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The Impact of Organizational Agility on Decision-Making Quality: The Mediating Role of Generative AI Adoption in Algerian Organizations

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Abstract
This study examines the mediating role of Generative AI Adoption (GAI) in the relationship between Organizational Agility (OA) and Decision-Making Quality (DMQ) in Algerian economic organizations. Drawing on Dynamic Capabilities Theory, the Technology Acceptance Model, the Resource-Based View, and Organizational Information Processing Theory, the study proposes a framework in which organizational agility acts as an antecedent capability that facilitates the adoption of generative AI technologies and enhances decision-making quality.

Data were collected through a structured questionnaire administered to employees and managers in Algerian organizations. A total of 300 valid responses were analyzed using Structural Equation Modeling (SEM) with SPSS 27 and AMOS 25.

The findings reveal significant positive effects of organizational agility on generative AI adoption and of generative AI adoption on decision-making quality. The results further confirm a significant mediating effect of generative AI adoption in the relationship between organizational agility and decision-making quality. The study demonstrates that the effectiveness of generative AI depends on organizational readiness and agility, highlighting the strategic role of agile organizations in leveraging emerging digital technologies to improve managerial decision-making.

Keywords: Generative AI Adoption; Organizational Agility; Decision-Making Quality; Digital Transformation; Algeria

1. Introduction

In today’s volatile, uncertain, complex, and ambiguous (VUCA) business environment, organizations globally—and particularly in emerging economies such as Algeria—face increasing pressure to adapt rapidly to technological disruptions and evolving market conditions. In this context, high-quality decision-making has become a critical organizational capability for sustaining competitiveness and ensuring long-term performance.

While traditional information systems have long supported managerial decision-making, the emergence of Generative Artificial Intelligence (GAI) has fundamentally transformed how organizations process information, generate knowledge, and support strategic decisions. Through applications such as ChatGPT, Copilot, and DALL·E, organizations can enhance information processing, automate cognitive tasks, and improve decision-support capabilities. Nevertheless, the successful adoption of GAI technologies does not automatically translate into superior organizational outcomes. According to Dynamic Capabilities Theory (DCT), the value derived from technological innovations depends largely on the organizational capabilities that enable their effective deployment and utilization.

Among these capabilities, Organizational Agility has emerged as a strategic capability that allows organizations to sense environmental changes, adapt rapidly to evolving conditions, innovate continuously, and reconfigure resources effectively. However, despite the growing literature on artificial intelligence and organizational performance, two important research gaps remain. First, existing studies predominantly view artificial intelligence as a driver of organizational agility, whereas limited attention has been given to examining Organizational Agility as an antecedent capability that facilitates the successful adoption of Generative Artificial Intelligence technologies. Second, empirical evidence regarding the relationships among Organizational Agility, Generative AI Adoption, and Decision-Making Quality remains limited in developing-country contexts, particularly within Algerian organizations undergoing digital transformation.

At the same time, Decision-Making Quality has become a critical determinant of organizational success in increasingly dynamic environments. High-quality decisions require timely access to relevant information, objective evaluation of alternatives, and effective responses to emerging challenges. In this regard, GAI technologies offer substantial potential to improve information processing and support evidence-based managerial decision-making.

Against this backdrop, the present study seeks to answer the following research question:

To what extent does Generative AI Adoption mediate the relationship between Organizational Agility and Decision-Making Quality in Algerian organizations?

The primary theoretical contribution of this study lies in challenging the dominant assumption that artificial intelligence is merely a driver of organizational agility. Instead, it proposes that Organizational Agility constitutes an antecedent organizational capability that facilitates the successful adoption of GAI technologies. By positioning Generative AI Adoption as a mediating mechanism between Organizational Agility and Decision-Making Quality, the study provides a more comprehensive explanation of how agile organizations transform their adaptive capabilities into superior decision outcomes. Furthermore, the study contributes empirical evidence from the context of Algerian organizations, thereby enriching the emerging literature on Generative AI adoption and AI-enabled decision-making in developing economies.

2. Literature Review

Recent years have witnessed growing scholarly interest in organizational agility, generative artificial intelligence (GAI) adoption, and decision-making quality due to their significant role in enhancing organizational performance and enabling adaptation to dynamic business environments. Accordingly, this section reviews the theoretical and empirical literature related to the study variables and their respective dimensions.

2.1 Organizational Agility

Organizational agility (OA) has emerged as one of the most prominent contemporary management concepts in response to rapid environmental changes, technological advancements, increasing uncertainty, and intense competition. The concept has evolved through several stages. Early studies viewed organizational agility as a managerial philosophy aimed at enhancing an organization's ability to adapt to environmental changes (Sharp et al., 1999), whereas later research conceptualized it as a strategic capability that enables firms to respond rapidly to emerging opportunities and threats (Chakravarty, Grewal, & Sambamurthy, 2013).

With the evolution of organizational research, the dominant perspective now considers organizational agility a dynamic capability that enables organizations to sense environmental changes, seize opportunities, and continuously reconfigure their resources and capabilities to sustain competitiveness and achieve strategic objectives. In this regard, Walter (2021) defines organizational agility as the organization's ability to detect changes in both internal and external environments and respond effectively through the reconfiguration of resources and processes to maintain competitive advantage and accomplish organizational goals (Walter, 2021, p. 344). Similarly, Chakravarty et al. (2013), along with Hazen et al. (2017), Lu and Ramamurthy (2011), Tallon and Pinsonneault (2011), Teece et al. (2016), and Vickery et al. (2010), conceptualize organizational agility as a dynamic organizational capability arising from an organization's ability to build, integrate, and reconfigure internal and external resources continuously to preserve and strengthen its competitive position. This perspective dominates contemporary literature because it emphasizes the organization's capacity to sense environmental shifts and respond rapidly and effectively in increasingly dynamic business environments.

Teece et al. (2016) further define organizational agility as the ability of an organization to efficiently reallocate and redirect resources toward higher-value activities in response to changing internal and external conditions. Such agility is considered a capability that is difficult for competitors to imitate, thereby contributing to sustainable competitive advantage (Teece, Peteraf, & Leih, 2016).

From another perspective, Lee et al. (2003) proposed a more comprehensive view of organizational agility as a two-dimensional dynamic capability consisting of :

- **Offensive Entrepreneurial Dimension :** Reflecting the organization's ability to explore new opportunities and proactively pursue innovation.
- **Defensive Adaptive Dimension :** Reflecting the organization's ability to adapt effectively to environmental threats and changes.

In the context of digital transformation, organizational agility has become a critical determinant of successful digital initiatives. Agile organizations are better positioned to identify, adopt, and exploit emerging technologies due to their flexibility and responsiveness to environmental changes. In the present study, Organizational Agility is operationalized through four dimensions. The measurement dimensions adopted in this study were selected based on the seminal organizational agility literature, particularly the contributions of Sharifi and Zhang (1999) and Tallon and Pinsonneault (2011) (Sharifi & Zhang, 1999) :

- **Responsiveness to Change :** Responsiveness to change refers to an organization's ability to sense internal and external changes and respond quickly and effectively by adjusting its policies and processes to align with environmental, technological, and stakeholder requirements (Tallon, Queiroz, Coltman, & Sharma, 2019) **.**
- **Flexibility :** Organizational flexibility refers to the organization's ability to reconfigure resources, structures, and operational procedures to adapt to changing conditions without negatively affecting performance or strategic objectives (Sherehiy, Karwowski, & Layer, 2007).
- **Innovation :** Innovation reflects the organization's capability to develop new ideas, methods, products, and services or improve existing ones in ways that create added value and strengthen competitive advantage (OECD, 2018).
- **Operational Efficiency :** Operational efficiency refers to the organization's ability to maximize outputs using available resources with minimum cost, effort, and time while maintaining high performance quality (Slack, Brandon-Jones, & Johnston, 2022).

2.2 Generative Artificial Intelligence Adoption

Recent years have witnessed rapid advancements in generative artificial intelligence (GAI), making it one of the most influential digital innovations in contemporary business environments. GAI refers to a class of artificial intelligence systems capable of creating new content, including text, images, reports, recommendations, and other outputs based on deep learning models and large-scale datasets. The rapid evolution of this technology has increased organizational interest in its adoption and integration across various business functions.

Generative AI adoption refers to the extent to which individuals or organizations accept, utilize, and integrate AI technologies capable of generating new content into their daily activities and organizational processes to improve performance and support decision-making (Suhluli, 2026). Adoption extends beyond mere technical use and encompasses the degree to which the technology is embedded within organizational operations and contributes to value creation.

