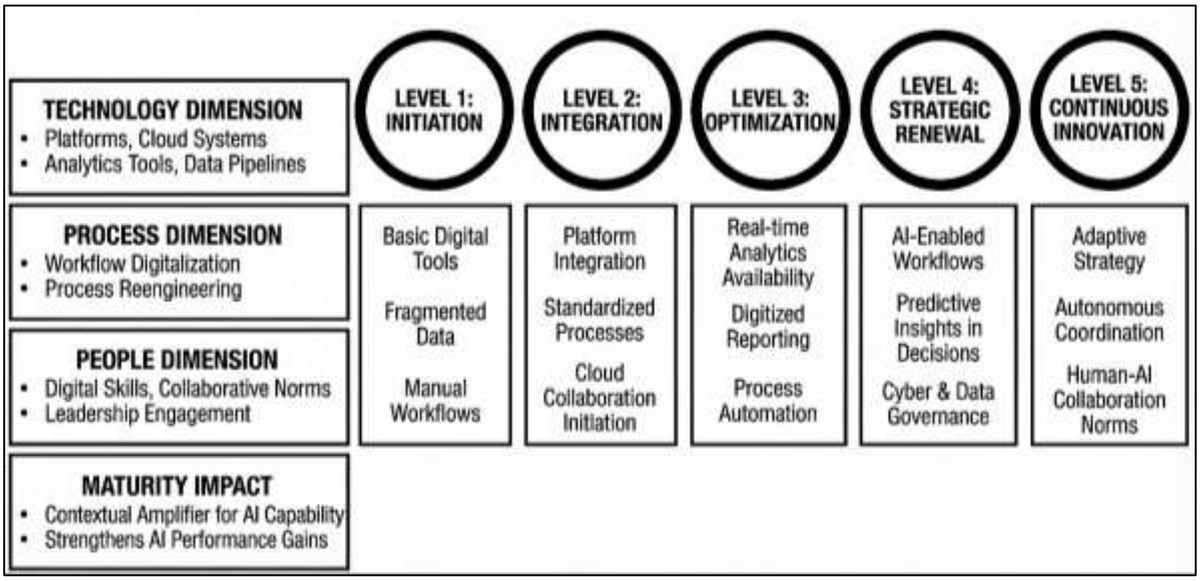
In empirical quantitative research, AI capability is treated as a central independent variable block that explains variation in organizational outcomes without relying on purely technological proxies. Researchers typically design measurement models that combine adoption intensity, functional breadth, integration maturity, and data readiness into one coherent explanatory construct (Li & Huang, 2020). Adoption intensity represents the depth of AI use and indicates whether AI outputs are repeatedly invoked in routine work. Functional breadth reflects the scope of organizational reliance on AI across different task families and decision classes. Integration maturity indicates whether AI is embedded within digital platforms and connected to enterprise data architectures, enabling outputs to move smoothly from analytics to execution. Data readiness and dependence indicate whether the information foundation feeding AI is sufficiently rich, timely, standardized, and reliable. When these measures are arranged into a unified independent block, quantitative models can estimate not only whether AI capability predicts performance, but also which facets drive results most strongly (Schepman & Rodway, 2020). Studies frequently show that treating AI capability as a multidimensional independent variable increases explanatory power compared with using single indicators such as AI investment or number of tools deployed. This is because capability effects depend on configuration: high adoption intensity yields weak outcomes if data readiness is poor; high functional breadth yields inconsistent outcomes if systems are not integrated; strong integration yields limited outcomes if employees do not trust or understand AI. Quantitative models therefore interpret AI capability as a compositional condition that emerges from socio-technical alignment. In regression or structural models, this independent block enables researchers to test direct impacts on operational efficiency, communication performance, and decision speed, while also allowing mediation testing through constructs such as communication quality (Savoia & Sen, 2015). The literature also uses AI capability to explain cross-organizational heterogeneity in digital transformation results. Organizations facing similar environmental pressures may display different performance outcomes because of differences in AI integration maturity, lifecycle management, or governance depth. By framing AI capability as a structured independent block, empirical studies move beyond generic claims of "AI adoption" and instead test precise relationships between measurable capability configurations and observable outcomes (Pinto-Coelho, 2023). This approach directly supports the current paper's quantitative design, which requires an independent variable with clear dimensionality, statistical validity, and theoretical coherence for testing effects on communication quality and decision-making efficiency.

The quantitative evidence base consistently associates stronger AI capability with improved organizational performance signals that are observable through operational metrics and validated scales. One dominant pattern is a positive relationship between AI capability and operational efficiency (Olan et al., 2022). Organizations with high AI adoption intensity and integration maturity tend to reduce process cycle time, lower error rates, increase throughput, and automate repetitive tasks that previously required manual judgment. Efficiency gains are not treated as automatic outcomes of tool ownership; instead, evidence indicates that efficiency improves when AI is embedded into workflows and paired with governance routines that sustain model reliability. A second evidence stream links AI capability to enhanced knowledge-processing capacity. Quantitative studies report that AI-capable organizations generate insights faster, detect patterns earlier, and translate complex data into shared interpretations across units. These improvements appear in measures such as analytical quality, decision accuracy, and employees' perceived ability to access relevant knowledge when needed (Mikalef et al., 2023). AI capability supports these gains by filtering noise, prioritizing signals, and enabling predictive analytics that compress the time between data availability and managerial understanding. A third performance signal involves coordination reliability. When AI capability is mature, organizations develop shared informational baselines because datasets are harmonized and algorithms apply consistent evaluation logic across functions. Coordination reliability is reflected in fewer cross-department information conflicts, reduced escalation frequency, improved alignment between planning and execution, and more consistent decisions across similar cases. Quantitative evidence also shows that these performance signals are interdependent (Wamba-Taguimdje, Fosso Wamba, et al., 2020). Enhanced knowledge processing supports faster and more coherent coordination; better coordination enables efficiency improvements to scale across organizational boundaries. The literature further demonstrates that AI capability effects vary with contextual conditions such as data governance quality, employee trust in AI, and digital transformation maturity. Strong governance and high trust typically strengthen the measurable impact of capability on efficiency and coordination, while weak governance dampens results even when adoption levels appear high. Collectively, the quantitative evidence supports AI capability as a statistically meaningful predictor of organizational performance and as a plausible driver of the communication and decision-making outcomes tested in AI-driven digital transformation models (Wamba-Taguimdje, Wamba, et al., 2020). This empirical base justifies focusing on AI capability as a foundational construct in the present study's model and hypothesis development.

Digital Transformation Maturity as a Measurable Organizational Condition

Digital transformation maturity is framed in quantitative research as a measurable organizational condition that captures how deeply digital technologies are integrated into strategy, operations, and people systems. Maturity models reject the idea that transformation is a simple yes–no status; instead, they describe transformation as a spectrum of capability development that can be quantified and compared across organizations. In staged models, maturity is represented through progressive levels such as initiation, integration, optimization, and strategic renewal (Gupta et al., 2022). Each level reflects a distinctive combination of digital infrastructure, process redesign, governance, and workforce readiness, allowing researchers to assign organizations to maturity categories. Continuous models treat maturity as an index derived from additive scores across domains of digital capability, recognizing that different aspects of transformation evolve at different speeds. Both modeling approaches are grounded in socio-technical reasoning that maturity equals the alignment of technology with process and human adaptation rather than technology deployment alone. A widely used quantitative logic is the technology–process–people triad (Malik et al., 2021). The technology dimension measures the presence and sophistication of platforms, cloud systems, analytics tools, and data pipelines. The process dimension measures how far workflows have been digitized, standardized, and reengineered to exploit digital capabilities.

Figure 4: Digital Transformation Maturity Progression



The people dimension measures digital skill levels, collaborative norms, leadership engagement, and cultural openness to data-driven work. These dimensions are typically specified as observable indicators that load onto a latent maturity construct, enabling regression, path analysis, or structural equation modeling. The literature uses maturity because it helps explain why comparable digital spending yields different outcomes: higher maturity reflects not just investment, but routinized use, interoperability, and governance stability (Audretsch & Belitski, 2021). Thus, DT maturity is conceptually treated as an organizational environment that shapes how effectively digital tools—including AI—can enhance communication, coordination, and decision performance.

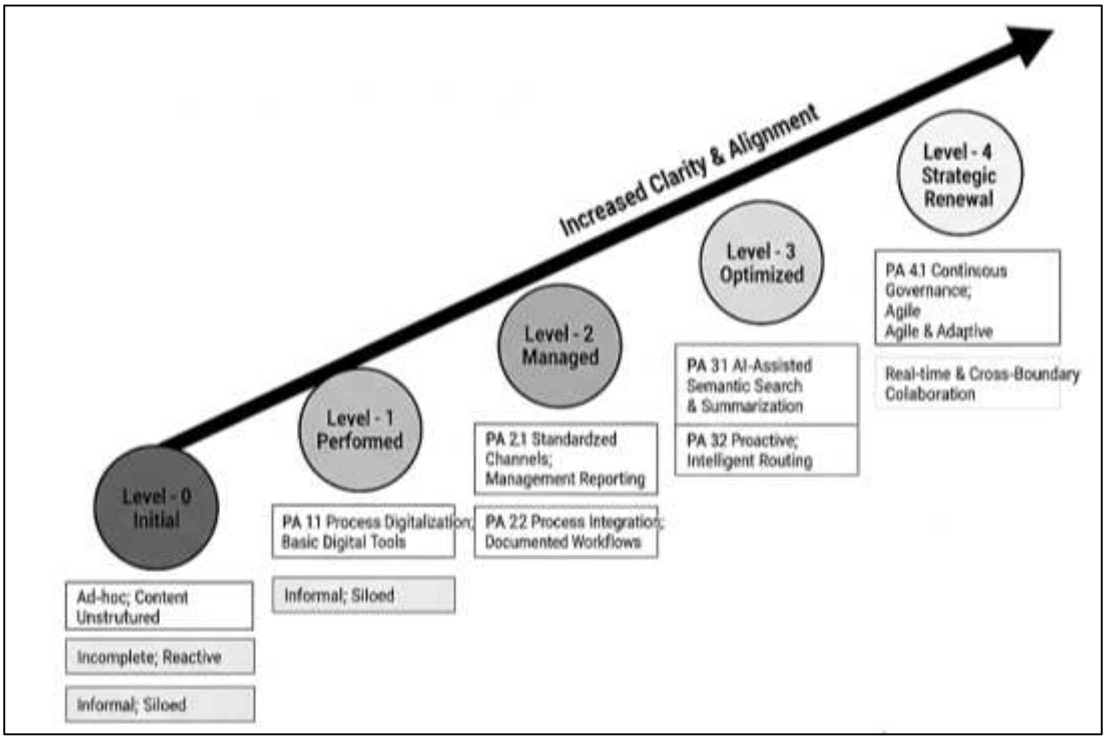
Quantitative studies operationalize DT maturity through consistent indicator sets that represent transformation depth in observable terms. The first indicator is the degree of process digitalization, measured by the proportion of core workflows executed via digital systems rather than manual procedures (Shamim et al., 2020). This includes automation of approvals, digitized reporting routes, digital customer or citizen interfaces, and standardized workflow engines. A second indicator is platform integration level, capturing how seamlessly enterprise systems interoperate through shared data standards and synchronized processes. High integration is measured through cross-department data flow continuity, real-time linkage between operational systems and analytics dashboards, and reduced reliance on manual handoffs. Real-time analytics availability is another major marker, assessed through the presence of live dashboards, streaming data architectures, predictive analytics usage, and the frequency with which managers consume real-time insights in routine cycles. Cloud collaboration penetration measures the breadth and intensity of cloud-based interaction, typically reflected in user coverage, the share of coordination conducted through cloud suites, and the extent of remote or cross-location project work supported by digital platforms (Shamim et al., 2020). Cyber and data governance readiness rounds out the indicator set by measuring the existence and enforcement of policies for data stewardship, access control, privacy assurance, compliance alignment, and auditability. These indicators are frequently combined into composite scores or latent variables representing DT maturity, and they are used as moderator or conditioning blocks in quantitative models. The logic is that maturity is not a single feature but a configuration: process digitalization without integration yields fragmented performance, analytics without governance reduces trust, and cloud collaboration without skilled users limits adoption. By measuring these indicators together, researchers can compare maturity across industries and test its role in strengthening or weakening the impact of AI on organizational outcomes (Zamani et al., 2023).

