

Generative Artificial Intelligence Adoption and Business Decision Quality: The Mediating Role of Organizational Learning Capability in Digital Enterprises

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Abstract. Generative Artificial Intelligence (GenAI) is increasingly adopted by digital enterprises to support data analysis, planning, information synthesis, and managerial decision-making. However, the organizational value of GenAI depends on the ability of enterprises to transform AI-generated insights into actionable knowledge and high-quality decisions. This study aimed to examine the direct effect of GenAI adoption on business decision quality and the mediating role of organizational learning capability. A quantitative explanatory design was employed involving 250 managers, supervisors, and professionals with experience using GenAI for organizational tasks. Data were collected using a five-point Likert scale questionnaire and analyzed through Structural Equation Modeling with Partial Least Squares. The results confirmed that the measurement model fulfilled the criteria for validity and reliability. GenAI adoption had a positive and significant effect on organizational learning capability and business decision quality. Organizational learning capability also positively and significantly influenced business decision quality and partially mediated the relationship between GenAI adoption and business decision quality. The study concludes that GenAI improves decision quality through direct analytical support and organizational learning processes that facilitate knowledge acquisition, sharing, interpretation, and utilization. Digital enterprises should therefore combine GenAI implementation with employee training, collaborative learning, knowledge-sharing mechanisms, reliable data governance, and systematic verification of AI-generated outputs to support accurate, timely, relevant, and strategically appropriate business decisions.

Keywords: Business Decision Quality; Digital Enterprises; Generative AI; Organizational Learning Capability; Technology Adoption.

1. INTRODUCTION

Generative artificial intelligence (GenAI) has become an important technological innovation in contemporary business environments. Digital enterprises increasingly adopt GenAI to support data analysis, strategic planning, forecasting, content generation, and managerial decision-making. This technology is changing how organizations process information and conduct knowledge-intensive activities (Mudrinic & Soda, 2024). GenAI also strengthens business intelligence by integrating extensive datasets, identifying complex patterns, and generating relevant analytical recommendations (Thiruneelakandan & Umamageswari, 2024). These capabilities enable organizations to automate routine analytical tasks while allowing managers to concentrate on strategic issues. Consequently, GenAI adoption is increasingly regarded as an essential component of enterprise digital transformation and sustainable organizational competitiveness.

The adoption of GenAI is particularly relevant because digital enterprises operate in dynamic markets characterized by technological disruption, changing customer expectations, and intense competition. Under these conditions, business decision quality determines whether

organizations can recognize opportunities, manage uncertainty, and respond appropriately to environmental changes. GenAI can influence enterprise performance by supporting managerial processes and improving access to relevant information (Ye et al., 2024). Nevertheless, technological adoption does not automatically produce superior decisions. Effective human–AI interaction remains necessary because managers must evaluate AI-generated recommendations according to organizational objectives, professional experience, and contextual understanding (Koteczki & Balassa, 2024). Decision quality therefore depends on technological capabilities and responsible managerial interpretation.

Conventional decision-making approaches frequently depend on personal experience, managerial intuition, and information collected separately from different organizational units. Although professional judgment remains valuable, these approaches may be affected by cognitive biases, incomplete evidence, and delayed information. Such limitations become increasingly problematic when organizations must process large and heterogeneous datasets within limited periods. GenAI can address these weaknesses by integrating multiple information sources and generating data-driven alternatives for managerial evaluation (Thiruneelakandan & Umamageswari, 2024). However, AI-generated information may contain inaccuracies, biases, or unsuitable recommendations. Ethical considerations, information reliability, and organizational oversight must therefore accompany adoption to ensure responsible decision-making and improved organizational performance (Rana et al., 2024).

The organizational value of GenAI is also influenced by the capacity to transform generated information into usable organizational knowledge. Organizational learning capability represents an organization's ability to acquire, interpret, share, and apply knowledge to support continuous adaptation and performance improvement (Mishra, 2025). This capability enables employees and managers to assess AI-generated insights, connect them with operational experience, and disseminate relevant knowledge across organizational functions. A supportive learning culture can encourage experimentation and critical reflection regarding the benefits and limitations of GenAI. Accordingly, technological outputs become strategically valuable when organizations possess appropriate learning routines, knowledge-sharing mechanisms, and employee competencies for converting information into coordinated managerial actions.