According to López-Solís et al. (2025), GAI has emerged as a strategic tool capable of supporting organizational decision-making through the analysis of complex information, the generation of alternative scenarios, and the provision of evidence-based recommendations. Building on this perspective, recent studies increasingly recognize GAI as a strategic enabler that enhances managerial effectiveness and organizational performance. Nevertheless, adoption levels continue to vary considerably across organizations because of differences in technological readiness, digital infrastructure, organizational culture, human competencies, and managerial support. Consequently, successful adoption depends not only on the availability of technological resources but also on the organizational conditions that facilitate their effective integration and utilization.

The dimensions used to measure Generative AI Adoption were derived from the Technology Acceptance Model (TAM) developed by Davis (1989) and the Technology–Organization–Environment (TOE) framework proposed by Tornatzky and Fleischer (1990):

- **Perceived Ease of Use :** Perceived ease of use refers to the degree to which individuals believe that using generative AI systems requires minimal effort and can be accomplished easily and clearly: (Davis, 1989).
- **Perceived Usefulness :** Perceived usefulness represents the extent to which users believe that generative AI enhances job performance, productivity, and work quality (Davis, 1989).
- **Management Support :** Management support refers to the extent to which top management provides the resources, infrastructure, training, and encouragement necessary for the successful implementation of AI technologies within the organization (Thong, 1999).
- **Organizational Integration :** Organizational integration refers to the extent to which generative AI applications are embedded within organizational processes and work systems, ensuring effective information flow and coordination among organizational units (Tornatzky & Fleischer, 1990).

2.3 Decision-Making Quality

Decision-making is one of the fundamental managerial functions upon which organizations depend to achieve their objectives, ensure sustainability, and strengthen competitiveness. The importance of decision-making quality has increased in contemporary business environments characterized by complexity and continuous change, where managerial decisions increasingly rely on vast amounts of information and data requiring advanced analytical capabilities.

Decision-making quality (DMQ) refers to the extent to which managerial decisions achieve intended objectives based on accurate, reliable, and timely information, thereby ensuring the selection of the most appropriate alternative and the achievement of optimal organizational outcomes.

According to Dean and Sharfman (1996), decision-making quality reflects the ability of managerial decisions to achieve desired objectives based on accurate and reliable information available at the appropriate time, leading to the selection of the best alternative and the attainment of favorable organizational outcome (Dean & Sharfman, 1996).

Decision-making quality is determined by several key characteristics, including information accuracy, alignment with organizational objectives, Decision Timeliness, objectivity, and effectiveness. These dimensions are particularly important in dynamic environments that require rapid and effective responses to emerging challenges and opportunities, The dimensions of Decision-Making Quality were selected based on the literature on decision support systems and information systems success, particularly the contributions of Dean and Sharfman (1996) and DeLone and McLean (2003) (DeLone & McLean, 2003):

- **Decision Accuracy :** Decision accuracy reflects the extent to which decisions are based on correct information and reliable analyses, leading to the selection of the most appropriate alternative for achieving organizational goals (Harrison & Pelletier, 2000).
- **Decision Timeliness :** refers to the organization's ability to reach appropriate decisions in a timely manner without delays that could reduce their effectiveness (Eisenhardt, 1989).
- **Decision Objectivity :** Decision objectivity refers to the extent to which decisions are based on facts, data, and rational analysis rather than personal biases and subjective judgments (Bazerman & Moore, 2013).
- **Decision Effectiveness :** Decision Effectiveness represents the degree to which a decision successfully achieves intended objectives, resolves organizational problems, and produces the expected outcomes (Dean & Sharfman, 1996).

3. Theoretical Foundation

The proposed conceptual framework is based on the assumption that organizational capabilities play a critical role in determining the successful adoption and utilization of emerging technologies. Among these capabilities, Organizational Agility enables firms to sense environmental changes, adapt rapidly to evolving conditions, and effectively reconfigure resources and processes, Such capabilities create favorable conditions for the adoption of Generative Artificial Intelligence technologies, which subsequently enhance information processing, knowledge generation, and decision-making quality. Accordingly, the framework conceptualizes Organizational Agility as an antecedent capability that facilitates Generative AI Adoption and ultimately contributes to superior Decision-Making Quality. The framework integrates four complementary theoretical perspectives : the Resource-Based View (RBV), Dynamic Capabilities Theory (DCT), Organizational Information Processing Theory (OIPT), and the Technology Acceptance Model.

3.1 Resource-Based View (RBV)

The Resource-Based View (RBV), developed by Barney, argues that organizations achieve sustainable competitive advantage when they possess valuable, rare, inimitable, and non-substitutable resources and capabilities. In the era of digital transformation, advanced technologies have become critical strategic resources that enable organizations to create value and enhance performance.

3.2 Dynamic Capabilities Theory (DCT)

Organizational agility is strongly rooted in Dynamic Capabilities Theory (DCT), developed by Teece, which posits that competitive advantage in rapidly changing environments depends not merely on possessing resources but on an organization's ability to sense opportunities and threats, seize them, and continuously reconfigure its resources and capabilities in response to environmental changes.

3.3 Organizational Information Processing Theory (OIPT)

Organizational Information Processing Theory (OIPT), proposed by Galbraith, provides a useful framework for understanding how organizations cope with uncertainty and environmental complexity. The theory assumes that organizational effectiveness depends largely on the ability to acquire, process, communicate, and utilize information to support decision-making. As environmental uncertainty increases, organizations face greater information-processing requirements and must therefore develop mechanisms and capabilities that enhance their information-processing capacity.

OA facilitates rapid responses to environmental changes by improving information flow and coordination across organizational levels. Simultaneously, GAI has emerged as a powerful technological tool that significantly enhances information-processing capabilities through the analysis of large volume of data, identification of hidden patterns, generation of knowledge, and creation of alternative scenarios. As a result, GAI reduces information gaps faced by decision-makers and contributes to higher-quality decisions.

According to OIPT, organizational agility strengthens the organization's ability to absorb information and respond to environmental changes, creating favorable conditions for the adoption of GAI technologies. The adoption of GAI, in turn, improves information-processing efficiency and supports both strategic and operational decision-making. Therefore, OIPT provides a strong theoretical explanation for the mediating role of GAI adoption in the relationship between organizational agility and decision-making quality, as organizational agility enhances information responsiveness while GAI transforms information into actionable insights that support superior decision outcomes.

3.4 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis, provides a theoretical framework for understanding the factors influencing individuals' acceptance and use of new technologies. The model is primarily based on two determinants: perceived usefulness, which reflects the extent to which users believe that a technology enhances their performance, and perceived ease of use, which refers to the degree to which the technology is perceived as effortless to use. Higher levels of these perceptions increase the likelihood of technology acceptance and actual usage.

In the context of this study, TAM helps explain the adoption of Generative Artificial Intelligence within organizations. The successful implementation of GAI depends on employees' perceptions of its usefulness, ease of use, and ability to support work-related tasks and decision-making processes. Organizational agility can also be viewed as an enabling organizational condition that fosters openness to innovation and change, thereby facilitating employees' acceptance and utilization of GAI technologies. Consequently, TAM provides a valuable explanation of how users' perceptions influence the adoption and effective utilization of GAI within organizations.

4. Conceptual Framework and Research Hypotheses

Based on the reviewed literature and the theoretical foundations discussed above, a conceptual framework was developed to explain the relationships among Organizational Agility (OA), Generative AI Adoption (GAI Adoption), and Decision-Making Quality (DMQ). Despite the growing interest in these constructs, limited empirical evidence exists regarding the mediating role of Generative AI adoption in the relationship between organizational agility and decision-making quality, particularly within the context of Algerian organizations.

To address this research gap, the present study investigates the level of GAI adoption and examines its mediating role in the relationship between organizational agility and decision-making quality. Accordingly, the study adopts a mediation model comprising three key constructs: an independent variable (Organizational Agility), a mediating variable (GAI Adoption), and a dependent variable (Decision-Making Quality).

The proposed research hypotheses are formulated as follows:

H1: Organizational Agility has a statistically significant positive direct impact on Generative AI Adoption in Algerian organizations.

H2: Generative AI Adoption has a statistically significant positive direct impact on Decision-Making Quality in Algerian organizations.

H3: Organizational Agility has a statistically significant positive direct impact on Decision-Making Quality in Algerian organizations.

H4: Generative AI Adoption significantly and partially mediates the relationship between Organizational Agility and Decision-Making Quality in Algerian organizations.

To achieve the study objectives, a structured questionnaire was employed as the primary data collection instrument. The collected data were analyzed, and the research hypotheses were tested using Structural Equation Modeling (SEM) with AMOS version 25.

The questionnaire consisted of two main sections :

- **Section I:** Demographic and occupational characteristics of the respondents.
- **Section II:** Measurement items related to the study constructs, organized into three dimensions corresponding to the research variables.