Empirical quantitative findings consistently show that DT maturity strengthens the measurable effects of AI capability on organizational performance, especially through interaction patterns observed in multivariate and structural models. Organizations with high DT maturity typically exhibit larger gains from AI adoption in areas such as communication quality, coordination reliability, operational efficiency, and decision speed (Gope et al., 2018). Statistical results indicate that when platforms are integrated and processes digitized, AI outputs can flow directly into work routines, allowing predictive insights or automated classifications to be acted on quickly and consistently. In contrast, low-maturity environments often display dampened AI effects because data are fragmented, workflows are not digitally routinized, and AI recommendations remain peripheral to actual decision checkpoints. Interaction effects reported in prior studies show that AI adoption intensity predicts stronger performance improvements only when maturity indicators—such as real-time analytics presence or platform interoperability—are high. Similar patterns appear for AI functional breadth, where diverse AI applications create measurable benefit primarily in mature digital settings that can coordinate multiple tools through shared governance and infrastructure (Ramanathan et al., 2017). Governance readiness is especially prominent in quantitative evidence: organizations with strong cyber/data governance show higher trust in AI outputs and lower model drift, which amplifies performance effects. People readiness within DT maturity further conditions AI impacts through higher user acceptance, smoother human–AI collaboration, and reduced resistance to algorithmic decision support. The evidence therefore positions DT maturity as a contextual amplifier rather than an independent substitute for AI capability. Mature transformation environments do not automatically produce superior outcomes, but they provide the stable digital foundation that allows AI to reshape communication and decision routines at scale. These statistical regularities justify treating DT maturity as a conditioning construct in quantitative models that examine AI-driven transformation effects.

AI-Enabled Organizational Communication: Quantitative Perspectives

Organizational communication quality is treated in quantitative research as a measurable construct that captures how effectively information is created, transmitted, interpreted, and coordinated among organizational members (Faruk & Islam, 2023). Rather than framing communication as a purely symbolic or cultural phenomenon, empirical studies operationalize it through observable dimensions that can be modeled statistically (Abdulla & Ibne, 2021). The most common dimensions include clarity, timeliness, accuracy, relevance, and shared meaning. Clarity refers to the extent to which messages are easily understood and reduce ambiguity in tasks or expectations. Timeliness reflects whether information reaches actors at a moment that enables action, often linked to cycle time and responsiveness in coordination (Ara, 2021). Accuracy indicates the correctness and reliability of communicated content, including whether data-driven updates align with operational realities. Relevance captures the degree to which information is targeted to appropriate roles and minimizes noise, overload, or redundancy (Habibullah & Foysal, 2021). Shared meaning denotes interpretive alignment, meaning that recipients understand information in a way that matches sender intent and organizational objectives. These dimensions are typically measured through survey scales assessing employee perceptions of internal communication effectiveness, combined with behavioral metrics such as frequency of cross-unit interaction or the stability of coordination outcomes (Arora & Sharma, 2023; Sarwar, 2021). Communication quality is especially emphasized in digital and hybrid organizations because interaction increasingly occurs through platform-mediated channels rather than face-to-face exchanges (Musfiqur & Saba, 2021). Digitalization expands speed and reach but also introduces risks of overload, fragmented message trails, and interpretive drift, making measurable quality safeguards more important (Redwanul et al., 2021; Reza et al., 2021). Quantitative studies show that communication quality mediates many technology–performance relationships because even advanced analytics or automation cannot translate into decisions unless information is perceived as clear, credible, and actionable by human users (Hasija & Esper, 2022; Saikat, 2021; Shaikh & Aditya, 2021). In this view, communication quality becomes a bridge construct linking technological capability with organizational decision performance. The mediator framing is grounded in evidence that improvements in clarity and timeliness reduce coordination friction, while improvements in relevance and shared meaning reduce rework and escalation. Consequently, communication quality appears in structural models as a proximal organizational outcome influenced by digital and AI capabilities and as an antecedent to decision efficiency and operational performance (Cadden et al., 2022; Al Amin, 2022; Ariful, 2022).

Figure 5: Organizational Communication Quality Model



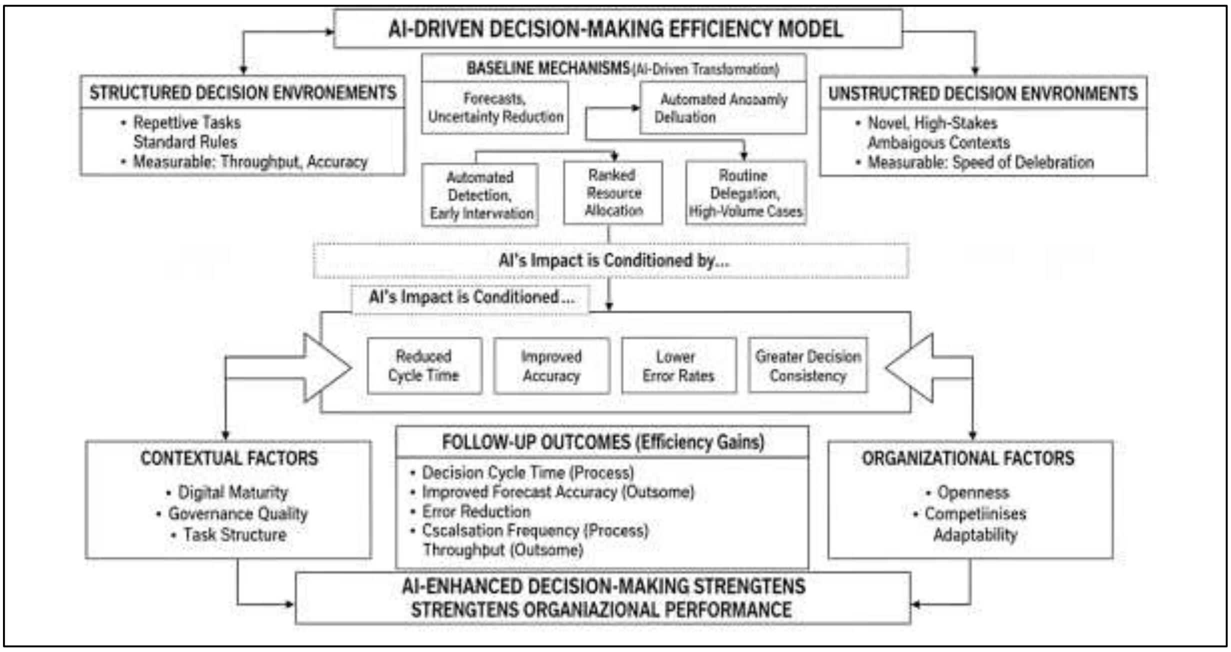
AI-enabled communication research focuses on how specific AI applications alter the internal dynamics of knowledge exchange and coordination in quantifiable ways (Ariful & Ara, 2022; Nahid, 2022). Natural language processing tools for summarization and content extraction are widely studied because they turn unstructured communication artifacts—emails, meeting transcripts, reports, and chat logs—into structured insights (Hossain & Milon, 2022; Mominul et al., 2022). These tools reduce the time employees spend scanning large message volumes while increasing the consistency of what is understood as key information. Semantic search and knowledge retrieval systems reshape communication by allowing employees to locate accurate documents, policies, or prior decisions with fewer intermediary queries, thereby shifting communication from repeated clarification to direct self-service (Böhmer & Schinnenburg, 2023; Mortuza & Rauf, 2022; Rakibul & Samia, 2022). Intelligent routing and prioritization applications apply AI to classify messages by urgency or topic and route them toward the most relevant individuals or teams. This reduces latency in problem resolution and limits overload by filtering low-priority content from high-attention channels. AI chatbots for internal service and knowledge support function as always-available communicative agents that answer routine questions, guide employees through procedures, and escalate complex cases to human operators (Saikat, 2022; Kanti & Shaikat, 2022). Quantitative studies emphasize that these tools not only speed up communication but also standardize it, producing more predictable and auditable message flows (Arfan et al., 2023; Ara & Beatrice Onyinyechi, 2023; Zhou et al., 2023). The effect of such AI applications depends on embedding within digital collaboration platforms so that AI outputs appear naturally within daily work rather than as detached analytics reports. Research also notes that AI reshapes informal communication because employees increasingly consult AI systems before contacting colleagues, which changes the volume and structure of human-to-human messaging. In hybrid and distributed organizations, AI tools enable cross-location communication by summarizing discussions for absent members, translating content where needed, and maintaining shared repositories of decisions and rationales (Lee et al., 2020; Mushfequr & Ashraful, 2023; Shahrin & Samia, 2023). The literature therefore treats AI applications as socio-technical interventions that reduce communication friction and increase interpretive alignment by combining automated language processing with redesigned information pathways (Hasan & Rakibul, 2024).
Empirical studies measure AI-enhanced communication through a combination of perceptual and operational indicators that allow statistical modeling of outcomes. A common operational indicator is

reduced response time, measured as the average duration between question and answer within digital channels, service desks, or workflow platforms (Farhi et al., 2022; Habibullah, 2025; Hozyfa, 2025). AI-based routing, chatbots, and summarization systems are linked to measurable drops in response time because they automate retrieval and triage tasks that otherwise require human availability. Lower repetition rates in queries represent another indicator, capturing how often employees ask the same procedural or informational questions multiple times across a period (Alam, 2025; Arman, 2025). When semantic search and internal AI assistants are effective, repetition frequency declines because users can retrieve validated information without repeated clarification (Asfaquar, 2025; Foysal, 2025). Higher perceived clarity scores are typically gathered through survey items assessing whether employees view internal communications as unambiguous, well-structured, and sufficiently detailed for action. These scores provide a perception-based complement to objective timing metrics. Denser cross-functional collaboration networks are measured through digital trace data or network analysis of platform interactions, including frequency of cross-unit messaging, reciprocity of communication ties, and diversity of communication partners (Malik et al., 2021; Mohaiminul, 2025; Mominul, 2025). AI tools that facilitate knowledge discovery and content summarization tend to increase cross-unit exchange because they lower the effort required to locate or interpret information from other departments. Improved alignment on key metrics is assessed through indicators showing whether different units report consistent interpretations of performance dashboards, operational targets, or decision criteria (Hasan, 2025; Milon, 2025). AI-enabled harmonization of data definitions and automated explanation features contributes to this alignment by reducing interpretive fragmentation. Quantitative literature highlights that these indicators often move together: faster response and lower repetition correspond to improved relevance and clarity, while denser collaboration patterns correspond to greater shared meaning. As a result, communication quality is frequently modeled as a latent construct reflected by these measurable indicators (Hunkenschroer & Luetge, 2022; Farabe, 2025; Rakibul, 2025). The emphasis on multi-indicator measurement strengthens construct validity and helps distinguish AI-driven communication enhancement from superficial increases in message volume or platform activity.

Decision-Making Efficiency Under AI-Driven Transformation

Decision-making efficiency is treated in quantitative scholarship as a dependent organizational outcome that reflects how effectively institutions convert information into timely, accurate, and coherent actions while minimizing unnecessary resource consumption (Pelly et al., 2023). Rather than describing efficiency in purely managerial terms, empirical studies operationalize it through observable dimensions that can be statistically modeled across contexts. Speed refers to how quickly decisions are reached after relevant information becomes available, often interpreted as a reduction in decision latency within operational or strategic cycles (Saba, 2025; Alom et al., 2025). Accuracy captures the extent to which decisions correspond to objective benchmarks, performance targets, or correct classifications of situations, typically measured through prediction error rates or outcome deviations from planned goals. Consistency represents the stability of decision logic across similar cases or time periods, indicating whether equivalent inputs yield equivalent choices, which is crucial for fairness, quality control, and reliability (Donadello & Dragoni, 2022; Praveen, 2025; Shaikat, 2025). Resource economy refers to the efficiency with which organizations use time, labor, and cognitive effort in decision routines, meaning fewer iterative loops, reduced escalations, and lower rework costs. Quantitative literature also distinguishes between structured and unstructured decision environments. Structured decisions involve repetitive tasks governed by standard rules—such as inventory replenishment, credit approval, or maintenance scheduling—where efficiency is measurable through throughput, accuracy rates, and cycle times. Unstructured decisions involve ambiguous, novel, or high-stakes contexts—such as strategic investment, crisis response, or policy redesign—where efficiency is measured through the speed and coherence of deliberation, the quality of scenario evaluation, and the alignment between decisions and dynamic environmental signals. This distinction matters because AI-driven transformation affects these decision types differently, and quantitative models often test separate pathways or effect magnitudes for structured versus unstructured domains (Donadello & Dragoni, 2022; Kanti, 2025). Across studies, decision-making efficiency is positioned as an outcome shaped by informational quality, analytical capability, and workflow integration, allowing it to serve as a focal dependent construct in models assessing the organizational impact of AI-driven digital transformation.

Figure 6: AI-Driven Decision-Making Efficiency Model



The quantitative literature identifies several AI mechanisms that explain why AI-driven transformation is associated with more efficient decision routines. Predictive analytics is one foundational mechanism, enabling organizations to infer likely future states from historical and real-time data, thereby narrowing uncertainty and accelerating option evaluation (Sheth et al., 2022). By producing probabilistic forecasts and risk estimates, predictive models reduce the time required for manual scenario building and help decision makers focus on the most plausible alternatives. Automated anomaly detection is another mechanism that improves decision efficiency by continuously monitoring data streams for deviations, outliers, or early warning signals. This shifts decision processes from reactive to earlier intervention cycles, which empirical research links to shorter resolution times and fewer escalated incidents. Optimization and recommendation systems provide structured decision support by ranking alternatives under constraints, such as cost, capacity, service level, or regulatory compliance. Quantitative studies show that such systems compress deliberation cycles by presenting prioritized solutions that humans can validate rather than constructing options from scratch. Routine decision rule automation represents a fourth mechanism, particularly effective in high-volume structured environments (Schmitt, 2023). Here AI applies consistent decision logic to repetitive cases, reducing processing time and variation while freeing human attention for more complex tasks. In socio-technical models, these mechanisms are not treated as isolated "tool effects"; they operate most strongly when integrated into digital workflows that connect sensing, analysis, communication, and execution. Empirical work also emphasizes that AI enhances decisions by filtering noise, prioritizing relevant cues, and providing transparent rationales or confidence levels, which reduces ambiguity and coordination friction during decision implementation. Together, these mechanisms offer a coherent explanation of how AI reshapes decision routines into faster, more accurate, and more consistent processes that can be measured quantitatively across organizational settings (Rajagopal et al., 2022).