Organizational learning capability may consequently explain how GenAI adoption improves business decision quality. GenAI initially produces analytical summaries, predictions, scenarios, and recommendations, whereas organizational learning processes determine whether these outputs are understood and effectively utilized. Digital transformation

requires not only technological investment but also an organizational culture that supports innovation, knowledge exchange, and continuous learning (Alles & Jimenez, 2024). Nevertheless, previous studies have predominantly examined the direct relationships between GenAI adoption, managerial processes, ethical considerations, and organizational performance (Rana et al., 2024; Ye et al., 2024). Limited empirical attention has been devoted to the learning mechanism connecting GenAI adoption with decision quality in digital enterprises.

Therefore, this study examines the influence of GenAI adoption on business decision quality and evaluates the mediating role of organizational learning capability in digital enterprises. The proposed relationship assumes that GenAI adoption directly improves decision quality through faster, broader, and more relevant analytical support. GenAI may also produce an indirect effect by strengthening organizational processes related to knowledge acquisition, interpretation, sharing, and application. Examining this mediation mechanism provides a more comprehensive explanation of how GenAI creates organizational value. The findings are expected to help digital enterprises align technological implementation with employee development, learning culture, knowledge management, and ethical governance to produce timely, accurate, adaptive, and strategically relevant business decisions.

2. LITERATURE REVIEW

Generative Artificial Intelligence Adoption

Generative artificial intelligence (GenAI) refers to artificial intelligence technology capable of producing new content, analyses, recommendations, and alternative solutions based on patterns learned from extensive datasets. In business organizations, GenAI is increasingly used to support reporting, customer service, market analysis, product development, strategic planning, and managerial decision-making. Its rapid diffusion has been encouraged by accessible applications that allow employees without advanced technical expertise to interact with artificial intelligence through natural language. Mudrinic and Soda (2024) explained that the emergence of GenAI is transforming organizational activities and business models. This development positions GenAI as both an operational technology and a strategic organizational resource.

GenAI adoption can provide organizations with significant benefits through increased automation, productivity, efficiency, and innovation. The technology enables firms to generate business content, explore alternative ideas, accelerate information processing, and improve their responsiveness to market changes. Master et al. (2024) emphasized the potential of GenAI to support business creativity and the development of innovative solutions. Its implementation

may also reduce operational costs by automating repetitive knowledge-based tasks and assisting employees in completing analytical activities. Nevertheless, these benefits depend on the extent to which GenAI is integrated into organizational processes rather than merely being used as an isolated productivity tool.

The organizational adoption of GenAI is influenced by technological, organizational, and environmental conditions. Perceived usefulness, technological compatibility, organizational readiness, managerial support, employee competence, and competitive pressure can encourage adoption. Agrawal (2024) explained that GenAI implementation in organizational settings requires consideration of the relationship between technological characteristics and organizational conditions. Organizations with adequate digital infrastructure, qualified employees, sufficient financial resources, and supportive leadership are more likely to integrate GenAI successfully. Conversely, organizations with limited technological readiness or unclear implementation objectives may experience difficulties converting GenAI investments into measurable operational and strategic benefits.

GenAI implementation also creates technological complexity, ethical concerns, privacy risks, employee resistance, and strategic uncertainty. Generated outputs may contain inaccurate information, embedded bias, or recommendations that are unsuitable for particular organizational contexts. Rana et al. (2024) demonstrated that ethical considerations are closely related to the organizational adoption of GenAI and its contribution to performance. Organizations must therefore establish data governance, accountability mechanisms, human supervision, and clear usage guidelines. Successful adoption requires leadership commitment and alignment between GenAI initiatives and organizational strategy so that technological experimentation develops into responsible, sustainable, and performance-oriented implementation.

Business Decision Quality

Business decision quality describes the extent to which managerial decisions are accurate, timely, evidence-based, consistent, and aligned with organizational objectives. High-quality decisions are based on relevant information, careful evaluation of alternatives, and an adequate understanding of potential consequences. In digital enterprises, decision quality is increasingly important because managers must respond to rapid technological change, market uncertainty, and growing data complexity. Digital transformation can improve enterprise performance by strengthening innovation and enabling organizations to use digital information more effectively (Peng & Tao, 2022). However, the availability of technology and data alone does not guarantee that managers will make appropriate decisions.