Table 1. Structure of the Questionnaire and Measurement Dimensions

Sections	Axis	Minor Variables	Statements
Section One	-	General Information	05
Section Two	The First Axis Independent Variable **Organizational Agility**	Responsiveness to Change	03
		Flexibility	03
		Innovation	03
		Operational Efficiency	03
	The Second Axis Mediating Variable **Generative Artificial Intelligence Adoption**	Perceived Ease of Use	03
		Perceived Usefulness	03
		Management Support	03
		Organizational Integration	03
	The Third Axis Dependent Variable **Decision-Making Quality**	Decision Accuracy	03
		Decision Timeliness/Speed	02
		Decision Objectivity	03
		Decision Effectiveness	03

Source : Prepared by the authors

The survey instrument comprised **35 items** designed to measure the study constructs. Responses were collected using a **five-point Likert scale**, ranging from Strongly Disagree (1) to Strongly Agree (5). This scale is commonly employed in behavioral and management research due to its reliability in capturing respondents' perceptions and attitudes. For all statistical analyses, a significance level of **0.05** was adopted as the critical threshold for hypothesis testing. Accordingly, the null hypothesis was rejected whenever the associated p-value was below 0.05.

5. Research Methodology

5.1. Sampling and Data Collection

The unit of analysis in this study was the individual employee/manager working within the selected Algerian economic organizations. This choice is justified by the nature of the research topic, which focuses on the adoption of Generative Artificial Intelligence Adoption and its relationship with Organizational Agility (OA) and Decision-Making Quality (DMQ). Consequently, obtaining the perceptions of employees and managers was essential, as they are the most knowledgeable about organizational practices and technological applications within their work environment.

The survey targeted employees from different organizational levels, including administrative staff, supervisors, and managers. To ensure broader representation, participants were selected from organizations operating in various sectors, including energy, postal services, telecommunications, banking, and insurance. Particular attention was also given to demographic diversity, including age, gender, educational level, and professional experience, in order to provide a comprehensive understanding of the adoption of GAI technologies in Algerian organizations and their influence on decision-making quality.

A non-probability convenience sampling technique was employed. Questionnaires were distributed to accessible employees within the selected organizations during the data collection period without prior stratification or random selection from a defined sampling frame.

Table 2. Study Population and Sample

Organization	Distributed Questionnaires	Returned Questionnaires	Rejected Questionnaires	Valid Questionnaires
Sonelgaz	70	62	7	55
Algeria Post	55	49	4	45
Algérie Télécom	50	44	4	40
BEA Bank	45	39	4	35
CPA Bank	40	35	5	30
BNA Bank	40	35	5	30
SAA Insurance	35	31	1	30
CAAT Insurance	40	38	3	35
Total	**375**	**333**	**33**	**300**

Source: Prepared by the authors.

A total of 375 questionnaires were distributed across the participating organizations. Of these, 333 questionnaires were returned. After data screening, 33 questionnaires were excluded due to incomplete, inconsistent, or patterned responses. Consequently, 300 valid questionnaires remained for statistical analysis, yielding a response rate of approximately 80%, which is considered adequate for Structural Equation Modeling (SEM) analysis.

5.2. Sample Size

Determining an appropriate sample size remains one of the most debated issues in multivariate statistical analysis, particularly in factor analysis and structural equation modeling. According to Tighaza (2012), factor analysis requires relatively large samples, and a minimum sample size of 100 observations is generally considered acceptable. Furthermore, Comrey and Lee (1992) classified a sample size of 300 as good for factor analysis.

Tighaza (2012) emphasized that the sample size should not be less than 200 observations (Tighaza, 2012, p. 24). Several methodological references also recommend maintaining a respondent-to-item ratio ranging from 10:1 to 15:1, meaning that each measurement item should be represented by at least 10 to 15 respondents. Given that the present study included 35 measurement items and collected data from 300 respondents, the sample size can be considered sufficient for conducting factor analysis and structural equation modeling.

To further assess sampling adequacy, the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity were employed.

5.3. Assessment of Sample Adequacy

To evaluate the suitability of the collected data for factor analysis, the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity were applied.

The KMO statistic assesses the degree of common variance among variables and determines whether the sample size is adequate for factor analysis. Values greater than 0.50 indicate sufficient sampling adequacy and acceptable intercorrelations among variables.

Bartlett's Test of Sphericity examines the null hypothesis that the correlation matrix is an identity matrix, implying that variables are unrelated and therefore unsuitable for factor analysis. A statistically significant result ($p < 0.05$) indicates that the correlation matrix contains sufficient relationships to justify factor extraction.

Table 3. KMO and Bartlett's Test Results for Sampling Adequacy

Study Constructs	KMO Value	Sig.
First Construct	0.962	0.000
Second Construct	0.935	0.001
Third Construct	0.937	0.001
Overall Questionnaire	**0.971**	**0.000**

Source: Prepared by the authors based on SPSS Version 27 output.

The Kaiser–Meyer–Olkin (KMO) measure was used to assess the adequacy of the sample for factor analysis. KMO values exceeding 0.50 indicate that the sample size is sufficient for conducting factor analysis, whereas values above 0.90 reflect excellent sampling adequacy (EL-Fardaoui, 2019).

As shown in Table 3, the KMO values for the study constructs ranged from 0.935 to 0.962, while the overall KMO value for the questionnaire reached 0.971. These results indicate an excellent level of sampling adequacy and confirm the suitability of the data for factor analysis. In addition, the correlation matrix was examined using Bartlett's Test of Sphericity. The test yielded a Chi-square value of 4868.20 with 325 degrees of freedom, which was statistically significant ($p < 0.001$). Since the significance level was below the threshold of 0.05, the null hypothesis that the correlation matrix is an identity matrix was rejected. Accordingly, the correlations among the study variables were statistically significant and sufficiently strong to allow the extraction of latent factors. These findings further confirm the suitability of the dataset for factor analysis and subsequent structural equation modeling procedures, as presented in the following table.

Table -4- : KMO and Bartlett's Test Results

Test	Value	
Kaiser-Meyer-Olkin Measure of Sampling Adequac	0.971	
Bartlett's Test of Sphericity	Approx.Chi-Square	4868.209
	Df	325
	Sig	.000

Source: primary data output

5.4. Reliability of the Research Instrument

The validity of a questionnaire refers to its ability to accurately represent the phenomenon under investigation and to generate responses that provide the information for which the instrument was designed. Reliability, on the other hand, reflects the consistency and stability of the measurement instrument. A questionnaire is considered reliable when it produces similar results if administered repeatedly to comparable samples drawn from the same population under similar conditions. The degree of consistency is expressed by the reliability coefficient. Based on the results of reliability testing, the questionnaire may either be accepted in its current form or revised to improve its measurement quality. Reliability analysis also helps determine the extent to which questionnaire items are internally consistent and measure the same underlying construct.

5.4.1. Cronbach's Alpha Test

Cronbach's Alpha is one of the most widely used indicators for assessing the internal consistency reliability of research instruments. It evaluates the degree of correlation among the questionnaire items that constitute each construct. Higher alpha values indicate greater consistency among the items and, consequently, a higher level of measurement reliability. Table 5 presents the Cronbach's Alpha coefficients for each study axis as well as for the overall questionnaire.

Table 5. Cronbach's Alpha Coefficients for Assessing the Reliability of the Study Axes.

Variables	The Dimension	Number of Statement	Cronbach's alpha

Organizational Agility	Responsiveness to Change	03	0.625
	Flexibility	03	0.579
	Innovation	03	0.736
	Operational Efficiency	03	0.683
The first axis		**12**	**0.855**
Generative Artificial Intelligence Adoption	Ease of Use	03	0.671
	Perceived Usefulness	03	0.714
	Management Support	03	0.743
	Organizational Integration	03	0.642
The second axis		**12**	**0.874**
Decision-Making Quality	Decision Accuracy	03	0.668
	Decision Speed	02	0.592
	Decision Objectivity	03	0.709
	Decision Effectiveness	03	0.832
The Third Axis		**11**	**0.884**
Total Measurement		**35**	**0.949**

Source: Prepared by the authors based on SPSS Version 27 output.

The results presented in Table 5 indicate that the overall Cronbach's alpha coefficient was 0.949, substantially exceeding the minimum acceptable threshold of 0.70, thereby confirming a high level of internal consistency.

5.4.2. Construct Validity Assessment

Construct validity was examined using Confirmatory Factor Analysis (CFA) to evaluate the adequacy of the measurement model and to determine whether the observed indicators adequately represent their respective latent constructs. CFA is widely used to assess the factorial structure of measurement scales and to verify the theoretical relationships between latent variables and their indicators (Tighaza, 2012).

