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Intelligent Quality Management as a Strategic Capability: The Impact of Artificial Intelligence and Predictive Analytics on Continuous Improvement and Competitive Advantage

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Abstract

This study investigates intelligent quality management as a strategic capability and examines how artificial intelligence and predictive analytics contribute to continuous improvement and competitive advantage. Against the backdrop of the accelerating shift toward data-driven management systems, the study moves beyond viewing artificial intelligence merely as a technological tool by examining how it can be transformed into an organizational and strategic capability capable of generating sustainable value. To achieve this objective, a conceptual model was developed to examine the direct, indirect, and moderating relationships among the study variables, using empirical data comprising 325 observations. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), while bootstrapping with 5,000 resamples was employed to assess the statistical significance of direct, indirect, and interaction effects. The findings demonstrate satisfactory levels of reliability, convergent validity, and discriminant validity for the measurement model. The structural model reveals significant positive effects of artificial intelligence on BMI and SCA, as well as significant positive effects of BMI and SCA on FP. Artificial intelligence also exhibits a significant direct effect on FP, in addition to significant indirect effects through BMI and SCA. Furthermore, the interaction between artificial intelligence and SCA has a statistically significant moderating effect on FP, whereas the interaction between artificial intelligence and BMI is not statistically significant. The model explains approximately 43.8% of the variance in FP, indicating substantial explanatory power. Overall, the findings suggest that the strategic value of artificial intelligence does not arise from technology alone, but rather from its integration into a broader system of organizational capabilities, intelligent quality management, and continuous improvement. Such integration enables firms to transform data and predictive insights into sustainable competitive value.

Keywords: Intelligent Quality Management; Artificial Intelligence; Predictive Analytics; Continuous Improvement; Strategic Capability; Competitive Advantage; Firm Performance; PLS-SEM.

Introduction

The increasing pace of technological development and digital transformation has reshaped the business environment and the ways in which companies manage their operations and quality. Quality is no longer limited to detecting errors after they occur; rather, it is increasingly moving toward intelligent and proactive models based on data and advanced analytics to predict problems and continuously improve processes. In this context, artificial intelligence and predictive analytics have emerged as tools capable of supporting decision-making, detecting deviations, predicting quality risks, and improving operational efficiency.

This transformation has led to the emergence of the concept of Intelligent Quality Management as an approach that goes beyond traditional quality management by integrating intelligent technologies, data, and analytics with continuous improvement practices. This approach enables companies to move from responding to problems to predicting them, and from decisions based solely on experience to evidence- and analytics-based decisions, thereby enhancing their ability to respond to changes and achieve more sustainable performance.

However, possessing artificial intelligence technologies does not necessarily guarantee competitive outcomes, as the value derived from these technologies depends on the company's ability to integrate them into its organizational and strategic capabilities. Therefore, it is important to view artificial intelligence not merely as an independent technology, but as a strategic capability that can contribute to developing organizational capabilities, supporting continuous improvement, and transforming information and analytics into economic and competitive value.

Research Problem: This study seeks to address this gap by examining the direct, indirect, and interaction effects between artificial intelligence, organizational capabilities, and firms' outcomes. Accordingly, the main research question can be formulated as follows:

To what extent does intelligent quality management based on artificial intelligence and predictive analytics contribute to enhancing continuous improvement and achieving competitive advantage for firms through the development of their strategic capabilities?

Research Hypotheses

H1: Artificial intelligence has a positive and statistically significant effect on FP.

H2: Artificial intelligence has a positive and statistically significant effect on BMI.

H3: Artificial intelligence has a positive and statistically significant effect on SCA.

H4: Both BMI and SCA have positive and statistically significant effects on FP.

H5: Both BMI and SCA mediate the relationship between artificial intelligence and FP.

H6: SCA moderates the relationship between artificial intelligence and FP.

Research Significance: The significance of this study stems from the increasing adoption of artificial intelligence and predictive analytics by firms in managing operations and quality, accompanied by a gradual transition from traditional quality management toward intelligent and proactive quality management. The main significance of the study lies in clarifying how artificial intelligence can be transformed from merely a technological tool into a strategic capability that contributes to supporting continuous improvement and enhancing firms' competitive outcomes.

The study also has practical significance through testing the direct, indirect, and interaction effects among the model variables using PLS-SEM. This makes it possible to identify the most influential paths leading to outcomes and provide insights that managers can use when designing intelligent transformation and quality management strategies.

Research Objectives: The primary objective of this study is to analyze the strategic role of intelligent quality management based on artificial intelligence and predictive analytics in improving firms' competitive outcomes. More specifically, the study aims to determine the effect of artificial intelligence on organizational capabilities, measure the effect of these capabilities on outcomes, examine the indirect effects of artificial intelligence, and determine whether strategic capabilities strengthen the relationship between artificial intelligence and competitive outcomes.

Research Methodology: The study adopts a quantitative analytical approach based on field data comprising 325 observations. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS. In addition, the Bootstrapping technique with 5,000 subsamples was employed to test the significance of path coefficients and the direct, indirect, and interaction effects.

First, the measurement model was assessed through outer loadings, internal consistency reliability, convergent validity, and discriminant validity. The structural model was then evaluated using path coefficients, R^2, f^2, and tests of indirect and interaction effects.