GenAI can improve business decision quality by collecting and synthesizing extensive information, identifying patterns, generating predictive scenarios, and presenting alternative courses of action. These capabilities can shorten the time required for analysis while expanding the range of information considered by decision-makers. GenAI may also reduce reliance on fragmented information and unsupported intuition. However, decision quality depends on how managers assess, interpret, and apply AI-generated outputs. GenAI should function as a decision-support mechanism because final decisions still require contextual knowledge, ethical judgment, and managerial accountability. Consequently, its contribution is determined by the quality of human interaction with the technology and the organization's capacity to validate its outputs.

Digital transformation provides the broader environment in which GenAI-enabled decision-making develops. The transformation process allows organizations to restructure resources, integrate data, and redesign business processes around digital technologies. Su and Wu (2024) found that digital transformation can strengthen enterprise competencies and contribute to sustainable development. In addition, digital intelligence transformation can improve innovation resilience and firm performance when technological resources are incorporated into organizational capabilities (Zhang et al., 2024). These findings indicate that business decision quality emerges from the interaction between technological capabilities, organizational resources, and managerial processes rather than from the independent operation of GenAI systems.

Organizational Learning Capability

Organizational learning capability (OLC) refers to the organizational and managerial characteristics that facilitate the acquisition, dissemination, interpretation, and utilization of knowledge. OLC enables organizations to learn from experience, integrate new information, and modify existing practices in response to environmental changes. It therefore represents more than individual employee learning because it involves shared routines, organizational structures, and collective knowledge-development mechanisms. Kassim and Mohd Shoid (2013) demonstrated that organizational learning capabilities are closely associated with knowledge performance. Organizations possessing strong learning capabilities can distribute relevant knowledge more efficiently and apply it to operational improvement, problem-solving, innovation, and managerial decision-making.

Knowledge embeddedness is an important foundation of OLC because organizational knowledge is distributed across employees, relationships, technologies, tasks, routines, and structural arrangements. Wang and Sun (2018) identified these dimensions as influential

factors in developing organizational learning capability. Effective learning therefore requires mechanisms that connect individual knowledge with collective organizational practices. Digital platforms and GenAI applications can support this process by facilitating information access and knowledge exchange. However, technology only becomes meaningful when employees possess the willingness and ability to interpret information, share experience, question existing assumptions, and apply newly acquired knowledge to their responsibilities.

Organizational structure and culture also determine the effectiveness of learning processes. Flexible and decentralized structures facilitate communication, employee participation, experimentation, and rapid knowledge exchange across organizational units. Mallén et al. (2016) found that organizational organicity supports learning capability and contributes to stronger performance. A rigid hierarchy may limit knowledge flows because information remains concentrated within particular levels or departments. By contrast, an organic structure allows AI-generated insights to circulate among decision-makers and operational employees. This circulation enables organizations to compare technological recommendations with practical experience and develop more comprehensive interpretations before incorporating them into business decisions.

A supportive organizational culture encourages employees to exchange knowledge, collaborate, learn from errors, and participate in continuous improvement. Altruistic behavior can strengthen learning because employees become more willing to assist colleagues and share knowledge without prioritizing individual interests (Guinot et al., 2015). Training and development are equally important because employees require analytical, technological, and critical-evaluation competencies to use GenAI responsibly. Hussain et al. (2023) showed that training and development can strengthen OLC and organizational performance. Investment in employee competence therefore helps organizations transform AI-generated information into validated organizational knowledge and coordinated action.

Digital Transformation and Enterprise Capability

Digital transformation involves fundamental changes in organizational processes, capabilities, strategies, and business models through the integration of digital technologies. The effectiveness of transformation depends on the organization's capacity to combine technology with complementary managerial and organizational resources. Ravesteijn and Ongena (2019) highlighted the importance of electronic leadership in connecting information technology capabilities with digital transformation. Digital leaders establish strategic direction, encourage technology acceptance, coordinate organizational change, and ensure that digital initiatives support business priorities. Leadership is consequently important for preventing GenAI

adoption from becoming fragmented, experimental, or disconnected from organizational decision requirements.