The evaluation of construct validity relied on convergent validity, which assesses the extent to which indicators of the same construct share a high proportion of common variance.

a. Goodness-of-Fit Indices

Goodness-of-fit indices are essential for evaluating the adequacy of the measurement model and determining whether the hypothesized model is consistent with the observed data. The criteria used in this study were based on the recommendations of previous methodological studies (Bollen, 1989; Hu & Bentler, 1999; Schermelleh-Engel et al., 2003; Schreiber et al., 2006; Barrett, 2007; Schumacker & Lomax, 2016; Hair et al., 2019; Kline, 2023).

Table 6. Indicators of Goodness of Fit.

Index	The Ideal Range of the Indicator
(Chi-square)	Not statistically significant
Degrees of freedom) (Chi-square/df)	Less than 5 indicates acceptance and less than 3 good fit
Comparative fit index (CFI)	Greater than 0,95 indicates a better fit
Tucker-lewis index (TLI)	> 0.9
(REMSEA) Root mean square error of approximation	>0.05Rmsea 0.08 >
Goodness of fit index (GFI)	> 0.90
Adjusted goodness of fit index (AGFI)	> 0.90
Normed fit index (NFI)	> 0.90
Incremental fit index (IFI)	> 0.95
SRMR/RMR	>0.08
PCLOSE	> 0.05

Source ; Kline Rex B. (2023). Principles and Practice of Structural Equation Modeling (5thed.).

b. Reliability and Convergent Validity

The assessment of reliability and convergent validity represents a critical stage in evaluating the quality of the measurement model. It aims to verify the consistency of the indicators associated with each latent construct and to ensure that they adequately capture the intended theoretical concept.

To assess convergent validity and reliability, the study relied on two widely accepted indicators in Structural Equation Modeling (SEM):

- **Composite Reliability (CR)**, which evaluates the internal consistency of the indicators associated with a latent construct.
- **Average Variance Extracted (AVE)**, which measures the amount of variance captured by a construct relative to the variance attributable to measurement error.

The following formulas were used:

- **Composite Reliability (CR)**

$$CR = (\Sigma\lambda)^2 / [(\Sigma\lambda)^2 + \Sigma(1 - \lambda^2)]$$

- **Average Variance Extracted (AVE)**

$$AVE = \Sigma(\lambda^2) / n$$

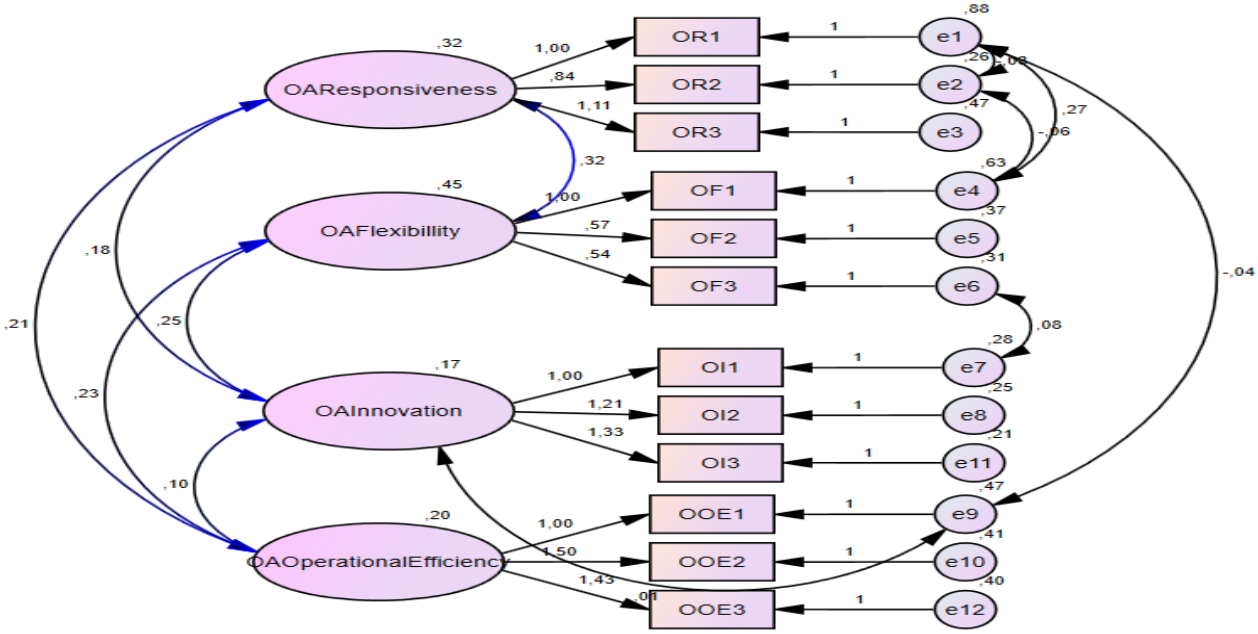
Where:

λ = standardized factor loading.

n = number of indicators (items) associated with the construct.

The results of the confirmatory factor analysis and the corresponding model fit statistics are presented in the following figures.

Figure 1. Confirmatory Factor Analysis of Organizational Agility



Chi-square = 73.039
Degrees of freedom = 42
Probability level = ,002
Source : outputs *AMOS v25*

Table 7. Goodness-of-Fit Indices of the Measurement Model

Index	**χ²/df**	**CFI**	**TLI**	**RMSEA**	**GFI**	**AGFI**	**NFI**	**IFI**
Obtained Value	1.739	0.971	0.955	0.050	0.959	0.925	0.936	0.972
Evaluation	**Acceptable Fit**	**Excellent Fit**	**Excellent Fit**	**Good Fit**	**Excellent Fit**	**Excellent Fit**	**Excellent Fit**	**Excellent Fit**

Source: Prepared by the authors based on AMOS v25 outputs

Table 8. Composite Reliability and Convergent Validity of Organizational Agility Dimensions

Construct	**CR**	**AVE**	**Assessment**
Responsiveness to Change	0.72	0.36	Acceptable
Flexibility	0.73	0.38	Acceptable
Innovation	0.81	0.59	Good
Operational Efficiency	0.77	0.52	Good
Organizational Agility	**0.86**	**0.61**	**Very Good**

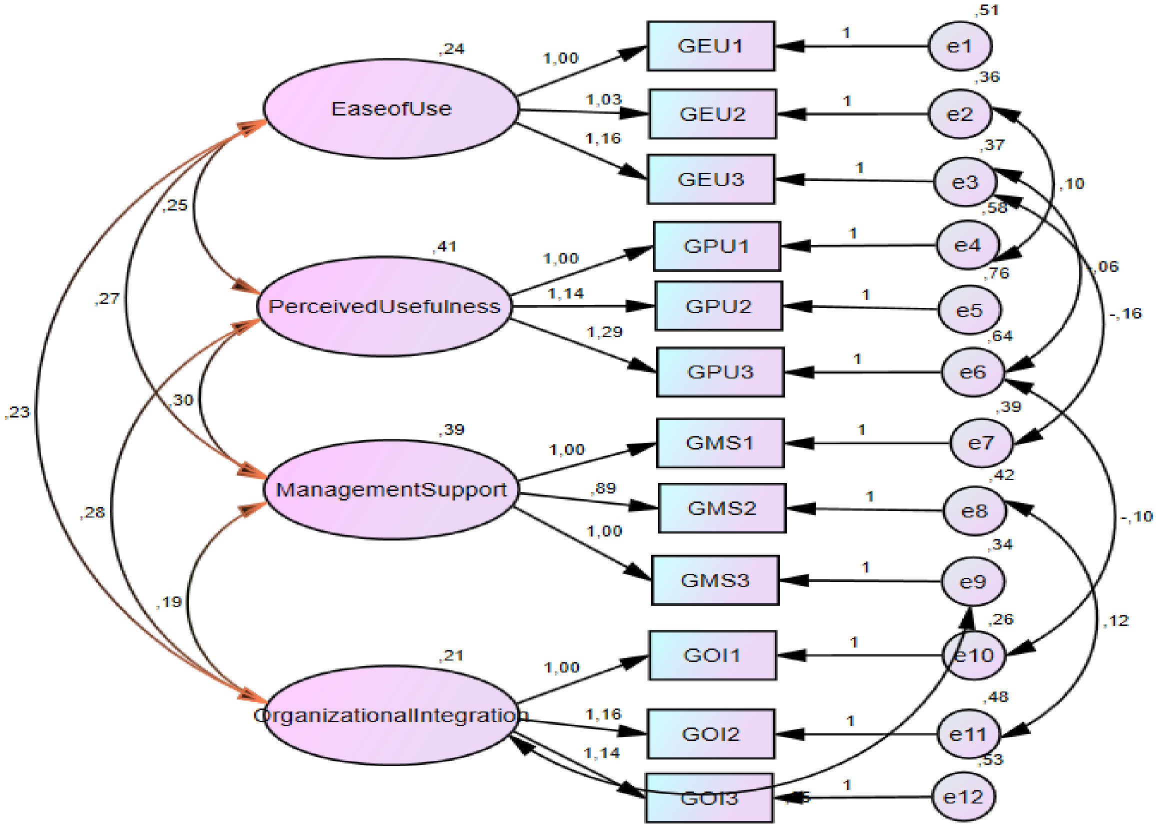
Source: Prepared by the authors based on AMOS v25 outputs

The results presented in Figure 1 and Tables 7 and 8 indicate that the measurement model of Organizational Agility demonstrates an excellent level of fit. The model achieved a χ^2/df value of 1.739, which is well below the recommended threshold, indicating a satisfactory model fit.