Previous Studies: Recent literature has examined the relationship between artificial intelligence, quality management, and organizational performance from various perspectives. However, most previous studies have addressed these relationships only partially, leaving room for developing a more integrated model combining technology, organizational capabilities, and competitive outcomes.

1. Mikalef et al. (2021): The study by Mikalef et al. (2021) is considered one of the key studies in developing the concept of Artificial Intelligence Capability. Rather than treating artificial intelligence merely as a technology, the study conceptualized it as an organizational capability that can be measured and linked to organizational outcomes. The empirical findings showed that AI capability contributes to organizational creativity and firm performance based on the resource-based view.

This study is similar to the current study in viewing artificial intelligence as a capability capable of generating organizational value and in linking AI to organizational outcomes. However, the current study extends this perspective by incorporating intelligent quality management, mediating capabilities, and interaction effects within a single model.

2. Sullivan & Fosso Wamba (2024): The study by Sullivan and Fosso Wamba, published in the *Journal of Business Research*, examined how AI-enabled capabilities contribute to firms' ability to respond to market changes. The study adopted a dynamic capabilities perspective and distinguished between AI-enabled automation, analytics, and relational capabilities. The findings showed that these capabilities enhance firms' responses to market changes, which in turn are positively associated with firm performance and product and process innovation.

The current study is similar in considering artificial intelligence as a source of organizational capabilities rather than merely a technology and in focusing on the transmission of the effect of AI to outcomes through mediating capabilities. However, the current study differs by focusing on intelligent quality management and continuous improvement and by introducing SCA as a moderating factor in the relationship between AI and outcomes.

3. Carvalho et al. (2024): The study by Carvalho et al. (2024), published in the *Quality Management Journal*, focused on developing a roadmap for the transition toward Quality 4.0. It concluded that digital transformation in quality management does not depend solely on technology but also requires the gradual development of organizational, human, and managerial capabilities. The study further emphasized that the transition toward Quality 4.0 requires alignment between technology, quality management practices, and human resources.

This study is consistent with the current study in linking technology with quality management and organizational capabilities, and in emphasizing the transition from traditional quality management to intelligent quality management. However, it primarily provides a conceptual foundation and roadmap rather than testing a quantitative causal model linking artificial intelligence, capabilities, and competitive outcomes.

4. Godinho Filho & Nascimento (2026): The study by Godinho Filho and Nascimento (2026) is among the studies most closely related to the current research. It empirically examined the impact of artificial intelligence adoption on quality management processes within service organizations, using a multiple-case study approach and drawing on dynamic capabilities theory. The findings showed that AI adoption supports quality management, particularly through organizations' ability to learn rapidly, develop new solutions and procedures for quality control and assurance, and integrate them into organizational processes. It also helps organizations predict problems and take proactive actions to improve quality and performance.

This study is directly similar to the current study in combining artificial intelligence, quality management, proactive orientation, and performance improvement. However, it differs methodologically, as it employed a multiple-case study approach, whereas the current study uses a quantitative model to test direct, indirect, and interaction effects using PLS-SEM.

Similarities Between Previous Studies and the Current Study: The four previous studies converge with the current study in several fundamental aspects. Most importantly, artificial intelligence is no longer viewed merely as an operational technology, but rather as a source of organizational and strategic capabilities. The studies also agree that the real value of artificial intelligence emerges when it is integrated into organizational processes, quality management, and decision-making.

Previous studies also agree with the current study on the importance of shifting from traditional management and responding to problems after they occur toward proactive management based on data, analytics, and prediction. They further emphasize that technology requires organizational, human, and managerial capabilities to be transformed into actual value.

Differences Between Previous Studies and the Current Study: The current study differs from previous studies in several respects. First, it focuses on intelligent quality management as a strategic capability, rather than examining artificial intelligence or Quality 4.0 separately.

Second, the current study combines artificial intelligence, organizational capabilities, final outcomes, and direct, indirect, and interaction effects within a single model, whereas previous studies have generally focused on a specific relationship or dimension.

Third, the current study examines the mediating role of organizational capabilities in transmitting the effect of artificial intelligence to outcomes, in addition to testing the moderating role of SCA, a dimension that does not appear in the same integrated form in the four previous studies.

Fourth, the current study differs methodologically through the use of PLS-SEM and Bootstrapping with 5,000 subsamples to test the proposed model, whereas previous studies employed a combination of conceptual studies, reviews, case studies, and different quantitative approaches.

Fifth, the current study focuses on explaining how artificial intelligence is transformed into organizational outcomes through capabilities, quality management, and continuous improvement, rather than merely establishing a relationship between technology adoption and performance.

Research Gap: Despite the considerable development in studies addressing artificial intelligence and Quality 4.0, the literature reveals a clear research gap, namely the lack of an integrated empirical model explaining

how artificial intelligence and predictive analytics, through intelligent quality management and strategic capabilities, translate into continuous improvement and competitive outcomes.

Previous studies have examined the relationship between AI capability and performance, investigated the role of artificial intelligence in quality management, or proposed frameworks and roadmaps for the transition toward Quality 4.0. However, the empirical integration of these components within a single model remains limited.

Furthermore, studies addressing AI and performance have not given sufficient attention to how organizational capabilities mediate this effect or to the conditions under which the impact of artificial intelligence may become stronger or weaker. Therefore, the main contribution of the current study lies in developing and testing a model linking artificial intelligence, intelligent quality management, strategic capabilities, continuous improvement, and competitive outcomes, while examining direct, indirect, and interaction effects.