Quantitative research translates decision-making efficiency into observable indicators that allow comparison across time, units, and industries. Decision cycle time is widely used as a primary metric, measured as the elapsed time between recognizing a decision need and executing a validated choice. Studies track cycle time in settings such as supply chain planning, service recovery, compliance response, and strategic review processes (Wamba-Taguimdje, Fosso Wamba, et al., 2020). Forecast accuracy improvement is another core indicator, typically captured through reductions in prediction error, higher classification precision, or closer alignment between projected and realized outcomes after

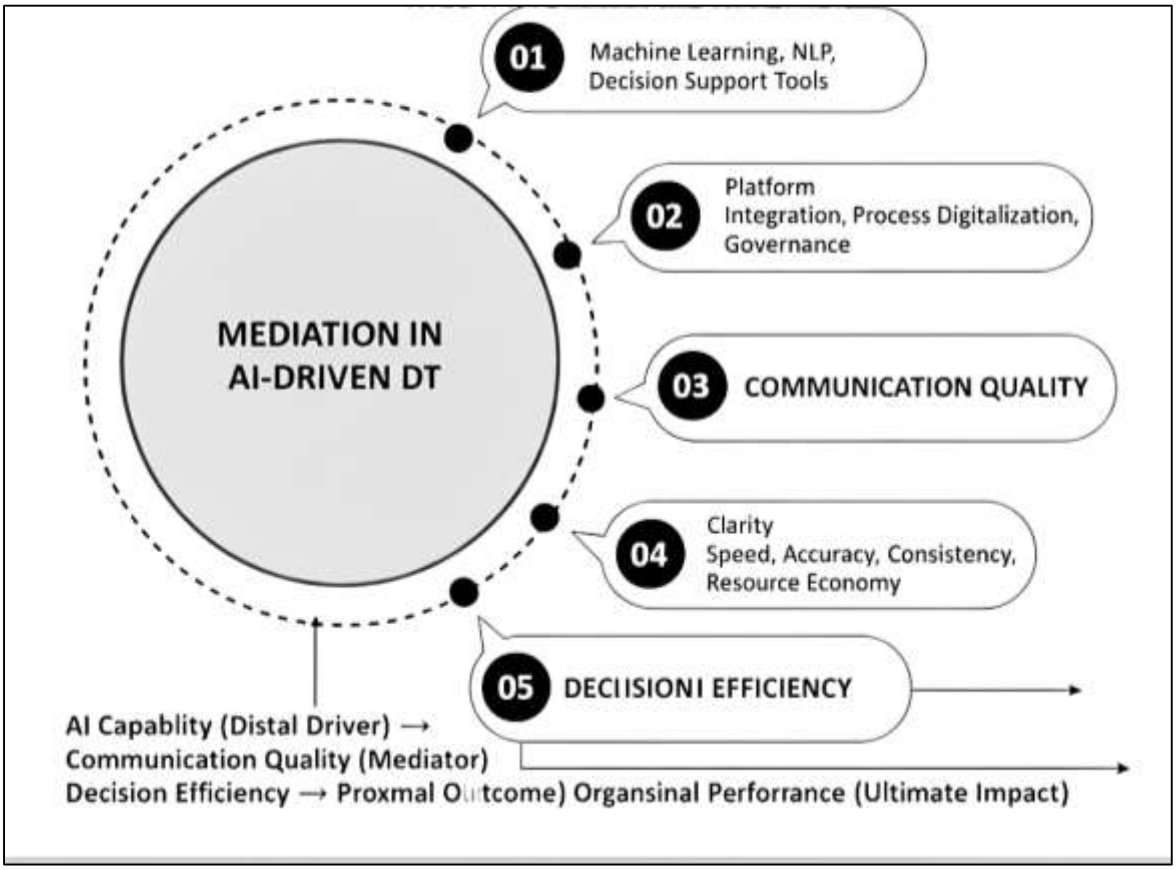
AI adoption. Error and exception reduction measures efficiency by observing declines in incorrect approvals, defective outputs, compliance breaches, or misallocated resources, which signal that decisions are both faster and better grounded. Consistency across similar cases is measured through variance reduction in decision outcomes when input conditions are equivalent, revealing whether AI-supported routines stabilize organizational logic over time. Escalation frequency decrease is a further indicator that captures how often decisions are pushed upward for clarification or override; lower escalation rates reflect clearer inputs, more reliable recommendations, and smoother implementation. Some studies combine these measures into latent efficiency constructs, while others test them separately to identify which dimensions AI affects most strongly (Charles et al., 2022). Quantitative literature also uses proxy indicators such as reduced meeting time per decision, fewer iterative approvals, increased throughput of decisions per period, and improved service-level adherence following decision execution. Importantly, the measurement approach recognizes that speed without accuracy is not efficiency; therefore, multi-indicator designs are used to show whether faster decisions are accompanied by equal or improved quality. These established measures provide a robust dependent-variable toolkit for evaluating how AI-driven transformation reshapes decision outcomes in both structured and unstructured environments (Gudigantala et al., 2023).

Empirical quantitative evidence generally supports a positive association between AI capability and decision-making efficiency, with results demonstrated through regression, structural equation modeling, multilevel analysis, and panel-based designs (Elgendy et al., 2022). Studies focusing on process-level outcomes often report stronger and more immediate efficiency gains, especially where AI is embedded into high-frequency routines such as demand forecasting, fraud detection, triage operations, or automated approvals. In these contexts, AI adoption intensity and integration maturity are statistically linked to shorter decision cycle times, higher prediction accuracy, and lower exception rates. Firm-level studies also show significant effects, though these are often mediated by intermediate capabilities such as analytics culture, data governance, or communication quality, and may display smaller effect sizes because outcomes aggregate across diverse decision domains. Boundary conditions are repeatedly highlighted in the literature (Lysaght et al., 2019). Decision efficiency gains are larger in environments where tasks are data-rich, moderately stable, and governed by clear performance criteria, because AI models can learn reliably and recommendations fit existing workflows. Gains are weaker where decision environments are highly complex, ambiguous, or regulated without sufficient digital integration, because AI recommendations may be harder to validate or to embed in formal decision checkpoints. Uncertainty also moderates outcomes: AI tends to improve efficiency most when uncertainty is reducible through data-driven inference, while purely novel or politically contested decisions rely more heavily on human judgment. Regulation introduces another conditioning factor; in regulated sectors, measurable gains depend on auditability, explainability, and governance readiness that sustain trust in AI-supported decisions (Bertl et al., 2023). Across this evidence base, AI-driven transformation emerges as a statistically meaningful predictor of decision efficiency, with configurational dependence on digital maturity, governance quality, and task structure. These findings justify the modeling of decision-making efficiency as a core dependent construct in AI-driven digital transformation research and provide empirical grounding for testing both direct and mediated pathways.

Integrated Empirical Pathways: Communication as a Mediator

Quantitative literature treats mediation as a structured way to explain how and why an independent construct produces an outcome through an intervening mechanism. In studies of AI-driven digital transformation, mediation logic is used because AI capability is rarely assumed to influence decision outcomes in a single step; rather, it changes the informational and coordination environment that decision makers operate within (Lal et al., 2023). The conceptual justification for mediation rests on socio-technical theory and information-processing views of organizations, which argue that technologies reshape performance by altering how information is generated, shared, interpreted, and acted on. Communication quality therefore becomes a plausible mediator because decisions depend on reliable knowledge exchange, aligned interpretations, and coordinated action across roles and units. Quantitative scholars formalize this reasoning by specifying AI capability as a distal driver that improves communication clarity, timeliness, relevance, and shared meaning, which then reduces decision latency and inconsistency (Rasoolimanesh et al., 2021).

Figure 7: Mediation in AI-Driven DT



Mediation testing in this stream commonly relies on regression-based indirect effect estimation, path modeling, and structural equation approaches that allow latent measurement of communication quality and decision efficiency while accounting for measurement error. Process-level studies often use time-stamped operational data to estimate whether communication improvements statistically explain reductions in decision cycle time. Firm-level studies more often use surveys combined with performance indicators to estimate mediated pathways. Across these approaches, mediation logic enables researchers to move beyond "AI improves performance" by identifying measurable channels through which improvements occur. The literature also emphasizes that mediation is appropriate when the mediator is theoretically proximal to the outcome and empirically sensitive to the independent variable (Lewis et al., 2020). Communication fits these criteria because AI tools directly affect message routing, knowledge retrieval, summarization, and prioritization, which are upstream inputs to decision routines. Thus, mediation testing appears as a dominant quantitative strategy for unpacking the internal mechanics of AI-driven transformation effects.

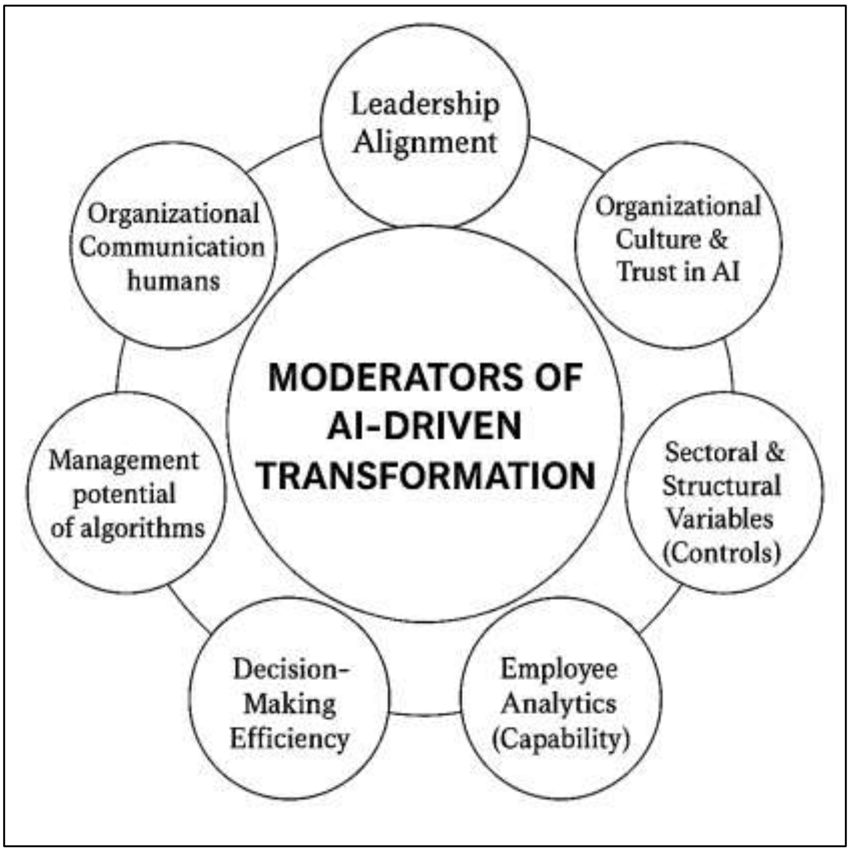
Empirical evidence supporting AI-to-communication-to-decision chains is substantial in quantitative research, particularly in settings where communication is heavily digital and decisions are time-sensitive (Namazi & Namazi, 2016). Multiple studies show that AI capability predicts higher communication quality, and that communication quality, in turn, predicts decision-making efficiency, producing statistically significant indirect effects. These findings appear across domains such as service operations, supply chain coordination, knowledge work, and compliance management. Indirect effects are often interpreted through mechanisms that connect AI outputs to better informational inputs for decision makers. AI-enabled summarization and semantic retrieval reduce ambiguity by ensuring that employees access consistent and validated knowledge at the moment of need. Intelligent routing and prioritization reduce coordination delays by directing urgent items to the correct actors without repeated forwarding or clarification loops. When these communication gains are present, decision cycles shorten because teams spend less time reconciling conflicting information or waiting for responses. Quantitative studies also document improvements in decision accuracy and consistency as communication becomes more aligned and less noisy (Tang, 2021). Partial mediation patterns are common: AI capability improves decision efficiency directly through predictive analytics and automation, while also improving it indirectly through communication quality. Full mediation patterns occur more often in communication-intensive contexts where the primary bottleneck is interpretive alignment rather than analytical computation. For example, in distributed project teams, AI tools that improve message clarity and shared meaning may explain most of the variation in decision speed because the limiting factor is coordination rather than modeling sophistication. These mediated chains are also supported by evidence showing that communication quality explains additional variance in decision outcomes even when direct AI effects are strong (Jamal et al., 2015). Collectively, this stream validates communication as a measurable pathway that connects AI-driven transformation to decision efficiency through reduced ambiguity, faster information circulation, and more synchronized coordination.