Business–IT integration represents another essential capability within digital enterprises. It enables organizations to align technological resources with business needs, operational processes, and strategic priorities. Riedinger et al. (2024) explained that digital enterprises require organizational capabilities that facilitate effective integration between business functions and information technology. This integration supports the systematic incorporation of GenAI into workflows and decision processes. Without business–IT alignment, GenAI applications may produce technically sophisticated outputs that do not address relevant managerial problems. Effective integration ensures that system design, data availability, user competence, and organizational objectives collectively support high-quality business decisions.

The development of enterprise digital resource capability also requires organizations to configure data, infrastructure, human expertise, and managerial resources as an integrated system. Zhang et al. (2024) emphasized that digital resource capability is constructed through coordinated organizational mechanisms rather than the simple acquisition of technology. External business conditions also influence digital transformation by shaping competitive pressure, access to resources, and incentives for technological change (Luo et al., 2023). Organizations must therefore consider internal readiness and environmental demands when implementing GenAI. Failure to align technology, strategy, structure, and human resources can undermine transformation initiatives and prevent the realization of their anticipated value (Ma, 2023).

Dynamic Capability Perspective

The dynamic capability perspective explains how organizations identify opportunities, mobilize resources, and reconfigure processes in response to technological and environmental change. From this perspective, GenAI adoption is not a single purchasing or implementation decision but an ongoing organizational process. Firms must sense opportunities arising from GenAI, select suitable applications, and reorganize their resources to incorporate the technology effectively. Carcary et al. (2016) positioned dynamic capabilities as a foundational element of digital transformation. This perspective is relevant because differences in sensing, learning, integration, and reconfiguration capabilities may explain why organizations adopting similar technologies achieve different performance and decision-making outcomes.

Technology adoption is closely associated with the ability of organizations to recognize valuable external knowledge, assimilate it, and apply it to commercial or operational purposes. Research conducted by Arifin et al. (2016) showed that organizational capabilities influence technology adoption and its contribution to firm performance. Dynamic capabilities also allow organizations to adjust technology utilization as business conditions and user requirements change. Remedi-Rumi and Arzuaga-Williams (2024) found that dynamic capabilities are connected to technology adoption and performance in industrial small and medium-sized enterprises. These findings support the view that GenAI adoption requires continuous organizational learning rather than one-time technological implementation.

Digital transformation and dynamic capabilities may reinforce one another. Digital technologies provide new information and analytical possibilities, whereas dynamic capabilities allow organizations to translate those possibilities into redesigned processes and innovative outcomes. Ding et al. (2023) demonstrated that dynamic capability mediates the relationship between enterprise digital transformation and green innovation. This evidence indicates that technological transformation creates value through organizational mechanisms that enable adaptation and reconfiguration. In the present research context, OLC constitutes a learning-oriented dynamic capability that enables digital enterprises to absorb GenAI-generated insights, disseminate them across organizational boundaries, and use them to improve business decisions.

Relationships Among the Research Variables

GenAI adoption is expected to improve business decision quality because it provides faster information processing, broader analytical coverage, and alternative decision scenarios. Nevertheless, these outputs cannot independently guarantee accurate decisions. Their usefulness depends on organizational processes that evaluate information, compare it with existing knowledge, and adapt it to specific business conditions. Agrawal (2024) indicated that organizational factors are fundamental to the successful adoption and utilization of GenAI. Therefore, organizations that integrate GenAI into business processes should be better positioned to improve decision quality, provided that managers and employees can use its outputs critically and appropriately.

GenAI adoption can also strengthen OLC by expanding access to information, supporting knowledge creation, and facilitating the dissemination of analytical insights. Employees can use GenAI to explore organizational problems, summarize complex data, compare alternatives, and develop new interpretations. These activities potentially increase knowledge acquisition and encourage learning across functional boundaries. However,

responsible learning remains essential because generated information must be verified before being incorporated into organizational routines. Ethical governance and managerial supervision help ensure that organizational learning supported by GenAI remains reliable and aligned with organizational interests (Rana et al., 2024).