This research gap becomes particularly important in light of recent literature indicating that AI adoption does not automatically lead to improved performance and that realizing value from AI requires organizational capabilities capable of transforming technology and data into decisions, processes, and tangible value. Similarly, recent Quality 4.0 literature emphasizes the need for more integrated models connecting technology, capabilities, and outcomes.

Accordingly, the current study seeks to address this gap by moving beyond the question of **"Does artificial intelligence affect outcomes?"** toward the deeper question of **"How and under what conditions does artificial intelligence become a strategic capability that creates value through intelligent quality management and continuous improvement?"** This provides the study with a more integrated theoretical and practical contribution.

Chapter One: The Theoretical Framework of Intelligent Quality Management, Artificial Intelligence, and Predictive Analytics

The rapid development of Fourth Industrial Revolution technologies has brought about a fundamental transformation in quality management practices within firms. Quality is no longer based solely on post hoc control and the detection of errors after they occur; rather, it is increasingly moving toward more intelligent and proactive systems that rely on data, advanced analytics, and the prediction of problems before they occur. In this context, the concept of Quality 4.0 has emerged as a digital extension of quality management practices through the integration of Fourth Industrial Revolution technologies with quality principles, with the aim of improving efficiency, reducing costs, enhancing time and quality, and strengthening competitiveness. **(Liu, Liu, Gu, & Yang, 2023)**

Artificial intelligence has become one of the most important technologies supporting this transformation due to its ability to process large volumes of data, identify complex patterns and relationships, predict future events, and support managerial decision-making. Predictive analytics also enables a shift from analyzing what happened in the past to estimating what may happen in the future, thereby enhancing firms' ability to intervene at an early stage and continuously improve their processes. From this perspective, intelligent quality management has emerged as a managerial approach that combines the principles of quality management with digital technologies, artificial intelligence, and predictive analytics, enabling quality management to evolve from a control-oriented function into an organizational and strategic capability capable of creating value, improving performance, and strengthening competitive advantage.

First: The Evolution of Quality Management toward Quality 4.0

Historically, quality management evolved from a focus on inspection and the detection of defective products toward process control and subsequently toward Total Quality Management, which emphasized prevention, continuous improvement, employee involvement, and a focus on customer needs. With the emergence of the Fourth Industrial Revolution, digital technologies began to reshape these practices, leading to the emergence of the concept of Quality 4.0.

Quality 4.0 refers to the integration of Industry 4.0 technologies with traditional quality management principles with the aim of developing quality processes and improving organizational performance. The literature indicates that this concept encompasses a range of dimensions related to technology, processes, and people, particularly digitalization, predictive quality management, and intelligent quality management. **(Liu, Liu, Gu, & Yang, 2023)**

This transformation represents a shift from reactive quality management toward a more proactive approach, whereby the organization does not merely detect deviations after they occur, but instead uses data and intelligent technologies to predict potential deviations, identify sources of risk, and take corrective actions promptly. Thus, Quality 4.0 does not simply mean the digitalization of traditional quality tools; rather, it represents a transformation in the way quality is designed, managed, measured, and improved.

Second: Intelligent Quality Management

Intelligent quality management can be defined as an advanced approach to quality management that relies on the integration of artificial intelligence, advanced analytics, digital data, and smart technologies into planning, monitoring, diagnosis, prediction, and improvement processes. Intelligent quality management is characterized by its ability to continuously process data, analyze complex relationships and patterns that are difficult to detect using traditional methods, and provide indicators that support proactive managerial decision-making.

Accordingly, organizations move from detecting problems to predicting their likelihood of occurrence, and from addressing the causes of defects after they emerge to preventing or mitigating them before they occur.

Recent literature confirms that artificial intelligence is playing an increasingly important role in areas such as quality monitoring, problem diagnosis, process improvement, and the prediction of failures and deviations. The recent review conducted by **(Huang , Tan, Li, Li, & Tsui, 2026),** Machine learning and deep learning technologies have become important tools for improving quality, monitoring, diagnosis, and process control. Accordingly, intelligent quality management can be viewed as an organizational capability that enables firms to transform data into information, information into knowledge, and knowledge into measurable decisions and improvement actions.

Third: Artificial Intelligence as a Strategic Capability

Artificial intelligence is no longer viewed in the recent literature merely as an independent technology; rather, it is increasingly studied as an organizational and strategic capability. This perspective is grounded in the Resource-Based View (RBV), which argues that technology does not generate sustainable value simply through ownership, but rather through an organization's ability to integrate and effectively exploit technological, human, and organizational resources.

In this context, **(Mikalef & Gupta, 2021)** introduced the concept of AI Capability and developed a scale for its empirical measurement, while also examining its relationship with organizational creativity and firm performance. Their study demonstrates that realizing value from artificial intelligence requires a combination of resources, skills, and organizational capabilities that enable firms to deploy the technology effectively.

This perspective is consistent with the review conducted by **(Enholm, Papagiannidis, & Mikalef, 2022)**, which demonstrated that the business value of artificial intelligence is not determined by the technology itself, but rather by the organizational capability to deploy and utilize AI applications in pursuit of organizational objectives. Accordingly, the strategic value of artificial intelligence emerges when organizations are able to integrate it with data, human skills, and organizational processes, thereby enabling improved decision-making, process development, adaptation to change, and the creation of new sources of value.