Furthermore, the absolute and incremental fit indices showed strong values (GFI = 0.959, CFI = 0.971, and TLI = 0.955), confirming the robustness of the measurement model. In addition, the RMSEA value of 0.050 indicates a very low approximation error and further supports the adequacy of the model.

Regarding reliability and convergent validity, the results reveal that all dimensions of Organizational Agility achieved acceptable levels of internal consistency, with Composite Reliability (CR) values exceeding the recommended threshold of 0.70. This confirms the reliability of the measurement scales. As for the Average Variance Extracted (AVE), the values ranged between 0.36 and 0.59. The dimensions Innovation and Operational Efficiency exceeded the recommended benchmark of 0.50, indicating satisfactory convergent validity. Although the AVE values of Responsiveness to Change and Flexibility remained below the recommended threshold, these dimensions were retained because their CR values exceeded 0.70, which is considered acceptable according to the criterion proposed by Fornell and Larcker (1981). Therefore, the results provide adequate evidence for the reliability and convergent validity of the Organizational Agility construct.

Figure 2. Confirmatory Factor Analysis (CFA) of the Generative AI Adoption Construct



Chi-square = 97.516
Degrees of freedom = 42
Probability level = ,000
Source : outputs *AMOS v25*

Table 9. Goodness-of-Fit Indices for the Generative AI Adoption Measurement Model

Indicator	χ^2/df	CFI	TLI	RMSEA	GFI	AGFI	NFI	IFI
Value	2.322	0.955	0.929	0.066	0.949	0.905	0.925	0.956
Assessment	**Good Fit**	**Good Fit**	**Good Fit**	**Good Fit**	**Good Fit**	**Good Fit**	**Good Fit**	**Good Fit**

Source: Prepared by the authors based on AMOS v25 outputs

Table 10. Composite Reliability and Convergent Validity of the Generative AI Adoption Construct

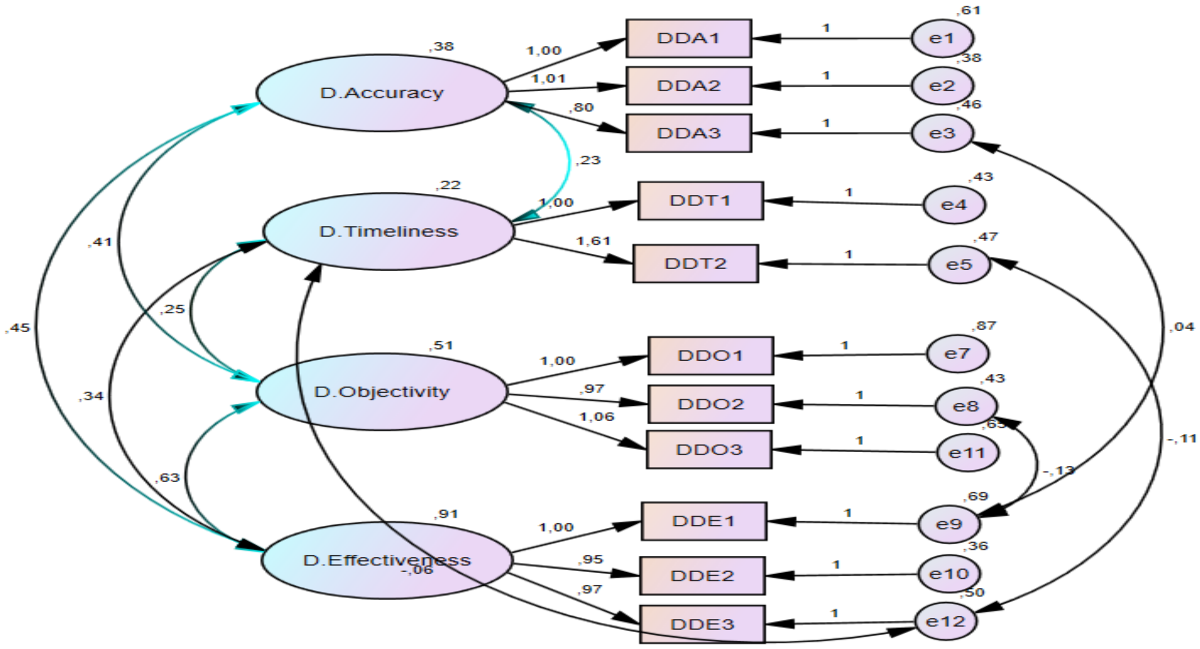
Construct	CR	AVE	Assessment
Management Support	0.82	0.60	Good
Organizational Integration	0.76	0.42	Acceptable
Perceived Ease of Use	0.76	0.41	Acceptable
Perceived Usefulness	0.79	0.48	Acceptable (Near the Recommended Threshold)
Generative Artificial Intelligence Adoption	**0.91**	**0.71**	**Excellent**

Source : Prepared by the authors based on AMOS v25 outputs.

As shown in Figure 2 and Tables 9 and 10, the goodness-of-fit indices indicate that the confirmatory factor analysis (CFA) model for Generative Artificial Intelligence Adoption demonstrates a satisfactory fit to the observed data. Specifically, the χ^2/df ratio reached 2.322, which falls within the acceptable statistical threshold. Furthermore, the absolute and incremental fit indices exhibited favorable values, with GFI = 0.949, CFI = 0.955, and TLI = 0.929, all exceeding the recommended cutoff values. In addition, the RMSEA value of 0.066 indicates an acceptable level of approximation error, further supporting the adequacy of the measurement model for subsequent hypothesis testing (Hair et al., 2019).

The composite reliability results further reveal that all dimensions of Generative Artificial Intelligence Adoption achieved acceptable levels of internal consistency, as all Composite Reliability (CR) values exceeded the recommended threshold of 0.70 (Hair et al., 2019), indicating satisfactory reliability among the measurement items. Regarding convergent validity, the Average Variance Extracted (AVE) values ranged between 0.41 and 0.60. The Management Support dimension recorded the highest AVE value (0.60), while the remaining dimensions exhibited AVE values between 0.41 and 0.48. Although some AVE values were slightly below the recommended threshold of 0.50, they remain acceptable when accompanied by high CR values. According to Fornell and Larcker (1981), convergent validity can be considered adequate when Composite Reliability is sufficiently high, even if AVE falls below 0.50. Therefore, the results provide adequate evidence of the reliability and convergent validity of the GAI measurement model, supporting its suitability for structural model assessment.

Figure 3. Confirmatory Factor Analysis (CFA) of the Decision-Making Quality Construct



Chi-square = 69.912
Degrees of freedom = 34
Probability level = ,000
Source : outputs *AMOS v25*

Table 11. Goodness-of-Fit Indices for the Decision-Making Quality Measurement Model

Indicator	**χ^2/df**	**CFI**	**TLI**	**RMSEA**	**GFI**	**AGFI**	**NFI**	**IFI**
Value	2.056	0.972	0.955	0.059	0.961	0.923	0.948	0.973
Assessment	**Good Fit**	**Good Fit**	**Good Fit**	**Good Fit**	**Good Fit**	**Good Fit**	**Good Fit**	**Good Fit**

Source: Prepared by the authors based on AMOS v25 outputs.

Table 12. Composite Reliability and Convergent Validity of the Decision-Making Quality Construct

Construct	**CR**	**AVE**	**Assessment**
Decision Accuracy	0.74	0.42	Acceptable
Decision Timeliness	0.66	0.44	Marginally Acceptable
Decision Objectivity	0.76	0.46	Acceptable
Decision Effectiveness	0.88	0.59	Good
Decision-Making Quality (DMQ)	**0.83**	**0.55**	**Good**

Source: Prepared by the authors based on AMOS v25 outputs.

As shown in Figure 3 and Tables 11 and 12, the structural equation modeling results indicate that the Decision-Making Quality (DMQ) construct demonstrates a satisfactory level of model fit. The χ^2/df ratio reached 2.056, which falls within the acceptable threshold adopted in this study. Furthermore, both the absolute and incremental fit indices exhibited strong values, with GFI = 0.961, CFI = 0.972, and TLI = 0.955, indicating a high degree of consistency between the theoretical model and the observed data. In addition, the RMSEA value was 0.059, which is within the recommended range, suggesting a low approximation error and further supporting the adequacy of the measurement model.