OLC is expected to improve business decision quality by enabling organizations to convert dispersed information into collective knowledge. Through knowledge sharing and interpretation, decision-makers can incorporate technical analysis, operational experience, and strategic considerations into their evaluations. Strong learning capability also allows organizations to assess previous outcomes and continuously refine decision processes. Mallén et al. (2016) associated OLC with improved organizational performance, while Hussain et al. (2023) demonstrated its connection with employee development and organizational outcomes. These findings suggest that learning capability provides an organizational foundation for accurate, adaptable, and evidence-based managerial decisions.

OLC may ultimately mediate the relationship between GenAI adoption and business decision quality. GenAI provides information and analytical possibilities, while OLC converts those outputs into shared understanding and actionable organizational knowledge. This mediation perspective clarifies why GenAI adoption may produce different decision outcomes across enterprises. Organizations with strong learning capabilities can validate and distribute AI-generated insights before applying them to strategic and operational decisions. Conversely, enterprises with weak learning mechanisms may possess advanced GenAI applications but fail to realize their decision-making value. OLC therefore represents the principal mechanism connecting technological adoption with improved decision quality in digital enterprises.

Hypothesis Development

GenAI adoption enables organizations to access, process, and generate knowledge more efficiently. When GenAI is integrated into organizational activities, employees can obtain new insights, exchange information, and develop collective interpretations of business problems. Therefore, greater GenAI adoption is expected to strengthen organizational learning capability.

H1: Generative AI adoption has a positive effect on organizational learning capability.

GenAI provides analytical summaries, predictions, and alternative recommendations that can improve the accuracy, timeliness, relevance, and effectiveness of managerial decisions. Its integration into organizational tasks is therefore expected to improve business decision quality.

H2: Generative AI adoption has a positive effect on business decision quality.

Organizational learning capability enables enterprises to acquire, share, interpret, and utilize knowledge. These processes help managers combine AI-generated information with organizational experience and contextual understanding, thereby producing more informed and strategically appropriate decisions.

H3: Organizational learning capability has a positive effect on business decision quality.

GenAI-generated outputs do not automatically create valuable business decisions. Organizational learning capability is needed to transform these outputs into shared and actionable knowledge. Therefore, GenAI adoption is expected to improve business decision quality indirectly by strengthening organizational learning capability.

H4: Organizational learning capability mediates the effect of Generative AI adoption on business decision quality.

3. METHODOLOGY

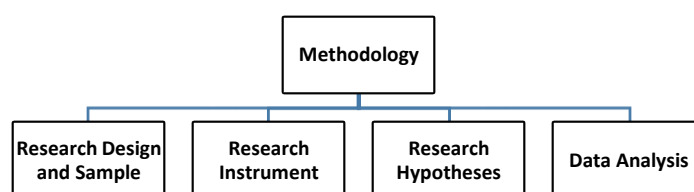


Figure 1. Research Flowchart.

Research Design and Sample

This study employed a quantitative explanatory design to examine the relationships among Generative AI adoption, organizational learning capability, and business decision quality. The study involved 250 managers, supervisors, and professionals selected through purposive sampling. Eligible respondents were employed in digital or digitally dependent enterprises, held organizational or managerial responsibilities, and had experience using GenAI for data analysis, reporting, planning, problem-solving, information synthesis, or decision support.

Research Instrument

Data were collected using an electronic questionnaire with a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Generative AI adoption was measured through usage intensity, perceived usefulness, functional integration, and organizational utilization. Organizational learning capability was assessed through knowledge acquisition, sharing, interpretation, and utilization. Business decision quality was measured using indicators of accuracy, timeliness, relevance, consistency, and effectiveness. Participation was voluntary and anonymous to protect respondent confidentiality.

Research Hypotheses

The study examined four hypotheses:

H1: Generative AI adoption has a positive effect on organizational learning capability.

H2: Generative AI adoption has a positive effect on business decision quality.

H3: Organizational learning capability has a positive effect on business decision quality.

H4: Organizational learning capability mediates the effect of Generative AI adoption on business decision quality.

Data Analysis

Data were analyzed using Structural Equation Modeling with Partial Least Squares (SEM-PLS). The measurement model was evaluated through outer loadings, average variance extracted, Cronbach's alpha, composite reliability, and the heterotrait–monotrait ratio. The structural model was assessed using collinearity, path coefficients, coefficients of determination, effect sizes, and predictive relevance. Direct and mediation effects were tested through bootstrapping. A relationship was considered significant when its p-value was below 0.05 and its confidence interval did not include zero.