Fourth: Artificial Intelligence in Quality Management

Artificial intelligence offers a wide range of capabilities that can be employed in quality management, including data analysis, pattern recognition, anomaly detection, failure prediction, root-cause diagnosis, and process optimization.

The importance of artificial intelligence in quality management becomes particularly evident when organizations are required to deal with large, diverse, and continuously changing datasets. In such circumstances, traditional methods may have limited capacity to detect complex relationships, whereas machine learning algorithms can analyze large volumes of data and extract patterns that can be used to support decision-making. **(Huang , Tan, Li, Li, & Tsui, 2026)** confirm that applications of artificial intelligence in quality management increasingly encompass quality improvement, monitoring, diagnosis, and process control, reflecting the transition of quality management toward more data-driven and predictive models.

Accordingly, artificial intelligence can enhance intelligent quality management by facilitating the transition from traditional control to intelligent and predictive control, from problem-solving to problem prevention, and from decisions based on historical data to decisions based on future forecasts.

Fifth: Predictive Analytics and Its Role in Quality Management

Predictive analytics refers to a set of methods that use historical and current data, together with statistical techniques and machine learning algorithms, to estimate future outcomes and events. Predictive analytics differs from descriptive analytics, which focuses on understanding what has happened, and diagnostic analytics, which seeks to determine why it happened. Instead, predictive analytics focuses on the question of what may happen in the future.

Predictive analytics is particularly important in quality management because it enables organizations to anticipate defects, failures, and deviations before they occur, thereby allowing management to take proactive measures. Predictive Quality represents one of the key directions associated with the development of Quality 4.0 **(Liu, Liu, Gu, & Yang, 2023)**. Furthermore, combining predictive analytics with artificial intelligence makes it possible to develop systems capable of learning from historical data and continuously improving their predictive capabilities, thereby supporting continuous improvement and reducing the costs of poor quality.

Sixth: Intelligent Quality Management and Continuous Improvement

Continuous improvement represents one of the fundamental principles of quality management and is based on the ongoing search for opportunities to improve processes, products, and services while reducing waste and errors. The integration of artificial intelligence and predictive analytics has contributed to the development of the concept of continuous improvement, enabling organizations to identify sources of variation more rapidly, analyze the causes of problems, predict future problems, and determine areas requiring intervention.

Accordingly, the improvement process shifts from a reactive model, which relies on addressing problems after they occur, toward a proactive model based on predicting problems before they occur. This transformation

represents one of the most important contributions of Quality 4.0 to modern quality management **(Liu, Liu, Gu, & Yang, 2023)**.

From a strategic perspective, data-driven continuous improvement contributes to enhancing process efficiency, reducing errors and waste, lowering quality-related costs, and improving response speed. These factors can ultimately strengthen the organization's competitive capability.

Seventh: Strategic Capabilities and Their Role in Transforming Technology into Value

The Dynamic Capabilities Theory explains that realizing value from technological resources does not depend solely on possessing them, but rather on an organization's ability to integrate, reconfigure, and deploy them in ways that are consistent with changes in the external environment. In the case of artificial intelligence, possessing algorithms and digital platforms alone is not sufficient to achieve better outcomes. Organizations also require human skills, high-quality data, supportive leadership, an appropriate organizational culture, and processes capable of absorbing and leveraging technology. This perspective is supported by **(Sullivan & Fosso Wamba, 2024)**, who examined how AI-enabled capabilities can enhance organizations' ability to respond to market changes. Their findings showed that capabilities related to AI-supported automation, analytics, and relationships are associated with adaptive responsiveness, which in turn is related to firm performance and innovation.

The importance of this finding for the present study lies in demonstrating that artificial intelligence does not operate independently of organizational capabilities. Rather, organizations require appropriate capabilities that enable them to transform technological potential into tangible organizational outcomes.

Eighth: Intelligent Quality Management and Competitive Advantage

Competitive advantage in the digital environment has become increasingly associated with firms' ability to use data and technology to improve efficiency, respond rapidly to changes, and enhance the quality of products and services. Intelligent quality management can contribute to achieving such advantage by reducing defects and errors, improving resource utilization, lowering quality-related costs, accelerating problem detection, and enhancing responsiveness to customers.

The Quality 4.0 literature indicates that integrating Fourth Industrial Revolution technologies into quality management can contribute to improvements in cost, time, efficiency, product quality, and organizational competitiveness **(Liu, Liu, Gu, & Yang, 2023)**. Furthermore, firms' ability to use artificial intelligence more effectively than their competitors can become a source of differentiation, particularly when this capability is supported by human and organizational resources that are difficult to imitate.

Accordingly, the relationship between artificial intelligence and competitive advantage should not be viewed merely as a direct technological relationship, but rather as a relationship that operates through organizational capabilities, intelligent quality management, and continuous improvement.

Ninth: Theoretical Integration of the Study Variables

Based on the foregoing discussion, the theoretical rationale of the present study can be established on the premise that artificial intelligence and predictive analytics represent technological inputs capable of enhancing a firm's organizational and strategic capabilities. However, transforming these technological potentials into tangible outcomes requires intelligent quality management and capabilities that can effectively absorb the technology and utilize its outputs.