The reliability and convergent validity assessment revealed varying levels of measurement quality across the dimensions of Decision-Making Quality. The Decision Effectiveness dimension exhibited the highest level of reliability, with a Composite Reliability (CR) value of 0.88 and an Average Variance Extracted (AVE) value of 0.59, indicating strong measurement properties. The remaining dimensions reported CR values ranging from 0.66 to 0.76, reflecting acceptable levels of internal consistency. Likewise, the AVE values ranged between 0.42 and 0.46. Although some AVE values were below the recommended threshold of 0.50, they remain acceptable in applied research when supported by satisfactory CR values. According to Fornell and Larcker (1981) and Hair et al. (2019), convergent validity can be considered adequate when Composite Reliability exceeds the recommended minimum level, even if AVE values are slightly below 0.50. Therefore, the results provide sufficient evidence of the reliability and convergent validity of the Decision-Making Quality measurement model.

6. Hypothesis Testing and Results Analysis

To test the proposed hypotheses, Path Analysis was employed as part of the Structural Equation Modeling (SEM) approach. SEM is a multivariate statistical technique used to examine and analyze the relationships among independent and dependent variables simultaneously, allowing researchers to identify the most influential factors affecting the endogenous constructs. By integrating the strengths of both multiple regression analysis and factor analysis, SEM provides a comprehensive framework for evaluating complex causal relationships.

Path analysis can be viewed as an extension of multiple regression analysis; however, it offers greater analytical capability by accounting for interrelationships among variables, measurement errors, nonlinear effects, and multicollinearity issues. Moreover, path analysis enables the estimation of both direct and indirect effects among study variables, making it particularly suitable for mediation analysis. In contrast to full structural equation models, path analysis focuses on the relationships among observed constructs without incorporating additional latent-variable measurement structures (AL-Ariqi, 2015). Accordingly, the proposed hypotheses were tested using AMOS v25, and the results are presented in the following tables.

6.1. Testing and Analysis of Hypothesis H1

H0: Organizational Agility has no significant effect on Generative Artificial Intelligence Adoption in the organizations under study.

H1: Organizational Agility has a significant positive effect on Generative Artificial Intelligence Adoption in the organizations under study.

Table 13. Regression Weights, Standard Error, and Significance Level for the Effect of (OA) on GAI Adoption

Construct	Path	Construct	*Estimate*	*S.E.*	*C.R.*	P value	Decision
GAI Adoption	<--	Organizational Agility	**0.722**	0.060	11.987	***	**H1 Supported**

OAR	<---	Organizational Agility	1				
OAF	<---	Organizational Agility	0.699	0.52	13.327	***	
OAI	<---	Organizational Agility	0.645	0.59	10.938	***	
OAOE	<---	Organizational Agility	0.658	0.61	10.826	***	

Source: Prepared by the authors based on AMOS v25 outputs.

As presented in Table 13, the results reveal a positive and statistically significant effect of Organizational Agility on Generative Artificial Intelligence Adoption. The standardized path coefficient reached $\beta = 0.722$, indicating a relatively strong effect. Furthermore, the critical ratio (C.R. = 11.987) substantially exceeds the recommended threshold of 1.96, while the significance level was below 0.001 ($p < 0.001$), confirming the statistical significance of the relationship at the 5% significance level.

This finding suggests that higher levels of organizational agility enhance an organization's ability to adopt and effectively utilize GAI technologies across various administrative and operational activities. Organizations characterized by rapid responsiveness to environmental changes, flexible resource allocation, and adaptability to technological developments are more likely to integrate and exploit AI-based solutions successfully.

The measurement indicators associated with Organizational Agility also demonstrated strong statistical significance. The dimensions of Flexibility (OAF), Innovation (OAI), and Operational Efficiency (OAOE) reported critical ratios of 13.327, 10.938, and 10.826, respectively, all significant at $p < 0.001$. These results confirm the adequacy of these dimensions in representing and measuring the (OA) construct.

From a theoretical perspective, these findings provide support for Dynamic Capabilities Theory and the Resource-Based View. Organizational agility enables firms to sense environmental changes, mobilize resources, and adapt internal processes more effectively, thereby creating favorable conditions for the adoption of emerging technologies. In the context of GAI, agile organizations are more capable of experimenting with new digital tools, integrating AI applications into existing workflows, and overcoming organizational resistance to technological change.

More importantly, the results contribute to the growing literature on GAI by suggesting that organizational agility functions as an antecedent capability rather than merely an outcome of technological adoption. While much of the existing literature emphasizes the role of artificial intelligence in enhancing organizational agility, the present findings indicate that agile organizations are inherently better positioned to adopt and leverage GAI technologies. This perspective extends current understanding by highlighting the organizational conditions necessary for successful AI adoption and implementation.

Based on these statistical results, the null hypothesis (H0) is rejected, and the alternative hypothesis (H1) is accepted. Therefore, it can be concluded that Organizational Agility exerts a positive and statistically significant effect on Generative Artificial Intelligence Adoption in the organizations under study.

6.2. Testing and Analysis of Hypothesis H2

H0: Generative Artificial Intelligence Adoption has no significant effect on Decision-Making Quality in the organizations under study.

H1: Generative Artificial Intelligence Adoption has a significant positive effect on Decision-Making Quality in the organizations under study.

Table 14. Regression Weights, Standard Error, and Significance Level for the Effect of GAI Adoption on DMQ

Construct	Path	Construct	*Estimate*	*S.E.*	*C.R.*	P value	Decision
Decision Making Quality	<--	GAI Adoption	**0.597**	0.114	5.263	***	**H2 Supported**
GOI	<---	GAI Adoption	1				
GMS	<---	GAI Adoption	0.901	0.083	10.837	***	
GPU	<---	GAI Adoption	1.033	0.080	12.878	***	
GEU	<---	GAI Adoption	0.944	0.083	11.389	***	

Source: Prepared by the authors based on AMOS v25 outputs.

As presented in Table 14, the results indicate a positive and statistically significant effect of Generative Artificial Intelligence (GAI) Adoption on Decision-Making Quality. The standardized path coefficient reached $\beta = 0.597$, reflecting a moderate-to-strong positive effect. Furthermore, the critical ratio (C.R. = 5.263) exceeded the recommended threshold of 1.96, while the significance level was below 0.001 ($p < 0.001$), confirming the statistical significance of the relationship at the 5% significance level.

This finding suggests that higher levels of GAI Adoption contribute significantly to improving organizational decision-making quality. The positive effect indicates that organizations capable of effectively integrating GAI technologies can enhance their information-processing capabilities and reduce uncertainty in managerial decision-making. By facilitating the analysis of large volumes of data, generating contextual insights, and supporting the evaluation of strategic alternatives, generative AI enables decision-makers to make more accurate, objective, timely, and effective decisions. These findings are consistent with the Technology Acceptance Model (TAM), which argues that the perceived usefulness of a technology increases its contribution to organizational outcomes. They also support previous research highlighting the role of AI-enabled analytical capabilities in strengthening managerial decision processes and improving organizational performance.

Based on these results, the null hypothesis (H0) is rejected and the alternative hypothesis (H2) is accepted. Therefore, it can be concluded that Generative Artificial Intelligence Adoption has a positive and statistically significant effect on Decision-Making Quality in the organizations under study.

6.3. Testing and Analysis of the Third Hypothesis H3

H0: Organizational Agility has no significant effect on Decision-Making Quality in the organizations under study.

H1: Organizational Agility has a significant effect on Decision-Making Quality in the organizations under study.

Table 15. Regression Weights, Standard Errors, and Significance Levels for the Effect of OA on DMQ

Construct	Path	Construct	*Estimate*	*S.E.*	*C.R.*	P value	Decision
Decision - Making Quality	<--	Organizational Agility	**0.401**	0.097	4.155	***	**H3 Supported**
DDA	<---	Decision -Making Quality	1				
DDO	<---	Decision -Making Quality	1.121	0.082	13.695	***	
DDE	<---	Decision -Making Quality	1.256	0.094	13.402	***	
DDT	<---	Decision -Making Quality	0.858	0.075	11.380	***	

Source: AMOS v25 Output.

The results indicate a positive and statistically significant direct effect of Organizational Agility on Decision-Making Quality, with a standardized path coefficient of $\beta = 0.401$ and a significance level of $p < 0.001$. The critical ratio (C.R. = 4.155) exceeds the recommended threshold of 1.96, confirming the statistical significance of the relationship at the 5% significance level.