4. RESULTS AND DISCUSSION

Results

A total of 250 valid responses from managers, supervisors, and professionals were analyzed using SEM-PLS. Respondents had experience using GenAI for data analysis, reporting, planning, information synthesis, problem-solving, and decision support. The analysis covered descriptive statistics, measurement-model evaluation, structural-model evaluation, and mediation testing. The descriptive, validity, and reliability results are presented in Table 1.

Table 1. Descriptive Statistics, Validity, and Reliability Results.

Construct	Mean	Outer Loadings	Cronbach's Alpha	Composite Reliability	AVE
Generative AI adoption	4.08	0.782–0.874	0.861	0.906	0.706
Organizational learning capability	3.97	0.795–0.889	0.879	0.917	0.734
Business decision quality	4.02	0.771–0.883	0.894	0.922	0.704

Table 1 shows that all research constructs received high mean scores. Generative AI adoption had the highest mean, followed by business decision quality and organizational learning capability. All outer-loading values exceeded 0.70, while Cronbach's alpha and composite reliability values were above 0.70. The AVE values also exceeded 0.50. Furthermore, all HTMT values were below 0.90. These findings confirm that the measurement

model satisfied indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

The structural model was subsequently evaluated to determine its explanatory and predictive power. Generative AI adoption explained 37.5% of the variance in organizational learning capability. Meanwhile, GenAI adoption and organizational learning capability collectively explained 51.8% of the variance in business decision quality. The results of the structural-model evaluation are presented in Table 2.

Table 2. Structural-Model Evaluation.

Endogenous construct	R ²	Adjusted R ²	Q ²	Interpretation
Organizational learning capability	0.375	0.372	0.269	Moderate
Business decision quality	0.518	0.514	0.354	Moderate

Note. R² = coefficient of determination; Q² = predictive relevance.

Table 2 indicates that the model had moderate explanatory power for organizational learning capability and business decision quality. Both Q² values were greater than zero, confirming the model's predictive relevance. The higher R² and Q² values for business decision quality demonstrate that combining GenAI adoption with organizational learning capability provided meaningful explanatory and predictive information regarding the quality of organizational decisions.

The direct and mediation effects were examined through bootstrapping. The analysis tested the effects of GenAI adoption on organizational learning capability and business decision quality, the effect of organizational learning capability on business decision quality, and the indirect effect through organizational learning capability. The results are presented in Table 3.

Table 3. Direct- and Mediation-Effect Testing.

Hypothesis	Relationship	β	t-Value	p-Value	Result
H1	GenAI adoption → Organizational learning capability	0.612	11.846	< .001	Supported
H2	GenAI adoption → Business decision quality	0.301	4.982	< .001	Supported
H3	Organizational learning capability → Business decision quality	0.458	7.736	< .001	Supported
H4	GenAI adoption → Organizational learning capability → Business decision quality	0.280	6.487	< .001	Supported

Note. β = standardized path coefficient.

Table 3 shows that all direct and indirect effects were positive and statistically significant. GenAI adoption had its strongest effect on organizational learning capability. Organizational learning capability subsequently had a substantial effect on business decision quality. The significant indirect effect confirmed the mediating role of organizational learning

capability. Because the direct effect of GenAI adoption on business decision quality remained significant, organizational learning capability provided complementary partial mediation. Therefore, all four hypotheses were supported.

The relative strengths of the relationships in the SEM-PLS model are presented in Figure 1. The diagram compares the standardized coefficients of the three direct effects and the indirect effect of GenAI adoption on business decision quality through organizational learning capability.