Accordingly, the study assumes that artificial intelligence influences the capabilities represented by the model variables, which in turn affect the outcomes. The study also examines the indirect effects of artificial intelligence, in addition to the moderating role of strategic capabilities.

The theoretical rationale of the study can be summarized as follows:

Artificial Intelligence and Predictive Analytics → Intelligent Quality Management and Strategic Capabilities → Continuous Improvement → Competitive Outcomes

This framework provides the theoretical foundation for the empirical part of the study, where the analysis moves from the theoretical discussion to testing the hypothesized relationships among the variables using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Section Two: The Empirical Study and Analysis of the Results of the Proposed Model Using Partial Least Squares Structural Equation Modeling (PLS-SEM)

After addressing the theoretical and conceptual foundations related to intelligent quality management, artificial intelligence, predictive analytics, continuous improvement, and competitive advantage, this section aims to empirically test the proposed conceptual model and examine the hypothesized relationships among its variables based on field data analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The PLS-SEM methodology was selected due to its ability to analyze models involving several latent variables, direct and indirect relationships, and interaction effects, as well as its suitability for studies aimed at explaining relationships and predicting dependent variables.

The analysis was conducted using SmartPLS, based on an actual sample of 325 observations. The PLS-SEM algorithm was used to estimate the model coefficients, followed by the application of the Bootstrapping technique with 5,000 subsamples to test the significance of the path coefficients and the direct, indirect, and interaction effects.

First: Methodology and Procedures of the Empirical Study

1. Population and Sample of the Study: The empirical study aimed to collect data that would allow testing the proposed model of the relationships between artificial intelligence and the other capabilities and organizational variables associated with performance. The number of observations actually used in the statistical analysis was 325 observations, which was the number adopted by SmartPLS for estimating the model and testing its properties.

This sample size is considered appropriate for applying PLS-SEM, particularly because the model includes several latent variables and direct and indirect paths, in addition to interaction variables used to measure the moderating effect.

2. Data Collection Instrument and Measurement of Variables: The study relied on a set of latent variables, which were represented by a group of **items** entered into the measurement model in SmartPLS. The variables appeared in the database and model using the following abbreviations:

AI, BMI, CE, FP, GS, LS, and SCA.

The model also included two interaction variables:

AI × BMI

AI × SCA

The indicators associated with each variable were treated as reflective measurement indicators. The quality of these indicators was then assessed through Outer Loadings, internal consistency reliability, convergent validity, and discriminant validity.

3. Statistical Analysis Methodology: The analysis was conducted in two main stages.

First stage – Assessment of the Measurement Model: This stage aimed to ensure that the indicators used to measure the latent variables possessed adequate levels of reliability and validity. The following criteria were assessed:

- ❖ Outer Loadings;
- ❖ Cronbach's Alpha;
- ❖ Composite Reliability;
- ❖ Average Variance Extracted (AVE);
- ❖ Discriminant Validity using HTMT;
- ❖ Multicollinearity using VIF.

Second stage – Assessment of the Structural Model: After confirming the quality of the measurement model, the relationships among the variables were tested using:

- ❖ Path Coefficients;
- ❖ t-values and p-values;
- ❖ Bootstrap Confidence Intervals;
- ❖ Coefficient of Determination (R^2);
- ❖ Effect Size (f^2);
- ❖ Analysis of Indirect Effects;
- ❖ Analysis of Total Effects;
- ❖ Moderation Analysis.

A total of 5,000 Bootstrapping resamples were used to test the statistical significance of the coefficients.

Second: Assessment of the Measurement Model

1. Analysis of Outer Loadings: Outer loadings represent the strength of the relationship between each indicator and the latent variable it is assumed to measure. High loading values indicate that the indicators adequately reflect the underlying theoretical construct.

The results showed that all indicators included in the model recorded high and statistically significant outer loadings.

Artificial Intelligence (AI): The loadings for AI were:

AI1 = 0.833
AI2 = 0.906
AI3 = 0.820

These values indicate a strong relationship between the AI indicators and the latent construct they represent. It can be observed that the highest loading was recorded for AI2, with a value of 0.906, while the remaining indicators also remained above the acceptable threshold, confirming the quality of the construct representation.

BMI: The loadings for BMI were:

BMI1 = 0.820
BMI2 = 0.871
BMI3 = 0.852
BMI4 = 0.858

All values ranged between 0.820 and 0.871, reflecting a good degree of consistency among the indicators of the variable.

CE: The loadings for CE were:

CE1 = 0.877
CE2 = 0.874
CE3 = 0.791

Although CE3 recorded the lowest loading relative to the other indicators, it remained above the acceptable threshold. Therefore, there is no statistical necessity to exclude it from the model.

FP: The loadings for FP were:

FP1 = 0.777
FP2 = 0.827
FP3 = 0.815
FP4 = 0.831
FP5 = 0.798

The results show that all indicators exceeded the acceptable threshold, confirming their ability to represent the latent construct FP.

GS: The loadings for GS were:

GS1 = 0.875
GS2 = 0.795
GS3 = 0.837
GS4 = 0.839
GS5 = 0.775

These results indicate a good level of consistency between the indicators and the latent construct.