These findings suggest that organizations exhibiting higher levels of agility are better positioned to make decisions that are accurate, timely, objective, and effective. Organizational agility enhances the ability of firms to adapt rapidly to environmental changes, reconfigure resources efficiently, and respond proactively to emerging operational and strategic challenges.

The measurement indicators of Decision-Making Quality also demonstrated strong statistical significance. The dimensions of Decision Accuracy (DDA), Decision Objectivity (DDO), Decision Effectiveness (DDE), and Decision Timeliness (DDT) exhibited high critical ratios, with DDO, DDE, and DDT recording values of 13.695, 13.402, and 11.380, respectively ($p < 0.001$). These results confirm the adequacy of the selected indicators in representing the latent construct of Decision-Making Quality.

From a theoretical perspective, this result can be explained by the fact that organizational agility improves information flow across organizational levels, strengthens coordination among departments, and reduces the time required to process information and respond to emerging issues. Consequently, agile organizations are more capable of making informed and effective decisions under dynamic conditions.

The finding is particularly relevant for the organizations included in this study—namely those operating in the energy, postal services, telecommunications, banking, and insurance sectors—which are characterized by relatively complex administrative structures, multiple decision-making levels, increasing service responsiveness requirements, and ongoing digital transformation initiatives.

Although the direct effect of Organizational Agility on Decision-Making Quality ($\beta = 0.401$) is lower than the effects reported in the first and second hypotheses, it remains positive, statistically significant, and practically meaningful. This finding further suggests that organizational agility may influence decision-making quality both directly and indirectly through intermediary mechanisms such as the adoption of advanced digital technologies and intelligent decision-support systems.

From a managerial perspective, these findings indicate that improving decision-making quality requires more than access to information or managerial expertise. Organizations must also develop the agility needed to process information efficiently, coordinate activities across functional units, and respond rapidly to changing environmental conditions. The results therefore highlight organizational agility as a critical capability that enhances managerial effectiveness and supports superior decision outcomes. Moreover, the significance of the direct effect suggests that agility contributes to decision-making quality independently of technological factors, while also creating favorable conditions for leveraging advanced digital technologies and intelligent decision-support systems.

Overall, the findings indicate that Organizational Agility constitutes a critical organizational prerequisite for achieving superior Decision-Making Quality. Accordingly, the null hypothesis (**H0**) is rejected, and the alternative hypothesis (**H1**) is accepted.

6.4. Testing and Analysis of the Fourth Hypothesis (H4)

H0: Organizational Agility has no indirect effect on Decision-Making Quality through Generative AI Adoption as a mediating variable in the organizations under study.

H1: Organizational Agility has an indirect effect on Decision-Making Quality through Generative AI Adoption as a mediating variable in the organizations under study.

To examine the indirect effect, the structural model illustrated through path analysis was estimated using AMOS v25, as shown in Figure 4. The model indicates the existence of an indirect relationship between the independent variable, Organizational Agility (OA), and the dependent variable, Decision-Making Quality (DMQ), through the mediating variable, GAI Adoption.

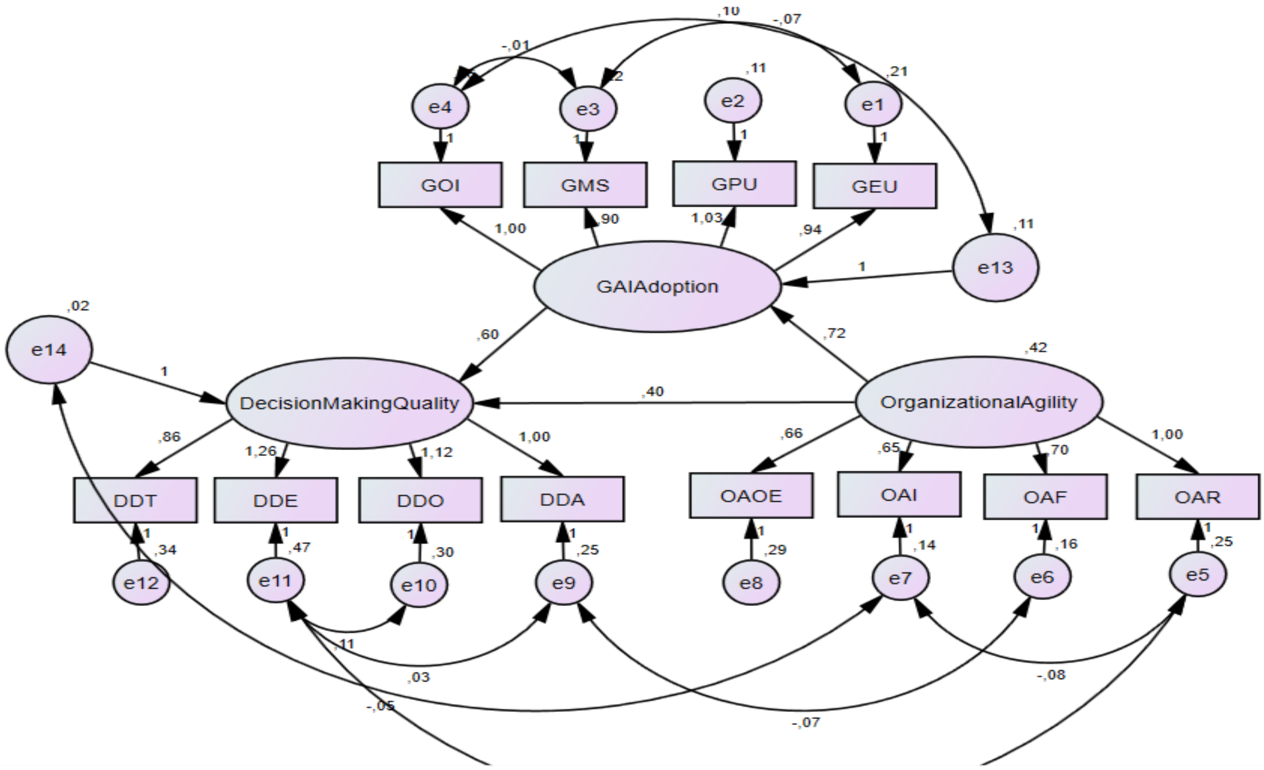
The mediation effect was assessed by estimating both the direct and indirect paths within the structural equation model. This approach allows for evaluating whether GAI Adoption serves as an underlying mechanism through which Organizational Agility influences Decision-Making Quality.

The proposed mediation model assumes that organizations characterized by higher levels of agility are more likely to adopt GAI technologies effectively. In turn, the adoption of these technologies enhances the quality of managerial decisions by improving data processing capabilities, generating actionable insights, reducing uncertainty, and supporting evidence-based decision-making.

Accordingly, the significance of the indirect effect was examined to determine whether GAI Adoption acts as a mediating variable in the relationship between Organizational Agility and

Decision-Making Quality. The results of this analysis are presented in the following tables and figures.

Figure 4. Proposed Structural Research Model



Chi-square = 65.519
Degrees of freedom = 42
Probability level = ,012
Source : outputs AMOS v25

Table 16. Goodness-of-Fit Indices for the Structural Model

Index	χ²/df	CFI	TLI	RMSEA	GFI	AGFI	NFI	IFI
Value	1.560	0.989	0.982	0.043	0.965	0.935	0.970	0.989
Assessment	Good Fit	Good Fit	Good Fit	Good Fit	Good Fit	Good Fit	Good Fit	Good Fit

Source: Prepared by the authors based on AMOS v25 output.

The evaluation of the goodness-of-fit indices indicates that the proposed structural model exhibits a high degree of statistical fit with the empirical data. All fit indices fall within their recommended thresholds, demonstrating an excellent model fit, which strengthens the reliability of the path analysis and mediation testing results and confirms the suitability of the structural model for examining the causal relationships among the study variables.

Based on the direct path analysis, the following results were obtained:

Table 17. Regression Weights, Standard Errors, and Significance Levels of the Direct Effects among the Study Variables

Hypothesis	Path Relationship	Path Coefficient	*C.R.*	P Value	Empirical Decision
H1	Organizational Agility → Generative AI Adoption	**0.722**	11.987	< 0.001	Supported
H2	Generative AI Adoption → Decision Making Quality	**0.597**	5.263	< 0.001	Supported
H3	Organizational Agility → Decision Making Quality	**0.401**	4.155	< 0.001	Supported
H4	Organizational Agility → Generative AI Adoption → Decision Making Quality	**0.431 (Indirect)**	**-**	< 0.01	Supported (Partial Mediation)

Source: AMOS v25 Output

The findings are consistent with the perspective of the Dynamic Capabilities Framework, which argues that an organization's ability to adapt and renew itself does not stem from technology alone, but rather from pre-existing organizational capabilities that enable it to sense environmental changes, seize opportunities, and continuously reconfigure its internal resources in response to digital transformation.