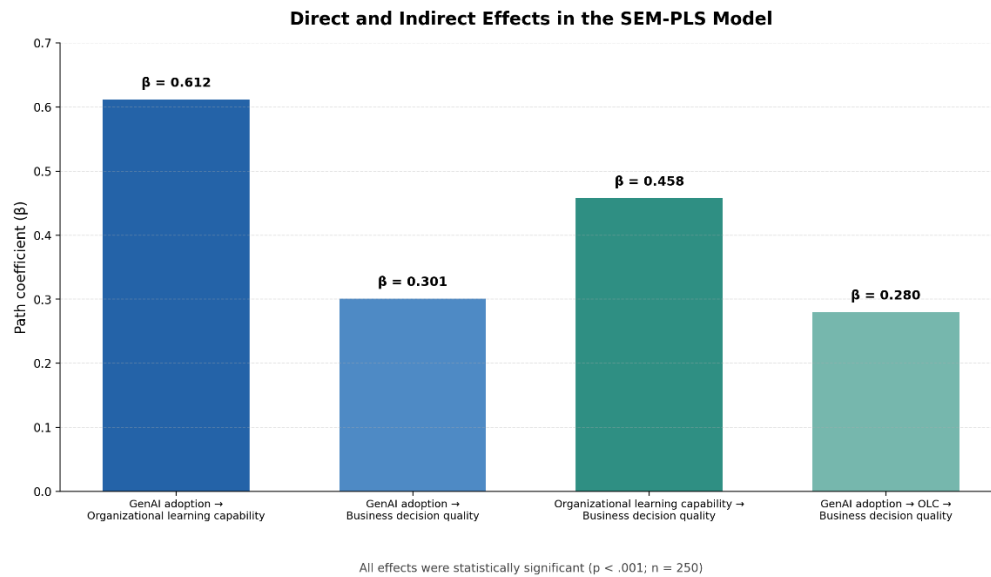


Figure 2. Direct and Indirect Effects in the SEM-PLS Model.

Figure 2 shows that GenAI adoption had the strongest effect on organizational learning capability, with a coefficient of 0.612. The effect of organizational learning capability on business decision quality reached 0.458, while the direct effect of GenAI adoption on business decision quality was 0.301. The indirect effect through organizational learning capability was 0.280. These results indicate that GenAI improves decision quality through direct analytical support and an indirect learning-based mechanism.

Discussion

The positive effect of GenAI adoption on organizational learning capability indicates that GenAI supports knowledge acquisition, sharing, interpretation, and utilization. Employees can use GenAI to access information, summarize complex materials, compare alternatives, and generate new perspectives on organizational problems. These capabilities support individual learning and facilitate knowledge exchange across organizational units. However, AI-generated information must be verified before it is incorporated into organizational knowledge and managerial practices.

GenAI adoption also positively influenced business decision quality. The technology enabled managers to process extensive information, identify risks, compare alternatives, and formulate evidence-based recommendations more efficiently. These capabilities contributed to decisions that were more accurate, timely, relevant, and consistent. Nevertheless, the direct-effect coefficient indicates that GenAI alone cannot guarantee high-quality decisions. Reliable data, contextual understanding, managerial judgment, ethical supervision, and human accountability remain important when interpreting and applying AI-generated recommendations.

Organizational learning capability demonstrated a substantial positive effect on business decision quality. Knowledge acquisition provides relevant information, while knowledge sharing allows managers to integrate perspectives from different organizational functions. Knowledge interpretation helps decision-makers understand the implications of GenAI-generated recommendations, whereas knowledge utilization converts these insights into organizational actions. Therefore, enterprises with stronger learning capabilities are better positioned to transform digital information into coordinated and strategically relevant decisions.

The mediation result represents the main contribution of this study. Organizational learning capability partially mediated the influence of GenAI adoption on business decision quality. GenAI consequently produces organizational value through two complementary pathways. The direct pathway provides rapid analytical support, while the indirect pathway transforms AI-generated information into shared and actionable knowledge. Digital enterprises should therefore combine GenAI adoption with employee training, collaborative learning, knowledge-sharing systems, and procedures for validating AI-generated outputs.

5. CONCLUSION AND RECOMMENDATIONS

This study concludes that Generative AI adoption positively improves business decision quality both directly and indirectly through organizational learning capability. GenAI supports faster information processing, broader analytical evaluation, and more accurate and relevant managerial decisions, while organizational learning capability enables enterprises to acquire, share, interpret, and utilize AI-generated knowledge effectively. Its complementary partial mediation confirms that technological adoption alone is insufficient without systematic organizational learning. Digital enterprises should therefore integrate GenAI implementation with employee training, collaborative learning, knowledge-sharing mechanisms, reliable data governance, and procedures for verifying AI-generated outputs. Future studies should examine

additional factors, including organizational readiness, human-AI collaboration, ethical governance, and managerial competence, across different industries and longitudinal research settings.

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