LS: The loadings for LS were:

LS1 = 0.822
LS2 = 0.832
LS3 = 0.837
LS4 = 0.826

All of these values are high and relatively close to one another, indicating good consistency among the indicators.

SCA: The loadings for SCA were:

SCA2 = 0.875
SCA3 = 0.892
SCA4 = 0.835
SCA5 = 0.750

These results indicate good quality of the indicators measuring the SCA variable, as all loading values exceeded the acceptable threshold. Accordingly, no indicators with sufficiently low loadings to warrant deletion were identified, allowing the measurement model structure to be retained as specified.

2. Internal Consistency Reliability: Internal consistency reliability was assessed using Cronbach's Alpha and Composite Reliability, in addition to rho_A.

Table 01. Internal Consistency Reliability and Convergent Validity of the Constructs

Construct	Cronbach's Alpha	rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)

AI	0.814	0.823	0.889	0.729
BMI	0.873	0.878	0.913	0.723
CE	0.809	0.841	0.885	0.719
FP	0.869	0.873	0.905	0.656
GS	0.882	0.884	0.914	0.680
LS	0.849	0.854	0.898	0.688
SCA	0.860	0.872	0.905	0.705

Source: Prepared by the researcher based on SmartPLS outputs.

3. Convergent Validity: Convergent validity was assessed using the Average Variance Extracted (AVE). The results showed that all AVE values exceeded 0.50, with the lowest value being 0.656 for FP, while the highest value was 0.729 for AI. This means that each latent construct explains more than half of the variance in its respective measurement indicators. Accordingly, the AVE results confirm the achievement of convergent validity for the various constructs of the model.

Third: Discriminant Validity

1. HTMT Test: The Heterotrait-Monotrait Ratio (HTMT) criterion was used to assess the ability of the latent variables to discriminate from one another. The results showed that the highest HTMT value among the main constructs was approximately 0.666, recorded between CE and FP, while most of the other relationships were considerably lower. Examples of the recorded values include:

AI ↔ BMI = 0.235

AI ↔ CE = 0.282

AI ↔ FP = 0.392

BMI ↔ FP = 0.573

CE ↔ FP = 0.666

GS ↔ FP = 0.565

LS ↔ FP = 0.402

SCA ↔ FP = 0.509

These results indicate that there is no excessive conceptual overlap among the constructs, and therefore discriminant validity is established. Furthermore, the HTMT values associated with the interaction terms AI × SCA and AI × BMI remained low, supporting the appropriateness of including the interaction variables in the model.

Fourth: Assessment of Multicollinearity

Multicollinearity was assessed at two levels: the measurement model and the structural model. The VIF results for the structural model showed very low values. Examples include:

AI → FP: VIF = 1.180

BMI → FP: VIF = 1.070

CE → AI: VIF = 1.175

GS → AI: VIF = 1.186

LS → AI: VIF = 1.113

These values are well below the levels that would indicate a multicollinearity problem. The two interaction variables also recorded low VIF values, indicating that their inclusion did not generate any substantial statistical problem in the model.

Therefore, it can be concluded that the model does not suffer from a multicollinearity problem and that the estimated path coefficients can be interpreted with an acceptable degree of stability.

Fifth: Assessment of the Structural Model

After confirming the validity of the measurement model, the structural model was assessed using path coefficients and tests of their statistical significance.

1. Direct Relationships Between the Variables: The PLS-SEM results revealed a number of important direct relationships.

Effect of AI on BMI

The path coefficient was: **β = 0.199965**

The Bootstrapping results showed that the bias-corrected confidence interval ranged from:

0.084827 to 0.304504

Since zero does not fall within the confidence interval, the relationship is statistically significant. This means that a higher level of **AI** is associated with a higher level of BMI.

Effect of AI on FP: The direct path coefficient was:

β = 0.124502

The Bootstrapping results indicate that the direct relationship is positive and statistically significant. Therefore, AI has a direct effect on FP, although the magnitude of this effect is lower than some of the mediating effects present in the model. This finding indicates that reliance on artificial intelligence can directly contribute to the organizational outcomes represented by FP.

Effect of AI on SCA:

The path coefficient was: **β = 0.249021**

The confidence interval was:

0.136801 – 0.349113

Since the interval does not include zero, AI has a positive and statistically significant effect on SCA. This relationship is important within the model because it indicates that the impact of artificial intelligence is not limited to final outcomes, but is also associated with the development of the capabilities or practices represented by SCA.

Effect of BMI on FP

The path coefficient was: **β = 0.416741**

The confidence interval was:

0.328171 – 0.502828

This result reveals a relatively strong positive effect of BMI on FP. Moreover, the magnitude of this path coefficient is among the highest in the model, highlighting the explanatory importance of BMI in explaining FP.

Effect of SCA on FP

The path coefficient was: **β = 0.320869**

The confidence interval ranged from:

0.231249 to 0.402549

This confirms the statistical significance of the relationship. The result indicates that higher levels of SCA are associated with improved FP, supporting the strategic role of the capabilities represented by this construct in enhancing organizational outcomes.

Sixth: Relationships Involving GS, LS, and CE

The model is not limited to the relationship between AI and FP, but also includes a number of paths explaining how the variables within the model are formed.

1. Effect of GS on AI

The path coefficient was: **β = 0.176925**

while the total effect was: **β = 0.291215**

This indicates a positive relationship between GS and AI, with part of the effect occurring through mediating paths.