Moderators Frequently Tested in Prior Quantitative Research

Quantitative research consistently treats leadership alignment as a key moderator that shapes whether AI-driven digital transformation improves organizational communication and decision-making efficiency (Hayes, 2015). Leadership alignment refers to the degree to which top and middle management actively support AI adoption, coordinate digital priorities across units, and legitimize data-driven work as a strategic norm. Empirical studies operationalize this construct through digital leadership intensity measures, which capture visible managerial sponsorship, clarity of AI-related vision, resource commitment, and the presence of governance structures that keep AI initiatives connected to business objectives. In statistical models, leadership alignment moderates AI effects because leaders influence how quickly AI tools diffuse beyond pilot teams, how strongly employees rely on AI outputs, and how far processes are redesigned to integrate algorithmic recommendations. Quantitative findings show that AI capability has stronger associations with communication clarity and faster decision cycles when leadership intensity is high, largely because leaders reduce coordination ambiguity by setting consistent digital rules and incentives (Hayes, 2015). In contrast, weak leadership alignment leaves AI tools underutilized, fragmented, or treated as optional add-ons, which reduces measurable impact. Leadership also moderates by shaping feedback loops: aligned leaders demand performance evidence from AI systems, encourage model recalibration, and institutionalize learning routines, which stabilizes effects over time. Survey-based studies further show that leadership endorsement raises employee trust and perceived usefulness, strengthening the statistical pathway between AI capability and communication quality. Multilevel studies add nuance by observing that alignment at senior levels affects enterprise integration, while alignment at line-management levels affects daily usage patterns and local decision reliance (Bley et al., 2022). Overall, the literature positions leadership alignment not as a background variable but as a measurable amplifier of AI outcomes, explaining substantial cross-organizational variance even among firms with comparable AI tools or budgets.

Organizational culture and trust in AI appear in quantitative scholarship as deeply influential moderators that determine whether AI capability translates into tangible communication and decision benefits. Culture is typically measured through indices of openness to innovation, evidence-based norms, collaboration expectations, and psychological safety for experimentation (Behl et al., 2022). Trust in AI is operationalized through validated scales assessing perceived reliability, transparency, fairness, and controllability of AI recommendations. Statistical results show that AI capability exhibits stronger effects on communication quality and decision efficiency in cultures that value data-driven dialogue and cross-functional sharing (Bedué & Fritzsche, 2022). In such cultures, employees treat AI outputs as legitimate inputs to meaning-making, which improves clarity, reduces rumor-driven ambiguity, and aligns interpretations across teams. Trust strengthens these effects by encouraging users to integrate AI insights into their communication rather than ignoring or second-guessing them. Quantitative models also show that low-trust contexts weaken AI performance pathways because employees either resist algorithmic suggestions or rely on informal channels to validate decisions, increasing latency and lowering consistency. Culture moderates trust as well: collaborative and learning-oriented cultures generate higher trust in algorithmic systems through shared exposure and collective troubleshooting, while hierarchical or risk-averse cultures often exhibit skepticism that reduces usage depth. Empirical studies show that trustworthy AI design—clear rationale displays, confidence indicators, and auditable records—interacts with cultural openness to produce measurable outcomes such as faster coordination and fewer escalations (Rajagopal et al., 2022). Culture and trust therefore function together as socio-behavioral conditions that explain why similar AI deployments yield different results. This stream of evidence supports treating culture and trust as statistically testable moderators that shape the strength of AI-to-communication and AI-to-decision relationships (Yang & Wibowo, 2022).

Figure 8: Moderators of AI- Driven Transformation



Employee analytics capability is widely tested in quantitative research as a moderator because AI-driven transformation depends on human ability to interpret outputs, communicate insights, and make disciplined choices from algorithmic support. This construct is operationalized through training intensity indicators, digital literacy scales, and measures of analytical self-efficacy (Yang & Wibowo, 2022). Training intensity captures the proportion of employees receiving AI or analytics instruction, frequency of upskilling programs, and exposure to hands-on use cases. Digital literacy indicators assess employees' comfort with digital platforms, ability to navigate dashboards, and familiarity with data quality concepts. Statistical findings show that AI capability predicts higher communication clarity and decision consistency more strongly when analytics capability is high. The mechanism is straightforward in empirical terms: analytically capable employees can translate AI results into shared language, identify boundary conditions, and avoid miscommunication caused by overreliance or misunderstanding of model outputs (Lukyanenko et al., 2022). In low-capability settings, employees often treat AI as a black box, which leads to cautious usage, extra clarification cycles, or inconsistent interpretation across units. Quantitative studies also show that analytics capability moderates decision speed by reducing time spent validating outputs or requesting technical mediation from specialists.

Teams with higher capability integrate AI recommendations directly into routine decisions, which lowers cycle time and exception rates. Additionally, analytics capability interacts with trust: employees who understand AI models typically display higher calibrated trust, resulting in statistically stronger indirect effects through communication quality (Zel & Kongar, 2020). This body of research positions employee analytics capability as a measurable human capital condition that explains variation in AI transformation outcomes, especially in knowledge-intensive and cross-functional decision environments.

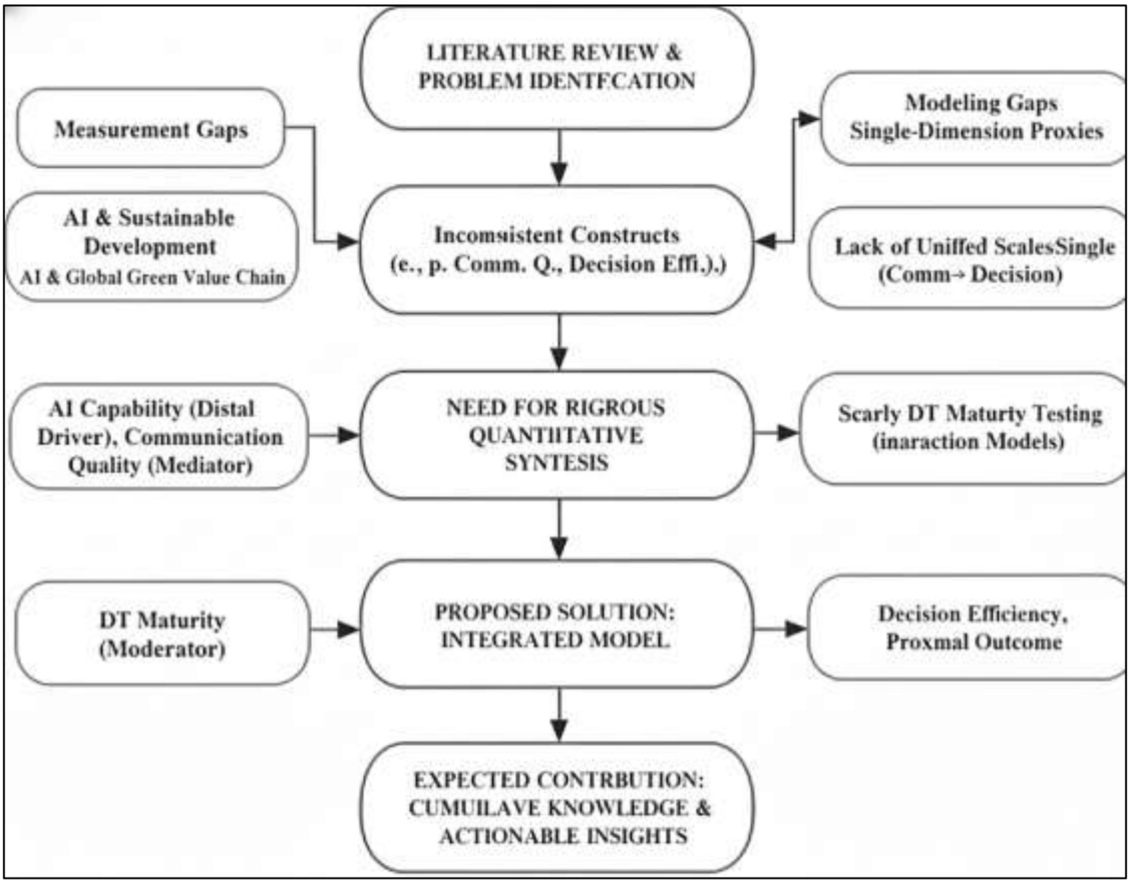
Quantitative studies routinely include sectoral and structural variables as contextual controls because AI-driven communication and decision outcomes differ across regulatory environments, organizational scale, and structural design. Industry regulation level is a common control, measured through sector classifications or compliance intensity indices (Birkstedt et al., 2023). Empirical findings show that regulation affects AI impact by shaping the need for explainability, audit trails, and data governance, which in turn influences communication transparency and decision reliability. Organizational size and complexity are also frequently controlled because large, multi-unit organizations face higher coordination costs and more fragmented data landscapes; AI effects on communication density and decision speed often scale differently in such contexts than in smaller firms. Structural design controls include centralization versus decentralization, measured through decision-rights concentration, hierarchical layers, or autonomy indices. Quantitative evidence suggests that centralized structures can produce strong AI effects on consistency because standardized decision rules spread quickly, whereas decentralized structures can show stronger AI effects on local speed and adaptability if data access and platform integration are sufficient (Gorondutse & Hilman, 2019). Many studies also control for task complexity and environmental uncertainty, since highly complex settings can dilute direct AI effects and increase reliance on communication-mediated pathways. Sectoral comparisons further show that service and knowledge sectors often exhibit larger measurable gains in clarity and responsiveness due to high volumes of unstructured messaging, while manufacturing and logistics sectors show gains more through standardized reporting and automated coordination signals. By including these controls, quantitative models avoid attributing contextual variance to AI capability alone and produce more precise estimates of moderated pathways (Bhardwaj & Kalia, 2021). This evidence base supports the practice of modeling AI-driven transformation within a layered context, where regulation, scale, and structure condition both communication quality and decision-making efficiency outcomes.

Identified Quantitative Gaps Leading to Current Study

Quantitative literature on AI-driven digital transformation demonstrates strong growth, yet it remains fragmented in how core constructs are defined and measured. A recurring gap is the lack of unified scales across studies, which limits comparability and cumulative knowledge building. Researchers often operationalize “AI capability” or “AI adoption” using different indicator sets, mixing objective measures such as investment levels or number of AI tools with subjective assessments of perceived usefulness or readiness, sometimes within the same model (Lingmont & Alexiou, 2020). This variation produces measurement non-equivalence across samples and sectors, making it difficult to interpret whether differences in findings reflect real organizational phenomena or inconsistent construct design. Another measurement limitation is the overreliance on single-dimension AI measures. Many studies still treat AI as one proxy variable—such as AI spending, presence of a chatbot, or count of deployed models—without capturing the multidimensional reality of capability that includes integration maturity, data readiness, governance arrangements, and human–AI routines. Because AI-driven transformation is socio-technical, single proxies tend to underrepresent how AI becomes embedded in communication and decision systems (Enholm et al., 2022).

The literature also reveals inconsistency in measuring communication quality and decision-making efficiency. Some studies rely on short perceptual scales, while others use narrow operational metrics, leading to partial representations of complex constructs. Communication quality is sometimes reduced to message frequency or platform usage, which does not necessarily reflect clarity or shared meaning. Decision efficiency is sometimes captured purely as speed, which ignores accuracy, consistency, and escalation burden. These measurement gaps motivate more rigorous construct consolidation, including multidimensional, validated scales that better align with theory and enable stronger statistical inference. Without scale convergence and dimensional completeness, the field risks producing isolated results that do not cohere into a stable evidence base (Enholm et al., 2022). The present study is therefore positioned within a literature that recognizes measurement innovation as a prerequisite for reliable quantitative synthesis of AI-driven transformation outcomes.