The results reveal that Organizational Agility represents a fundamental antecedent capability that plays a pivotal role in enabling organizations to adopt and effectively utilize modern digital technologies, including GAI. Therefore, Organizational Agility should not be viewed as a dependent outcome or a secondary mechanism; rather, it constitutes a foundational organizational capability that underpins successful digital transformation initiatives.

The findings further indicate that GAI does not function as an independent force driving organizational change. Instead, it should be understood as an enabling technology that enhances organizational analytical and cognitive capabilities and transforms agile organizational structures into more effective decision-making outcomes. In this sense, GAI is not the primary driver of change but rather a technological mechanism through which the benefits of organizational agility are translated into improved organizational performance and decision quality.

Accordingly, the causal relationships identified by the structural model reflect a coherent theoretical logic in which Organizational Agility precedes and positively influences GAI Adoption, which subsequently contributes to improving Decision-Making Quality. This finding provides further empirical support for the view that organizational capabilities constitute the primary foundation of successful digital transformation, while emerging technologies serve as complementary enablers that amplify the impact of these capabilities.

To further examine the mediating effect of GAI Adoption, the Sobel Test was employed as an additional statistical procedure to assess the significance of the indirect effect (Sobel, 1982).

Sobel test equation (Sobel, 1982)

$$z\text{-value} = a*b/\mathrm{SQRT}(b^2*s_a^2 + a^2*s_b^2)$$

Aroian test equation

$$z\text{-value} = a*b/\mathrm{SQRT}(b^2*s_a^2 + a^2*s_b^2 + s_a^2*s_b^2)$$

Goodman test equation

$$z\text{-value} = a*b/\mathrm{SQRT}(b^2*s_a^2 + a^2*s_b^2 - s_a^2*s_b^2)$$

mediation is assessed through three principal paths:

1. The effect of Organizational Agility on GAI Adoption (Path a).
2. The effect of GAI Adoption on Decision-Making Quality (Path b).
3. The direct effect of Organizational Agility on Decision-Making Quality (Path c′).

The indirect effect is calculated as follows (Sobel, 1982):

Indirect Effect = a × b

Indirect Effect = (Organizational Agility → GAI Adoption) × (GAI Adoption → Decision Making Quality)

- a path = 0.722
- b path = 0.597
- c' path = 0.401

Therefore:

Indirect Effect = 0.722 × 0.597

Indirect Effect = 0.431

The total effect is calculated as

Total Effect = Direct + Indirect

Total Effect = 0.401 + 0.431 = 0.832

Based on the results of the first three hypotheses:

- Organizational Agility was found to exert a significant positive effect on GAI Adoption (Path a).
- GAI Adoption was found to exert a significant positive effect on Decision-Making Quality (Path b).
- Organizational Agility was also found to exert a significant direct effect on Decision-Making Quality (Path c′).

Accordingly, the conditions for mediation proposed by Baron and Kenny (1986), as well as contemporary SEM guidelines (Hair et al., 2019), are fully satisfied. These results provide strong evidence of a statistically significant mediation effect, indicating that GAI Adoption serves as a substantial explanatory mechanism through which Organizational Agility enhances Decision-Making Quality. The findings specifically suggest the presence of strong partial mediation, given that both the direct and indirect effects remain statistically significant (Baron & Kenny, 1986).

To further validate the mediation effect, the Sobel Test was conducted using the online Sobel Test Calculator. The obtained z-values were compared with the critical value of the standard normal distribution at the 0.05 significance level (±1.96) (Walpole, Myers, & YE, 2012), following the methodology originally proposed by Sobel (1982) and later adopted by Baron and Kenny (1986).

Table 18. Sobel Test Results

Input:			Test statistic:	Std. Error:	p-value:
a	0.722	Sobel test:	4.80182735	0.08976458	0.00000157
b	0.597	Aroian test:	4.78794725	0.0900248	0.00000168
s_a	0.060	Goodman test:	4.81582886	0.0895036	0.00000147
s_b	0.114	Reset all	Calculate		

Input:			Test statistic:	p-value:
t_a	12.0333	Sobel test:	4.80179277	0.00000157
t_b	5.2368	Aroian test:	4.78791267	0.00000169
		Goodman test:	4.81579428	0.00000147
		Reset all	Calculate	

Source: Sobel Test Calculator (QuantPsy.org). (Kristopher, 2010-2026)

The Sobel test results indicate a statistically significant indirect effect of (OA) on (DMQ) Quality through GAI Adoption. The obtained z-values were approximately 4.80 for the Sobel test, 4.79 for the Aroian test, and 4.81 for the Goodman test. All values substantially exceed the critical threshold of ±1.96 at the 5% significance level. Furthermore, the associated probability values were lower than 0.001, providing strong evidence against the null hypothesis of no indirect effect.

These findings provide strong evidence that GAI Adoption functions as a significant explanatory mechanism through which Organizational Agility enhances Decision-Making Quality. The results indicate that organizational agility alone is not sufficient to maximize decision outcomes; rather, its benefits are partially realized through the successful adoption and utilization of advanced digital technologies. In this regard, agile organizations appear better equipped to integrate GAI into their operational and managerial processes, thereby improving information processing, reducing uncertainty, and supporting more accurate and effective decisions.

From a theoretical perspective, the mediation effect extends existing literature by demonstrating that Organizational Agility acts as an antecedent dynamic capability that facilitates the adoption of Generative AI, which subsequently translates organizational flexibility into superior decision outcomes. This finding contributes to a growing body of research emphasizing that the value of artificial intelligence depends not only on technological capabilities but also on the organizational conditions that enable its effective implementation and use.

Accordingly, the null hypothesis (H0) is rejected and the alternative hypothesis (H4) is accepted, confirming the existence of a statistically significant partial mediation effect of GAI Adoption in the relationship between Organizational Agility and Decision-Making Quality.

7. Conclusion and Study Findings

The findings of this study demonstrate that effective digital transformation does not depend solely on the adoption of GAI technologies. Rather, it fundamentally depends on the existence of organizational capabilities that enable institutions to absorb, integrate, and leverage such technologies effectively. In this regard, Organizational Agility emerges as the foundational dynamic capability that facilitates the successful adoption of GAI and enhances its contribution to improving Decision-Making Quality within organizations.

The study findings underscore the importance of investing in organizational capabilities and strengthening digital readiness, as these factors constitute essential prerequisites for maximizing the benefits of GAI applications and improving both administrative and strategic decision-making outcomes.

Overall, the study concludes that enhancing Decision-Making Quality in contemporary organizations depends on the integration of Organizational Agility as an antecedent dynamic capability and GAI Adoption as an enabling technological mechanism. This confirms that successful digital transformation cannot be achieved through technology alone; rather, it requires organizational readiness capable of supporting and leveraging technological innovations effectively.

The empirical findings can be summarized as follows:

- The analysis of the first hypothesis confirmed that Organizational Agility exerts a significant positive direct effect on GAI Adoption within the organizations under study.
- The analysis of the second hypothesis confirmed that GAI Adoption exerts a significant positive direct effect on Decision-Making Quality within the organizations under study.
- The analysis of the third hypothesis confirmed that Organizational Agility exerts a significant positive direct effect on Decision-Making Quality within the organizations under study.
- The analysis of the fourth hypothesis confirmed that Organizational Agility exerts a significant positive indirect effect on Decision-Making Quality through GAI Adoption as a mediating variable within the organizations under study.

8. Recommendations

- Based on the study findings, the following recommendations are proposed:
- Strengthen Organizational Agility by developing flexible organizational structures and simplifying administrative procedures to improve responsiveness to environmental and technological changes.
- Adopt a clear institutional strategy for GAI that defines implementation mechanisms, governance frameworks, monitoring procedures, and performance evaluation practices across organizational functions.
- Invest in digital infrastructure and provide the technological systems and platforms necessary to support GAI applications and integrate them into organizational processes.
- Enhance employees' digital competencies through specialized training programs focused on the effective use of GAI tools for decision support and organizational problem-solving.

- Foster a culture of innovation and organizational learning that encourages employees to leverage intelligent technologies and continuously improve traditional work practices.
- Utilize GAI as a decision-support tool rather than a substitute for managerial judgment, while maintaining the central role of human expertise in evaluating alternatives and making final decisions.
- Develop robust AI governance frameworks to ensure the responsible and ethical use of Generative AI technologies while safeguarding information security, privacy, and confidentiality.
- Encourage future research to examine additional mediating and moderating variables, such as organizational culture, digital transformation, technological readiness, and organizational innovation, to gain a deeper understanding of the relationships among Organizational Agility, GAI Adoption, and Decision-Making Quality, thereby enriching the growing body of knowledge on Artificial Intelligence applications in contemporary management.

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