2. Effect of GS on CE

The path coefficient was: **β = 0.302702**

This indicates a positive relationship between GS and CE.

3. Effect of GS on LS

The path coefficient was: **β = 0.270105**

This is a positive effect, indicating that GS is associated with higher levels of LS.

4. Effect of LS on AI

The path coefficient was: **β = 0.286219**

while the total effect was: **β = 0.304302**

This indicates a positive relationship between **LS and AI**.

5. Effect of LS on CE

The path coefficient was: **β = 0.170542**

indicating a positive effect on **CE**.

Seventh: Testing Indirect Effects and Mediation

Indirect effects represent an important component of the model because they allow the analysis to move beyond merely testing direct relationships toward explaining the mechanism through which the effect of an independent variable is transmitted to a dependent variable.

1. Mediation Through BMI

The model showed that **AI affects BMI** with a coefficient of: **β = 0.199965**

while **BMI affects FP** with a coefficient of: **β = 0.416741**

The indirect effect was:

AI → BMI → FP = 0.083334

The conditional analysis also showed that the indirect effect increased to:

0.096819 at **+1 SD of AI**, compared with: **0.069848** at **−1 SD of AI**.

These results indicate the presence of an important indirect pathway linking AI to FP through BMI. Given the presence of a direct effect of AI on FP as well, the nature of the relationship is consistent with partial mediation, rather than full mediation, provided that the mediation assessment is adopted at the theoretical hypothesis level.

2. Mediation Through SCA

The indirect effect was:

AI → SCA → FP = 0.079903

The conditional indirect effect also increased to:

0.110447 at **+1 SD of AI**, while it was: **0.049360** at **−1 SD**.

This demonstrates that SCA represents an important mechanism through which the effects of AI are transmitted to FP.

This finding is further supported by the direct relationships:

AI → SCA = 0.249021

and

SCA → FP = 0.320869.

Eighth: Testing the Moderating Effect

The model includes interaction effects that allow testing whether the effect of AI on FP changes according to the level of the moderating variable.

1. AI × BMI Interaction

The interaction coefficient was: **β = 0.067439**

The bias-corrected confidence interval ranged from:

−0.020154 to 0.158076

Since the confidence interval includes zero, there is insufficient statistical evidence for a moderating effect of BMI on the relationship between AI and FP. Therefore, the results do not support the hypothesis of a statistically significant moderation effect in this path.

2. AI × SCA Interaction

In contrast, the interaction coefficient was: **β = 0.122653**

and the confidence interval was:

0.027719 – 0.209090

Since the confidence interval does not include zero, the interaction between AI and SCA is statistically significant.

This finding indicates that the effect of AI on FP changes according to the level of SCA. It is one of the most important findings in the model because it goes beyond the idea of a simple direct effect and demonstrates that the effectiveness of artificial intelligence in improving organizational outcomes is associated with the strategic context and organizational capabilities represented by **SCA**.

Ninth: Conditional Analysis of the Moderating Effect

The Simple Slope/Conditional Effects results provide further support for this finding. The results showed that the effect of AI on the relationship leading to FP varies according to the levels of the moderating variable.

The findings also showed that the relationship at a high level of AI differs from the relationship at a low level of AI, which is consistent with the significance of the interaction coefficient.

Accordingly, interpreting artificial intelligence as an independent factor in isolation is insufficient to explain FP. Rather, AI should be viewed as a capability that becomes more effective when the appropriate organizational environment and strategic capabilities are available.

Tenth: Coefficient of Determination (R^2)

The R^2 coefficient is used to determine the proportion of variance in the dependent variable that can be explained by the independent variables included in the model.

The results showed the following:

Table X. Coefficient of Determination (R^2) and Adjusted R^2

Endogenous Variable	R^2	Adjusted R^2
AI	0.180	0.173
BMI	0.040	0.037
CE	0.149	0.143
FP	0.438	0.429

LS	0.073	0.070
SCA	0.062	0.059

Source: Prepared by the researcher based on SmartPLS outputs.

The results show that the model explains 18.0% of the variance in AI, with an adjusted R^2 of 17.3%. For BMI, the R^2 value is 0.040, indicating that the model explains 4.0% of its variance, while the adjusted R^2 is 3.7%.

Regarding CE, the R^2 value reached 0.149, meaning that the variables included in the model explain 14.9% of its variance, with an adjusted R^2 of 14.3%.

The highest explanatory power was observed for FP, with an R^2 value of 0.438 and an adjusted R^2 of 0.429. This means that the variables included in the structural model explain approximately 43.8% of the variance in FP, while the remaining 56.2% can be attributed to other factors not included in the model.

For LS, the R^2 value was 0.073, with an adjusted R^2 of 0.070, indicating that the model explains 7.3% of its variance. Finally, SCA recorded an R^2 value of 0.062 and an adjusted R^2 of 0.059, meaning that the model explains 6.2% of its variance.

Overall, the results indicate that the proposed model has its strongest explanatory power for FP, which represents the central outcome of the model. The R^2 value of 0.438 suggests that AI, BMI, SCA, and the other variables incorporated into the structural relationships provide a meaningful contribution to explaining variations in FP.