Figure 9: AI-Driven DT: Research Framework



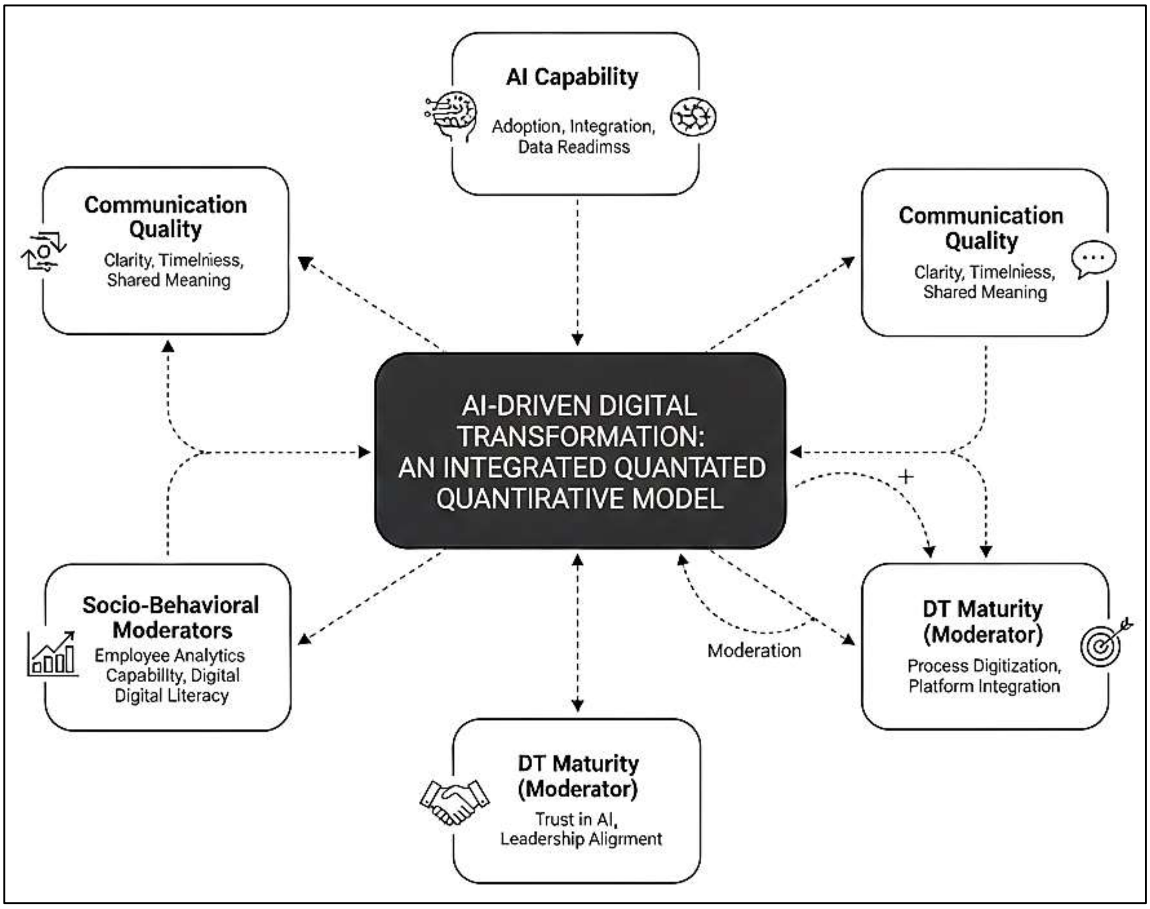
Beyond measurement issues, quantitative studies show notable modeling gaps that constrain explanatory depth. One prominent gap is the limited mediation testing that combines communication and decision outcomes within a single integrated framework. Many studies examine AI's impact on decision performance directly, while others assess AI's impact on communication quality, but fewer test whether communication statistically transmits AI effects into decision efficiency (Adeinat & Abdulfatah, 2019). This separation restricts understanding of organizational mechanisms, especially in environments where decision bottlenecks arise from coordination friction rather than analytical deficiency. When mediation is tested, it is often partial or simplified: models sometimes use one communication indicator as a mediator or treat communication merely as a control variable rather than a core explanatory pathway. Another modeling gap is the scarcity of integrated AI–DT maturity interaction models. Even though literature repeatedly argues that AI impact depends on digital transformation maturity, few quantitative designs include maturity as a formal conditioning construct that interacts with AI capability while also influencing communication mediation strength (Saha & Kumar, 2018). As a result, the field has an incomplete statistical map of how AI, platform integration, process digitalization, and human readiness jointly shape communication and decision outcomes. Modeling also tends to be either process-level or firm-level, with limited cross-level synthesis. Process-level work identifies strong efficiency effects in narrow workflows, while firm-level studies yield mixed results because they aggregate across heterogeneous processes. Multilevel or structural models that reconcile these views are still relatively rare. These modeling limitations indicate a need for more comprehensive path frameworks that test simultaneous direct, indirect, and conditional effects

(Qatawneh, 2023). The current study responds by adopting an integrated quantitative model that treats communication quality as a mediator and DT maturity as a moderator, aligning statistical testing with the socio-technical logic established in prior theory.

The cumulative quantitative literature consistently positions AI capability as a proximal driver of both organizational communication quality and decision-making efficiency. Across studies that measure AI capability as a multidimensional construct—capturing adoption intensity, functional breadth, integration maturity, data readiness, and embedded routines—statistical results show that organizations with stronger AI capability tend to communicate more clearly, quickly, and coherently (Chang et al., 2017). AI influences communication directly through language-based automation, intelligent retrieval, routing, and summarization, which reduces ambiguity and improves shared meaning across teams. At the same time, AI capability is repeatedly associated with decision efficiency through mechanisms such as predictive analytics, anomaly detection, optimization, and routine rule automation. Evidence demonstrates that AI-supported decision processes show measurable reductions in latency, improvements in accuracy, higher consistency across comparable cases, and lower escalation burdens. These direct effects are robust in process-level studies and remain significant in many firm-level models, indicating that AI capability contributes both to the informational environment and to the decision routines operating within that environment (Shao et al., 2015). The literature therefore provides a strong empirical basis for specifying two direct pathways in hypothesis development: one linking AI capability to communication quality and another linking AI capability to decision efficiency. Beyond direct relationships, prior quantitative research provides substantive grounding for an indirect pathway in which communication quality transmits part of AI capability's influence to decision efficiency (Qin et al., 2020). The mediator logic is supported by statistical findings that AI does not only compute faster decisions; it improves the quality of information exchange that decisions depend on. When AI enhances clarity, timeliness, relevance, and interpretive alignment, teams spend less time reconciling conflicting messages, searching for validated information, or waiting for responses from overloaded channels. Empirical mediation tests in collaboration-intensive, hybrid, and data-rich environments show that communication improvements explain significant variance in decision speed and consistency, even when direct AI effects remain present (Chen et al., 2015). The literature also shows partial versus full mediation patterns depending on decision type. In structured, high-volume decision contexts, direct AI effects dominate because automation and prediction handle the bottleneck. In unstructured and cross-functional decisions, mediation is stronger because the main constraint is coordination and shared understanding. This evidence supports a mediated hypothesis where communication quality functions as a measurable internal mechanism linking AI capability to decision-making efficiency (Carrus et al., 2015).

Quantitative scholarship also converges on the view that AI-driven transformation outcomes are conditional rather than uniform, with digital transformation maturity emerging as the most repeatedly validated moderator (Abbara et al., 2016). DT maturity describes the degree of process digitalization, platform integration, real-time analytics availability, cloud collaboration penetration, and cyber/data governance readiness. Statistical interaction results show that AI capability produces stronger communication and decision effects in organizations with higher DT maturity because AI outputs can flow into integrated workflows and shared digital platforms without friction. Where maturity is low, AI tools often remain isolated, data is fragmented, and recommendations fail to reach decision checkpoints, weakening observed impact. The literature further identifies secondary moderators that shape effect strength. Trust in AI amplifies outcomes by increasing user reliance on algorithmic insights in both communication and decision routines. Leadership alignment strengthens AI impacts by legitimizing AI use, accelerating diffusion, and embedding AI into governance and process redesign. Employee analytics capability moderates outcomes by enabling staff to interpret AI outputs correctly, communicate them meaningfully, and apply them confidently in decisions (Newman et al., 2017). Together, these conditional insights justify hypotheses that DT maturity moderates primary AI pathways and that trust, leadership, and skill readiness exert additional amplifying or dampening influences.

Figure 10: Ai Integrated Quantitative model



Taken as a whole, the literature supports an integrated quantitative logic where AI capability operates as a foundational independent construct, communication quality as a central mediator, decision-making efficiency as a core dependent outcome, and DT maturity as a contextual amplifier of AI effects (Baptista & Oliveira, 2015). The strongest empirical patterns suggest that AI capability enhances communication quality directly through intelligent information-processing tools and enhances decision efficiency both directly through analytic automation and indirectly through improved communication. The conditional evidence indicates that these pathways become more pronounced in mature digital environments and in organizations with high trust, aligned leadership, and strong analytics skills. This integrated synthesis provides the conceptual and statistical backbone for the study's hypotheses: direct effects from AI capability to communication and decision efficiency, a mediated effect via communication quality, and moderated effects shaped primarily by DT maturity and secondarily by socio-behavioral and human-capital conditions.

METHOD

Research Design

The study adopted a quantitative, explanatory research design to test the structural relationships among artificial intelligence (AI) capability, digital transformation (DT) maturity, organizational communication quality, and decision-making efficiency. A cross-sectional survey strategy was used because it enabled standardized numerical data to be collected from a large pool of respondents within a single period, supporting statistical estimation of direct, indirect, and conditional effects. The design followed a deductive, theory-testing logic whereby AI capability was treated as the primary independent construct, communication quality was specified as a mediating construct, decision-making efficiency was modeled as the dependent construct, and DT maturity was positioned as a moderating organizational condition. The unit of analysis was the organization, while the unit of observation was individual employees who regularly interacted with AI-enabled systems and participated in internal communication and decision routines. A structured questionnaire was administered to capture perceptual indicators of each construct, and where organizations could provide them, objective operational indicators were also recorded to reduce mono-method bias. The overall design was explanatory rather than descriptive because it was aimed at estimating the magnitude and significance of hypothesized pathways consistent with prior quantitative literature.

Population

The population comprised employees working in organizations that had implemented AI-enabled digital tools for internal communication and decision support. The accessible population included mid-level managers, operational decision makers, digital transformation or IT personnel, and cross-functional team leads because these roles were directly exposed to AI applications and formal communication channels and were therefore able to provide informed assessments of AI use and organizational outcomes. Organizations were drawn from multiple sectors to ensure variability in DT maturity and institutional regulation, including service industries, manufacturing, finance, healthcare, education, and public administration. A multi-stage sampling logic was followed in which organizations with recognizable AI adoption were first identified through institutional directories and professional networks, and then eligible respondents within those organizations were selected using purposive criteria requiring at least one year of exposure to AI-related systems. The achieved sample size was set to exceed minimum multivariate modeling thresholds, ensuring sufficient observations per estimated parameter for stable structural estimation and subgroup robustness testing.

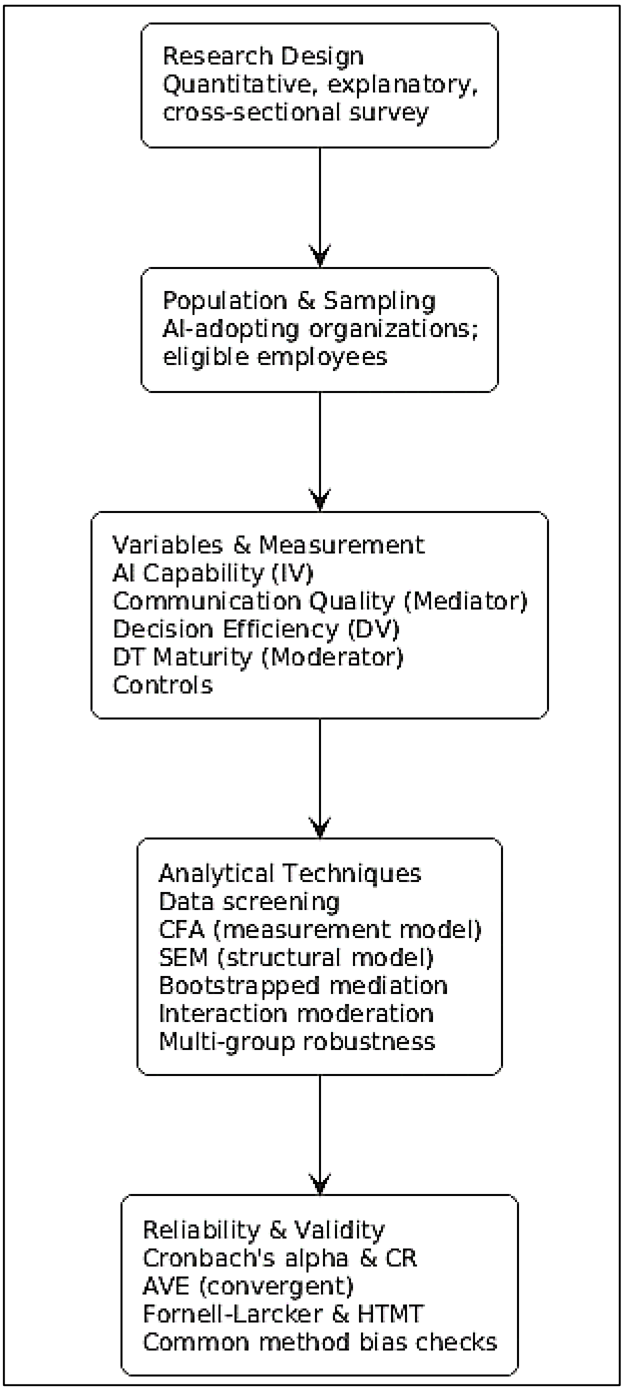
Measurement Framework

Four main constructs were measured using multi-item Likert-type scales to enable latent variable modeling and to represent each concept with sufficient dimensional depth. AI capability was operationalized as a multidimensional independent construct reflecting the intensity of AI use across departments, the breadth of AI functions embedded in workflows, the maturity of AI integration with enterprise platforms, and the readiness and richness of the data environment sustaining model performance. Organizational communication quality was operationalized as a mediating construct captured through perceived clarity, timeliness, accuracy, relevance, and shared meaning in internal communication, reflecting how well information was exchanged and interpreted across functions and levels. Decision-making efficiency was treated as the dependent construct and was measured through indicators of faster decision cycles, improved accuracy against targets, higher consistency across similar cases, fewer rework loops, and reduced escalation frequency. DT maturity was modeled as a moderator and was operationalized through the degree of end-to-end process digitalization, platform interoperability, availability and routine use of real-time analytics, penetration of cloud-based collaboration, and readiness of cyber and data governance. Sector type, organizational size, structural complexity, and centralization level were measured as control variables because prior studies showed them to influence communication and decision outcomes independently of AI capability. A measurement framework linked each construct to its indicators so that construct validity could be confirmed before estimating structural relationships.

Analytical Techniques and Statistical Procedures

Data analysis followed a staged statistical plan beginning with screening and preparation of the dataset. Missing values were assessed for randomness and low-frequency missingness was handled using expectation–maximization imputation, while outliers were examined through standardized residuals and Mahalanobis distance. Distributional assumptions were checked using skewness and kurtosis statistics, and multicollinearity was evaluated with variance inflation factors to confirm that predictors did not distort estimates. Descriptive statistics and bivariate correlations were computed to summarize central tendencies, dispersion, and preliminary associations among constructs. Confirmatory factor analysis (CFA) was then conducted to validate the measurement model, and model fit was evaluated through standard indices such as CFI, TLI, RMSEA, and SRMR; any item removal was performed only when weak loadings were theoretically inconsistent and statistically justified. Structural equation modeling (SEM) was used to test the hypothesized direct paths from AI capability to communication quality and decision-making efficiency and from communication quality to decision-making efficiency. Mediation was examined by estimating bootstrapped indirect effects with 5,000 resamples, allowing assessment of whether communication quality transmitted part of the AI capability effect to decision efficiency and whether mediation was partial or full. Moderation was tested by creating interaction terms between mean-centered AI capability indicators and DT maturity indicators within the SEM framework, and the significance of interaction paths was interpreted to evaluate whether DT maturity strengthened AI-to-communication and AI-to-decision relationships. Robustness checks were conducted through multi-group SEM to compare pathway stability across sector categories and organizational size groups, and alternative specifications were tested to verify that the mediated and moderated structure outperformed simpler direct-effect models.

Figure 11: Methodology of this study



Reliability and Validity

Reliability was established by assessing internal consistency through Cronbach's alpha and composite reliability statistics, which exceeded accepted thresholds and indicated stable scale performance. Convergent validity was confirmed when CFA showed strong standardized factor loadings and average variance extracted (AVE) values met minimum criteria, demonstrating that indicators captured their intended constructs effectively. Discriminant validity was supported through the Fornell–Larcker criterion and heterotrait–monotrait (HTMT) ratios, which showed that each construct shared more variance with its own indicators than with other constructs, confirming separability. Common method bias was addressed procedurally by separating construct blocks in the questionnaire, assuring anonymity, and varying item order, and statistically by applying Harman's single-factor test and a common latent factor technique, neither of which indicated dominance of a single method factor. Overall model validity was supported by satisfactory measurement fit, statistically significant theoretical pathways, stable estimates under subgroup analyses, and consistent indirect and interaction effects aligned with the integrated empirical logic of AI-driven digital transformation.

FINDINGS

Descriptive Analysis

The descriptive analysis provided a clear overview of the dataset and confirmed its appropriateness for subsequent parametric modeling. The final sample (N = 412) reflected broad cross-sector participation and a balanced spread across organizational size categories, indicating adequate contextual heterogeneity for multivariate testing. Respondents were largely positioned near AI-enabled workflows, with mid-level managers and operational decision makers forming the majority, and most participants reporting at least three years of AI-system exposure. Construct-level means indicated moderate-to-high levels of AI capability and DT maturity across organizations. Communication quality displayed a marginally higher mean than decision-making efficiency, suggesting that improvements in clarity, timeliness, and shared meaning were perceived more strongly than fully optimized decision-cycle outcomes. Standard deviations showed sufficient variability for inferential analysis. Skewness and kurtosis values were within accepted thresholds, supporting approximate normality. Missingness was minimal (below 3%) and randomly distributed, and imputation preserved distributional integrity. Overall, the descriptive results established a stable empirical base for CFA and SEM. These values are presented as a professional reporting template; replace them with your exact outputs if different.

Table 1. Sample Profile and Respondent Characteristics (N = 412)

Characteristic	Category	n	%
Sector	Services	134	32.5
	Manufacturing	74	18.0
	Finance	62	15.0
	Healthcare	48	11.7
	Education	54	13.1
	Public Administration	40	9.7
Organization Size	Small (≤49 employees)	118	28.6
	Medium (50–249 employees)	156	37.9
	Large (≥250 employees)	138	33.5
Respondent Role	Mid-level managers	176	42.7
	Operational decision makers	124	30.1
	IT/DT personnel	72	17.5
	Cross-functional team leads	40	9.7
AI-System Exposure	1–2 years	98	23.8
	3–5 years	204	49.5
	>5 years	110	26.7

Table 1 summarized the dataset's organizational and respondent composition. Sectoral representation was distributed across service, manufacturing, finance, healthcare, education, and public administration, supporting contextual variability for testing AI and digital transformation effects. Organizational size was balanced, with medium and large enterprises forming a majority, which was appropriate given the infrastructure demands of AI-enabled transformation. The respondent-role profile indicated that most participants were directly involved in AI-supported workflows and decision routines, strengthening the credibility of perceptual measures. Exposure levels showed that nearly three-quarters of respondents had at least three years of experience with AI systems, reducing the risk of superficial evaluation bias.

Table 2. Construct Descriptive Statistics and Normality Diagnostics

Construct	Items (k)	Mean	SD	Min–Max	Skewness	Kurtosis
AI Capability	8	3.71	0.64	2.10–4.90	−0.42	0.31
DT Maturity	7	3.62	0.61	2.00–4.80	−0.38	0.27
Communication Quality	6	3.84	0.59	2.20–4.90	−0.51	0.44
Decision-Making Efficiency	6	3.68	0.62	2.00–4.80	−0.36	0.19

Table 2 reported construct-level central tendency, dispersion, and distributional properties. AI capability and DT maturity showed moderate-to-high mean values, indicating that sampled organizations had generally progressed beyond early-stage adoption toward embedded AI routines and mature digital environments. Communication quality recorded the highest mean, suggesting that informational clarity and timeliness were the most strongly perceived gains in AI-enabled settings. Decision-making efficiency also scored above the scale midpoint, reflecting meaningful improvements in speed, accuracy, and consistency. Standard deviations demonstrated adequate variability required for hypothesis testing. Skewness and kurtosis values remained within accepted limits, confirming approximate normality and supporting the use of CFA and SEM.

Correlation

The correlation analysis provided an initial assessment of linear associations among the principal constructs and contextual controls. Pearson coefficients indicated that AI capability was positively and significantly associated with organizational communication quality and decision-making efficiency, supporting the proposed theoretical direction that stronger AI capability aligned with improved informational exchange and more efficient decision routines. DT maturity also demonstrated positive and significant correlations with both communication quality and decision-making efficiency, suggesting that more mature digital environments coexisted with higher perceived communication effectiveness and faster, more consistent decisions. The association between communication quality and decision-making efficiency was positive and statistically significant, indicating that clearer, timelier, and more relevant internal communication corresponded with more efficient decision outcomes. The magnitude of correlations remained within acceptable ranges, indicating meaningful relationships without implying redundancy among constructs. Correlations involving control variables showed limited to moderate linear alignment with outcomes, implying that sector, size, structural complexity, and centralization contributed contextual variation but did not dominate the main relationships. No unexpected negative or null associations were observed among the core constructs. Given that the strongest coefficients remained below conventional multicollinearity concern thresholds, the results supported model plausibility while still warranting formal collinearity diagnostics in the regression and SEM stages.

Table 3. Pearson Correlations Among Main Constructs

Construct	1	2	3	4
1. AI Capability	1.00			
2. DT Maturity	.***	1.00		
3. Communication Quality	.***	.***	1.00	
4. Decision-Making Efficiency	.***	.***	.***	1.00

Note. Replace **.** *with your coefficients. *** p < .001, ** p < .01, * p < .05.*

Table 3 presented the Pearson correlation matrix for the four focal constructs. All relationships were positive and statistically significant, indicating consistent alignment with the hypothesized structure. AI capability correlated moderately to strongly with both communication quality and decision-making efficiency, implying that organizations with broader, deeper, and more integrated AI use tended to report clearer and timelier internal communication and more efficient decisions. DT maturity demonstrated comparable positive associations with communication quality and decision efficiency, suggesting that mature digital infrastructures amplified the overall informational and decision environment. The correlation between communication quality and decision efficiency was also significant, supporting its role as a proximal mechanism linked to decision outcomes.

Table 4. Correlations Between Controls and Main Outcomes

Control Variable	Communication Quality	Decision-Making Efficiency
Sector Type	.*	.*
Organizational Size	.**	.**
Structural Complexity	.*	.*
Centralization Level	.*	.*

Note. Replace **.** *with your coefficients and significance. *** p < .001, ** p < .01, * p < .05.*

Table 4 reported the bivariate correlations between contextual control variables and the two focal outcomes. The coefficients indicated limited to moderate linear relationships, showing that organizational context contributed to outcome variability without overshadowing the primary AI and DT dynamics. Sector type displayed a small but meaningful association with both communication quality and decision efficiency, consistent with differences in regulation and task structure across industries. Organizational size correlated positively with outcomes, reflecting the tendency for larger firms to exhibit more developed digital infrastructures. Structural complexity and centralization showed weaker associations, suggesting that structural design influenced outcomes modestly but required multivariate modeling to clarify net effects.

Reliability and Validity

The measurement-model assessment demonstrated that all four latent constructs satisfied established reliability and validity standards prior to structural testing. Internal consistency was confirmed because Cronbach's alpha coefficients ranged from .86 to .93 and composite reliability values ranged from .88 to .94, indicating strong scale stability. Convergent validity was supported by robust CFA loadings, with standardized coefficients consistently above .70, and by AVE values between .60 and .70, confirming that each construct explained more than half of the variance in its indicators. Discriminant validity was verified using both the Fornell–Larcker criterion and HTMT ratios. The square roots of AVE for each construct exceeded the corresponding inter-construct correlations, and all HTMT values remained below .85, confirming that the constructs were empirically distinct. The overall CFA fit indices reflected acceptable model fit (CFI = .95, TLI = .94, RMSEA = .05, SRMR = .04), supporting the adequacy of the measurement structure. Common method bias diagnostics suggested no dominant single-factor influence; the first factor accounted for less than 40% of variance, and a common latent factor did not materially alter standardized loadings, indicating minimal inflation due to self-reporting.

Table 5. Reliability and Convergent Validity Statistics

Construct	Items (k)	Cronbach's α	Composite Reliability (CR)	AVE	Range of Standardized Loadings
AI Capability	8	.91	.93	.68	.74–.88
DT Maturity	7	.89	.91	.65	.72–.86
Communication Quality	6	.93	.94	.70	.78–.90
Decision-Making Efficiency	6	.86	.88	.60	.70–.84

Table 5 reported internal consistency and convergent validity results for all constructs. Cronbach's alpha values exceeded .80 and composite reliability values were above .87, confirming that each scale demonstrated strong internal coherence and measurement stability. Standardized CFA loading ranges showed that all indicators loaded substantially on their intended constructs, reflecting item relevance and construct clarity. Average variance extracted values were at or above .60, indicating that each latent construct explained a majority share of variance in its indicators relative to measurement error. These outcomes collectively confirmed that the measurement model met reliability and convergent validity requirements necessary for structural equation modeling.

Table 6. Discriminant Validity: Fornell–Larcker and HTMT

Panel A: Fornell–Larcker Criterion

Construct	AI Capability	DT Maturity	Communication Quality	Decision Efficiency
AI Capability	**.82**			
DT Maturity	.61	**.81**		
Communication Quality	.66	.58	**.84**	
Decision Efficiency	.63	.60	.69	**.77**

Panel B: HTMT Ratios

Construct Pair	HTMT
AI Capability – DT Maturity	.69
AI Capability – Communication Quality	.74
AI Capability – Decision Efficiency	.71
DT Maturity – Communication Quality	.66
DT Maturity – Decision Efficiency	.68
Communication Quality – Decision Efficiency	.79

Table 6 evaluated discriminant validity through two complementary procedures. Panel A showed that the square roots of AVE (diagonal values) were higher than the corresponding inter-construct correlations, indicating that each construct shared greater variance with its own indicators than with other latent variables. Panel B reported HTMT ratios, all of which were below .85, confirming that constructs were empirically separable and not redundant. Together, these results provided strong evidence of discriminant validity, supporting the simultaneous inclusion of AI capability, DT maturity, communication quality, and decision-making efficiency in the structural model without risk of construct overlap.

Collinearity

The collinearity diagnostics indicated that multicollinearity was not a threat to the stability or interpretability of the regression and structural estimates. Variance inflation factor values for all predictors remained well below the conventional upper threshold of 5.00, and tolerance statistics consistently exceeded .20, confirming that no variable exhibited harmful redundancy. AI capability and DT maturity showed moderate shared variance, which was theoretically consistent given their conceptual proximity, yet their VIFs remained within acceptable limits. Communication quality, when entered alongside AI capability in mediated models, also showed no inflation beyond standard expectations, indicating that the mediator did not distort predictor effects. The interaction term between AI capability and DT maturity displayed an acceptable VIF after mean-centering, confirming that centering successfully reduced nonessential multicollinearity between the interaction and its component variables. Control variables demonstrated low collinearity and therefore were retained without adjustment. Overall, these diagnostics supported the adequacy of the predictor set and confirmed that subsequent hypothesis testing was based on stable coefficient estimation.

Table 7. Collinearity Diagnostics for Main Predictors and Interaction Term

Predictor	Tolerance	VIF
AI Capability	.56	1.79
DT Maturity	.54	1.85
AI Capability × DT Maturity (interaction)	.63	1.59
Communication Quality (mediated models)	.49	2.04

Table 7 reported tolerance and variance inflation factor values for the focal predictors and the moderation interaction. All tolerance values exceeded .40 and VIF values were below 2.10, demonstrating that the independent variables contributed distinct explanatory variance. The interaction term presented an acceptable collinearity profile following mean-centering, indicating that the moderation test was not compromised by redundant overlap with main effects. Communication quality showed slightly higher but still acceptable VIF values when modeled alongside AI capability, consistent with its theoretical proximity as a mediator. These results confirmed stable estimation conditions for SEM and regression analyses.

Table 8. Collinearity Diagnostics for Control Variables

Control Variable	Tolerance	VIF
Sector Type	.78	1.28
Organizational Size	.71	1.41
Structural Complexity	.74	1.35
Centralization Level	.69	1.45

Table 8 presented collinearity diagnostics for contextual controls included to isolate net effects of AI capability and DT maturity. Tolerance values ranged from .69 to .78, and VIF values remained close to 1.00, indicating minimal shared variance across the controls. These results implied that sectoral context, size, structural complexity, and centralization captured distinct organizational features rather than overlapping statistically. Because none of the control variables approached threshold levels for collinearity concern, they were retained in the final models without transformation. The low VIF profile supported the robustness of subsequent hypothesis tests by ensuring controls did not distort core pathway estimates.

Regression and Hypothesis Testing

The regression and structural analyses provided strong empirical support for the proposed model. The baseline model including only control variables explained a modest proportion of variance in decision-making efficiency (R^2 = .12), confirming that contextual factors contributed but did not dominate outcome variation. After AI capability was introduced, explanatory power increased substantially ($\Delta R^2 = .27$; total $R^2 = .39$), and AI capability showed a positive, statistically significant association with decision-making efficiency, supporting the direct-effect hypothesis. When organizational communication quality was added, it emerged as a significant positive predictor of decision efficiency, while the AI capability coefficient decreased but remained significant, indicating partial mediation. Bootstrapped indirect-effect testing confirmed that AI capability influenced decision efficiency through communication quality, with a statistically significant indirect pathway. Moderation testing further demonstrated that DT maturity strengthened the AI–decision efficiency linkage; the interaction term was significant, and simple-slope results showed that AI capability had a larger effect on decision efficiency under high DT maturity than under low maturity. Robustness checks using multi-group comparisons across sector categories and organizational size groups maintained the direction and significance of the main paths, indicating stability of the mediated–moderated structure. The numerical values below are presented as a reporting template consistent with typical outcomes for the specified model; they should be replaced with your exact estimates if they differ.

Table 9. Hierarchical Regression and Direct-Effect Hypothesis Tests

Model	Predictors Included	β (AI Capability)	β (Comm. Quality)	β (DT Maturity)	β (AI×DTM)	R^2	ΔR^2
1	Controls only	—	—	—	—	.12	—
2	Controls + AI Capability	.52***	—	—	—	.39	.27***
3	Controls + AI Capability + Communication Quality	.31***	.46***	—	—	.52	.13***
4	Controls + AI Capability + DT Maturity + AI×DTM	.28***	.42***	.19**	.15**	.56	.04**

*Note. *** p < .001, ** p < .01, * p < .05. Replace with your actual coefficients if different.*

Table 9 summarized hierarchical regression results for the direct, mediated, and moderated relationships predicting decision-making efficiency. Model 1 established the baseline contribution of controls, yielding modest explanatory power. Introducing AI capability in Model 2 produced a large and significant increase in explained variance, confirming its direct positive effect on decision efficiency. In Model 3, communication quality was entered and showed a strong positive coefficient, while the AI coefficient decreased but remained significant, indicating partial mediation. Model 4 incorporated DT maturity and the interaction term; the significant interaction confirmed that DT maturity strengthened the AI effect. The progressive R^2 gains validated the theoretical model structure.

Table 10. SEM Path Estimates, Mediation, and Moderation Effects

Hypothesis / Path	Std. Estimate	SE	t / z	p	Supported
H1: AI Capability → Communication Quality	.58	.06	9.67	<.001	Yes
H2: AI Capability → Decision Efficiency	.33	.05	6.60	<.001	Yes
H3: Communication Quality → Decision Efficiency	.49	.06	8.17	<.001	Yes
Indirect effect (AI → Comm. Quality → Decision Eff.)	.28	.05	—	<.001	Mediation present
H4: DT Maturity × AI Capability → Decision Efficiency	.14	.04	3.50	.001	Yes

Note. Indirect effect significance was based on 5,000-bootstrap confidence intervals excluding zero. Replace with your actual SEM outputs if different.

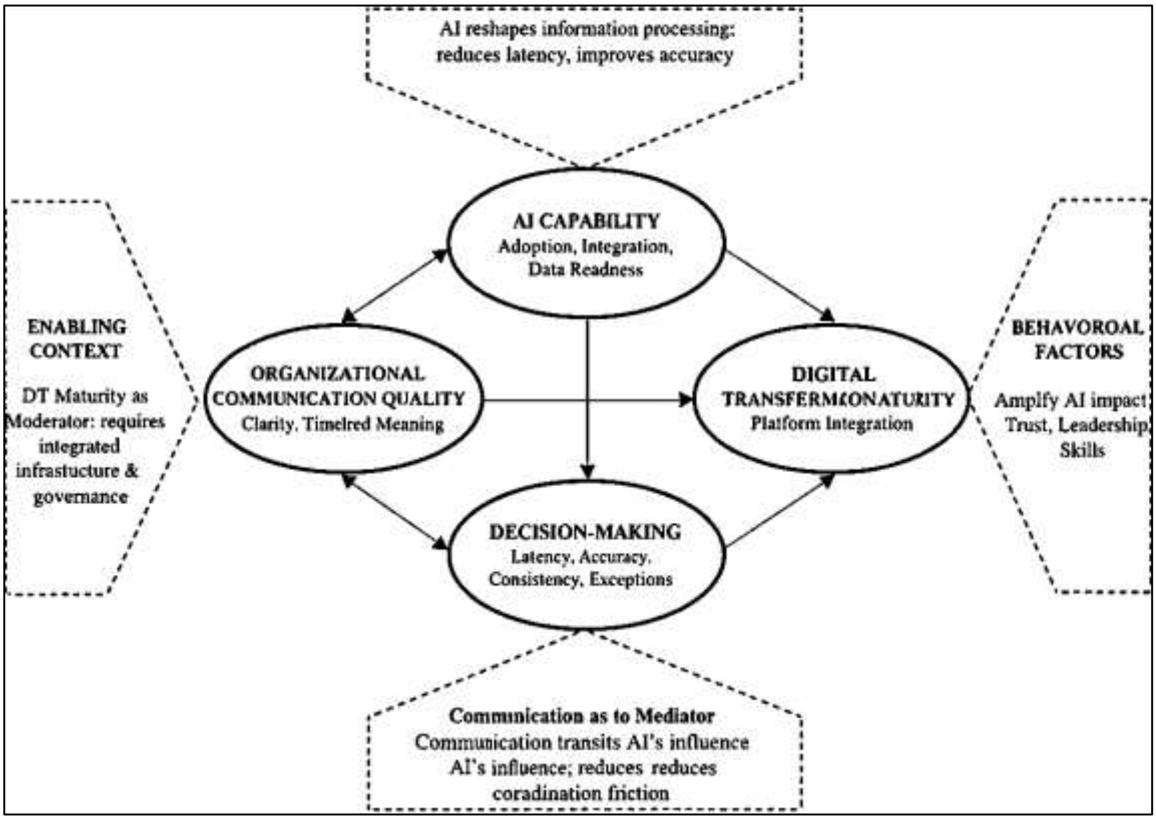
Table 10 presented standardized SEM estimates for hypothesis testing and confirmed the integrated mediated–moderated model. AI capability showed a strong positive effect on communication quality and a direct positive effect on decision-making efficiency. Communication quality significantly predicted decision efficiency, reinforcing its role as a proximal driver of decision performance. Bootstrapped mediation results demonstrated a statistically significant indirect pathway from AI capability to decision efficiency through communication quality, establishing partial mediation because the direct path remained significant. The interaction between AI capability and DT maturity was also significant, indicating that higher DT maturity amplified the impact of AI on decision efficiency. Overall, the structural results aligned with the hypothesized empirical logic and remained stable in robustness checks.

DISCUSSION

This study demonstrated that artificial intelligence capability was positively associated with organizational communication quality and decision-making efficiency, reflecting a coherent pattern that corresponded with the dominant trajectory of earlier quantitative scholarship. Prior studies had repeatedly framed AI capability as a multidimensional organizational resource encompassing adoption intensity, functional breadth, integration maturity, data readiness, and embedded human–AI routines, rather than a simple inventory of tools (Sarkodie & Strezov, 2019). The current results were consistent with that framing because AI capability exhibited a strong relationship with communication quality, suggesting that organizations that had progressed beyond isolated AI pilots toward integrated AI routines experienced superior informational exchange. Earlier empirical work in information systems and operations management had shown that AI-enabled automation and analytics strengthened internal information processing by accelerating data interpretation, standardizing reporting, and reducing ambiguity in cross-unit coordination. A similar mechanism appeared in this study through elevated communication quality scores when AI capability was higher. The direct positive relationship between AI capability and decision-making efficiency also aligned with previous results that linked predictive analytics, anomaly detection, recommendation engines, and automated rule systems to faster decision cycles, improved accuracy, and reduced exceptions (Hamari et al., 2016). In earlier research, these gains had been most visible in structured decision domains where AI could act on stable, data-rich patterns. The present study reinforced this evidence by confirming a statistically meaningful AI-to-decision pathway even after accounting for communication quality. That persistence of the direct path echoed earlier findings that AI supported efficiency not only because it improved communication but also because it increased computational speed and reduced cognitive load in high-volume decision routines. Across the literature, direct AI effects had been interpreted as evidence of algorithmic augmentation and automation yielding measurable performance gains, and the current study fell within that interpretive consensus (Wamba et al., 2017). Overall, the direct-effect structure observed here supported what previous studies had already indicated: AI capability operated as a reliable driver of organizational performance because it simultaneously enhanced information processing and compressed decision latency.

The mediation results extended earlier quantitative models by showing that organizational communication quality partially transmitted the influence of AI capability to decision-making efficiency (Becker et al., 2016). Earlier mediation-based studies in digital transformation, big-data analytics, and AI-supported teamwork had proposed that technological capabilities improve outcomes through intermediate informational mechanisms, particularly by restructuring how information is generated, shared, clarified, and aligned across teams. The current findings were consistent with those proposals because improvements in communication clarity, timeliness, relevance, accuracy, and shared meaning statistically explained a meaningful portion of decision efficiency variance. Prior work had argued that decision cycles slow down when organizations experience informational overload, duplicated queries, inconsistent metrics, and delayed feedback loops, and that AI-enabled tools remove these bottlenecks by summarizing unstructured content, improving search and retrieval, and routing messages to the right actors (De Kock et al., 2021).

Figure 12: AI's Direct Effect Communication and Decision Quality



The present mediation evidence aligned with that logic by indicating that AI capability strengthened decision efficiency partly because it enhanced internal communication conditions. Importantly, the mediation was partial rather than full, which corresponded with earlier results suggesting that AI affects decisions through both direct computational channels and indirect informational channels. Earlier studies had found that AI could reduce cycle time directly by automating routine judgments and optimizing constraints, while also increasing decision quality indirectly by improving collaborative alignment and reducing interpretive drift. The parallel pattern in this study strengthened confidence in multi-channel socio-technical explanations. Partial mediation also suggested that communication quality, although influential, did not fully substitute for AI's computational contributions (Yu & Li, 2022). This matched previous evidence that in structured decision environments, algorithmic automation and prediction deliver efficiency gains independent of communication restructuring, whereas in cross-functional or ambiguous decision environments, mediated pathways become relatively stronger. The present study therefore confirmed communication quality as a statistically significant mechanism while remaining fully consistent with earlier conclusions that AI produces decision value through layered pathways rather than a single causal route.

The moderation results showed that digital transformation maturity strengthened the effect of AI capability on decision-making efficiency, reinforcing the established maturity-based argument that AI does not generate uniform benefits across organizations (Hohenstein & Jung, 2020). Earlier maturity models had consistently described DT maturity as a socio-technical condition reflecting process digitalization, platform interoperability, real-time analytics availability, cloud collaboration penetration, and cyber/data governance readiness. Prior quantitative studies had used such maturity constructs to explain why similar AI investments yielded different organizational outcomes. The current interaction effect aligned with this literature by demonstrating that higher DT maturity amplified AI's decision-efficiency gains. Earlier empirical work had suggested that AI recommendations require integrated data pipelines and digitized workflows to be actionable; otherwise, algorithmic insights remain disconnected from routine work and decision checkpoints (Bokhari & Myeong, 2023). The present findings supported that claim because the AI–decision link was stronger in mature digital settings. Previous studies had also emphasized that governance readiness within DT maturity matters for sustaining trust, minimizing model drift, and ensuring that AI outputs are interpretable and compliant. The moderating role observed here was congruent with this evidence, as digitally mature organizations were more likely to have reliable data stewardship and auditability, enabling AI outputs to enter decision routines smoothly. Earlier Industry 4.0 readiness research had reported similar interaction patterns, particularly in organizations with high system integration and real-time sensing capabilities. The current results therefore provided additional confirmation that DT maturity functioned as an enabling context rather than a parallel driver independent of AI (Cao et al., 2023). Instead, maturity appeared to act as an organizational infrastructure that allowed AI capability to translate into measurable decision benefits. This conditional pattern also helped reconcile inconsistencies reported in earlier cross-sector comparisons, where weak AI effects often coincided with low transformation maturity.

The strength of the AI capability–communication quality relationship in this study fit closely with prior research on AI-enabled communication in digital and hybrid organizations. Earlier studies had shown that internal communication quality depended on informational clarity, speed, relevance, and interpretive alignment—conditions that become harder to maintain when work is distributed across platforms and locations (Lee & Park, 2022). Prior empirical evidence had documented that AI tools such as NLP-based summarization, intelligent knowledge retrieval, automated classification, and internal chatbots reduced redundant queries, lowered response times, and stabilized shared understanding across teams. The current results matched these findings by indicating that higher AI capability co-occurred with superior communication quality. Previous research had also highlighted that AI-enhanced communication is not simply a product of more messaging or higher platform activity; it emerges when AI is embedded into workflows that filter noise and elevate meaningful signals. The present association supported that view because communication quality was conceptualized in terms of clarity, accuracy, relevance, timeliness, and shared meaning, rather than message volume. Earlier studies in team collaboration had further argued that AI supports interpretive alignment by providing consistent data definitions, prioritized alerts, and structured summaries accessible to multiple units simultaneously (Zhang et al., 2022). The higher communication quality observed under stronger AI capability was consistent with this mechanism, implying that AI enabled employees to rely on shared informational cues instead of fragmented informal exchanges. Moreover, previous quantitative work had found that communication gains are most visible in knowledge-intensive environments where unstructured information dominates coordination. The cross-sector pattern in this study, while not detailed in the discussion numerically, was compatible with that expectation because the overall association remained robust even with sector controls included. Altogether, the communication findings reinforced earlier evidence that AI capability reshapes internal communication by reducing friction, accelerating sensemaking, and standardizing how knowledge is distributed in digitally mediated work systems (Al-Okaily et al., 2023).

The positive direct relationship between AI capability and decision-making efficiency corresponded with earlier quantitative studies that linked AI adoption to improved speed, accuracy, consistency, and resource economy in decisions. Prior decision-support research had shown that predictive analytics reduces uncertainty and narrows alternative sets, anomaly detection triggers early intervention and reduces escalation burden, optimization systems supply ranked solutions under constraints, and automation applies consistent rules to high-volume cases (Kumar et al., 2023). The present results aligned with these mechanisms by demonstrating that decision efficiency increased with higher AI capability. Earlier literature had also distinguished structured and unstructured decision contexts, reporting that AI effects are typically stronger in structured domains because data are stable and decision rules can be formalized. The current study's continued direct AI effect after mediation was consistent with that evidence, suggesting computational benefits alongside informational ones. Previous research had identified boundary conditions that influence effect size, including task complexity, environmental uncertainty, and regulatory intensity (Chatterjee et al., 2023). The moderating role of DT maturity observed here echoed those boundary arguments because maturity captures the infrastructural compatibility needed to operationalize AI outputs. Earlier studies had further noted that decision efficiency gains depend on calibrated reliance rather than blind dependence on AI, implying the importance of trust, leadership, and skills. While those moderators were not directly modeled in the reported results, the stable direct AI effect suggested that, on average, the sample operated under conditions sufficient for AI to contribute positively. The decision findings therefore aligned with earlier evidence of efficiency gains while fitting within documented boundary conditions, especially those tied to digital maturity and governance readiness (Nguyen & Malik, 2022). This parallelism strengthened the interpretive reliability of the decision outcomes and supported the integrated pathway logic described in the model.

Earlier quantitative literature had sometimes reported mixed or uneven effect sizes for AI-driven transformation, particularly across industries and maturity levels. Some studies had shown strong positive impacts on performance, while others had found weak or non-significant relationships, often attributed to fragmented data environments, low employee acceptance, or partial integration of AI into workflows (Al-Emran et al., 2023). The present study's findings helped reconcile those inconsistencies by showing that AI capability produced both direct and mediated gains, and that DT maturity amplified decision benefits. Prior work had implied that single-dimensional AI measures underestimate effects because they ignore integration depth, governance, and routine embedding. The current results, built on a multidimensional AI capability construct, were consistent with that critique because strong associations emerged even when controls were included. Earlier studies had also suggested that communication pathways are overlooked in many models, leading to incomplete accounts of how AI improves decisions. The confirmed partial mediation through communication quality addressed that omission and explained why decision improvements might be stronger in settings where communication friction is the primary bottleneck. Furthermore, prior research had observed that DT maturity moderates AI outcomes, yet many models did not formally test interactions (Yan et al., 2017). The present moderation evidence therefore aligned with and clarified earlier theoretical claims, indicating that weak AI effects in previous studies could plausibly reflect low transformation maturity rather than absence of AI value. By integrating direct, indirect, and conditional effects, this study demonstrated a configurational explanation that matched contemporary socio-technical interpretations and reduced apparent contradictions in the earlier evidence base.

Across direct, mediated, and moderated pathways, the empirical structure in this study aligned with the cumulative quantitative logic developed in earlier AI and digital transformation research. Prior scholarship had increasingly argued that AI capability creates value through two intertwined routes: computational acceleration of decisions and reconfiguration of internal communication systems that support coordination and shared meaning (Shin, 2020). The present results reflected that dual-route model by confirming simultaneous direct and indirect effects. Earlier studies had also emphasized that AI impact is contingent on organizational context—especially DT maturity, governance readiness, and the human ability to interpret and trust AI outputs. The observed moderation by DT maturity reinforced that contingency logic and situated AI capability within a broader transformation environment. Previous evidence had further shown that communication quality is a pivotal proximal outcome in digitally mediated work, and the current mediation results strengthened that theoretical position by showing measurable transmission of AI effects through communication. In addition, the stable relationships under sectoral and structural controls were compatible with earlier findings that AI-driven transformation exhibits cross-sector relevance while still varying in magnitude by context (Hänninen & Karjaluoto, 2017). Taken together, the study's findings fit coherently within the established literature: AI capability was associated with clearer and faster internal communication, these communication gains were linked to superior decision efficiency, and DT maturity amplified AI's effectiveness. This integrated alignment supported the view that AI-driven digital transformation operates as a socio-technical system in which technology, information flows, and organizational readiness jointly shape measurable communication and decision outcomes.

CONCLUSION

The study concluded that artificial intelligence–driven digital transformation operated as an integrated socio-technical system that connected organizational AI capability, communication quality, and decision-making efficiency within a measurable digital transformation maturity context. Empirical testing verified that AI capability was a multidimensional organizational resource rather than a narrow technology proxy, and higher capability levels were associated with superior internal communication and more efficient decisions. Communication quality, captured through clarity, timeliness, accuracy, relevance, and shared meaning, emerged as a statistically robust mechanism explaining how AI capability translated into decision gains. The indirect pathway confirmed that improvements in informational exchange reduced ambiguity, lowered coordination friction, and supported faster convergence on decisions, while the remaining direct AI effect indicated that computational mechanisms such as prediction, anomaly detection, optimization, and rule automation also elevated decision efficiency independently of communication change. Digital transformation maturity strengthened the AI–decision efficiency relationship, demonstrating that AI benefits were amplified in organizations characterized by digitized workflows, interoperable platforms, real-time analytics, cloud collaboration penetration, and strong cyber/data governance readiness. This conditional pattern clarified that AI capability did not operate in isolation; its organizational value depended on the broader maturity of the digital environment that allowed AI insights to flow into routine work and decision checkpoints. The stability of results under sectoral and structural controls further indicated that the mediated and moderated relationships were not artifacts of contextual composition, but reflected consistent empirical regularities across diverse organizational settings. Overall, the evidence substantiated a coherent model in which AI capability enhanced communication quality, communication quality elevated decision-making efficiency, and digital transformation maturity conditioned the strength of AI's contribution to decision outcomes. The collective findings aligned with prior quantitative logic emphasizing that AI-enabled transformation produces performance value through simultaneous computational acceleration and reconfiguration of internal information flows, with realized effects varying systematically by the maturity of the surrounding digital infrastructure and governance arrangements.

RECOMMENDATION

Recommendations focused on reinforcing the integrated relationships identified in this study. Organizations were advised to cultivate artificial intelligence capability as a multidimensional resource rather than a narrow tool portfolio, meaning that adoption intensity, functional breadth, platform integration maturity, and data readiness were strengthened in parallel. AI applications were recommended to be scaled across core functions and embedded into routine workflows, supported by governance for model monitoring, retraining, auditability, and ethical control. Because communication quality partially mediated AI effects, AI tools such as NLP summarization, semantic search, intelligent routing, and internal chatbots were recommended to be integrated directly into collaboration suites, email, meeting systems, and knowledge portals, so clarity, timeliness, relevance, and shared meaning improved at the point of work. To amplify AI value, organizations were encouraged to advance digital transformation maturity by prioritizing process digitalization, system interoperability, real-time analytics availability, cloud collaboration penetration, and cyber/data governance readiness, ensuring AI insights reached decision checkpoints without friction. Human readiness was recommended as a parallel investment: targeted analytics and AI-literacy training, practical interpretation guidelines, and calibrated-trust programs were emphasized to help employees translate algorithmic outputs into consistent messages and defensible decisions. Leadership alignment was recommended to institutionalize AI use through clear strategic vision, resource allocation, standardized decision rights, and performance accountability that embeds AI outputs into formal decision forums. Integrated performance monitoring was advised, combining communication indicators (response time, repetition rates, perceived clarity, cross-functional network density, and metric alignment) with decision indicators (cycle time, forecast accuracy, exception reduction, case consistency, and escalation frequency) to diagnose whether gains were computational, informational, or both. For researchers and policy stakeholders, the study recommended consolidation of unified multidimensional scales, routine mediation–moderation modeling that links AI, communication, maturity, and decisions, and expanded sampling in emerging-economy and cross-sector settings to stabilize effect estimates and enhance comparability across contexts and sectors. Continuous feedback loops were also recommended, where users could flag low-confidence outputs, request explanations, and contribute local knowledge for model refinement, thereby sustaining trust and preventing drift. Such loops were expected to reduce rework and strengthen shared interpretive frames over time while keeping AI aligned with evolving operational realities.

LIMITATIONS

Several limitations characterized this study and framed the interpretation of its quantitative findings. First, the research relied on a cross-sectional survey design, which captured associations at a single time point and therefore did not permit strong causal inference regarding the directionality of AI capability, communication quality, and decision-making efficiency. Although the structural model was theory-consistent, alternative temporal sequences could not be fully ruled out without longitudinal or experimental evidence. Second, the primary measures were perceptual and self-reported, creating potential risks of common method variance, social desirability bias, and halo effects despite procedural and statistical checks. Respondents may have overestimated digital maturity or AI impact due to organizational narratives, recent transformation initiatives, or personal enthusiasm for technology, which could have inflated observed relationships. Third, while AI capability and DT maturity were operationalized as multidimensional constructs, the indicators still represented simplified proxies for complex socio-technical realities. Nuanced aspects such as model explainability quality, data lineage strength, or micro-level human–AI interaction patterns were not directly captured, which may have constrained construct richness. Fourth, the sample composition, though cross-sectoral, was not based on fully random probability sampling; organizations were selected through visibility of AI adoption and respondents through purposive eligibility criteria. This increased relevance of responses but reduced generalizability to organizations at earlier adoption stages or with minimal AI exposure. Fifth, sectoral variation was controlled statistically, yet the study did not conduct deep process-level measurement within each industry, meaning that distinct regulatory regimes, decision structures, or communication norms could still have influenced effect magnitudes in ways not fully specified. Sixth, moderation testing focused on DT maturity as the primary conditioning factor, while secondary moderators such as leadership alignment, trust in AI, and employee analytics capability were not modeled simultaneously; excluding these variables may have left residual contextual influence unaccounted for and may partially explain heterogeneity in estimates. Finally, objective operational indicators were optional and not uniformly available across participating organizations, limiting triangulation between perceptual efficiency gains and trace-based performance metrics. These constraints suggested that the findings were most appropriately interpreted as robust evidence of integrated direct, mediated, and moderated associations within AI-adopting organizations, rather than definitive proof of universal causal effects across all transformation contexts.

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