Eleventh: Effect Size (f^2): The f^2 effect size was used to determine the practical contribution of each independent variable to explaining the variance of the dependent variable. The results showed the following:

- The effect of BMI on FP was 0.288771, indicating a relatively important effect.
- The effect of SCA on FP was 0.168127.
- The effect of AI on BMI was 0.041652.
- The effect of AI on FP was 0.023365.
- The effect of AI on SCA was 0.066111.
- The interaction effect of AI × SCA on FP was 0.024034.
- The interaction effect of AI × BMI on FP was 0.008013.

These results indicate that BMI and SCA represent the most important explanatory contributions to FP within the model, while the interaction effect of AI × SCA retains explanatory importance, although its magnitude is lower than the direct effects of BMI and SCA.

Furthermore, the small effect size of AI × BMI is consistent with its lack of statistical significance.

Twelfth: Assessment of Model Fit

The SmartPLS results showed that the SRMR for the saturated model was 0.0526. This is a relatively low value and indicates a good level of correspondence between the observed and estimated correlation matrices.

However, the SRMR for the estimated model was 0.1303, which is higher than the SRMR of the saturated model. Therefore, this value should be interpreted with caution and should not be used alone to assess the overall quality of the model.

The results also showed the following:

- d_ULS – Saturated Model = 1.1243
- d_ULS – Estimated Model = 6.8968
- d_G – Saturated Model = 0.4391

- d_G – Estimated Model = 0.5589
- Chi-square – Saturated Model = 873.03
- Chi-square – Estimated Model = 1004.94
- NFI – Saturated Model = 0.8265
- NFI – Estimated Model = 0.8003

Accordingly, model assessment should focus on an integrated set of indicators rather than relying on a single fit index, particularly because the primary objective of PLS-SEM is to explain variance and support prediction rather than to assess overall model fit in the same manner as traditional Covariance-Based Structural Equation Modeling (CB-SEM).

Thirteenth: Hypothesis Testing

Based on the results of the path coefficients and Bootstrapping analysis, the decisions regarding the main hypotheses can be summarized as follows:

Table X. Results of Hypothesis Testing Based on PLS-SEM

Path	β	Significance	Decision
AI → BMI	0.200	Significant	Hypothesis Accepted
AI → FP	0.125	Significant	Hypothesis Accepted
AI → SCA	0.249	Significant	Hypothesis Accepted
BMI → FP	0.417	Significant	Hypothesis Accepted
SCA → FP	0.321	Significant	Hypothesis Accepted
AI × BMI → FP	0.067	Not Significant	Hypothesis Rejected
AI × SCA → FP	0.123	Significant	Hypothesis Accepted
GS → AI	0.177	Significant	Hypothesis Accepted
GS → CE	0.303	Significant	Hypothesis Accepted
GS → LS	0.270	Significant	Hypothesis Accepted
LS → AI	0.286	Significant	Hypothesis Accepted
LS → CE	0.171	Significant	Hypothesis Accepted

Source: Prepared by the researcher based on SmartPLS outputs.

Interpretation

The results indicate that 11 out of the 12 tested relationships were statistically significant and therefore supported, whereas only the moderating effect of AI × BMI on FP was not statistically significant and was consequently rejected.

The strongest direct relationship in the model was observed for BMI → FP (β = 0.417), followed by SCA → FP (β = 0.321) and GS → CE (β = 0.303). In contrast, the AI × BMI → FP interaction recorded a relatively small coefficient (β = 0.067) and was not statistically significant.

Overall, the hypothesis-testing results provide substantial empirical support for the proposed structural model and highlight the important role of AI, BMI, and SCA in explaining FP, while also demonstrating the significant moderating role of SCA in the relationship between AI and FP.

Fourteenth: Discussion of the Empirical Results

The empirical results reveal that artificial intelligence represents an influential factor in the model; however, its effect should not be interpreted solely as a direct effect. Although AI demonstrated a positive direct

effect on FP, the magnitude of this direct effect was lower than that of some of the mediating paths. This indicates that the strategic value of artificial intelligence becomes more evident when it is integrated into organizational capabilities.

The relationship between AI and BMI confirms that the adoption of artificial intelligence may be associated with the development or improvement of the practices represented by BMI, while the BMI → FP path demonstrates that these practices can be translated into tangible performance outcomes.

On the other hand, the AI → SCA → FP path demonstrates that artificial intelligence can contribute to building strategic capabilities, which in turn are associated with improved final outcomes. This finding is particularly important for the subject of the study because it supports the shift from viewing artificial intelligence merely as a technological tool toward considering it a strategic capability that can influence an organization's ability to improve, adapt, and achieve better outcomes.

Furthermore, the significance of the AI × SCA → FP interaction represents a deeper finding. It indicates that the effect of artificial intelligence is not homogeneous across all situations, but depends partially on the level of SCA. In other words, investing in artificial intelligence technologies alone is not sufficient to achieve better outcomes. Organizations also need to possess the organizational and strategic capabilities required to transform these technologies into actual value.

In contrast, the AI × BMI → FP interaction was not statistically significant, indicating that BMI does not significantly alter the strength of the relationship between AI and FP based on the data used. This difference between the two interaction paths represents an important research finding, as it demonstrates that not all organizational capabilities play the same role in transforming artificial intelligence into performance outcomes.

Fifteenth: Total Effect of Artificial Intelligence on FP

It is important to distinguish between the direct effect and the total effect.

The direct effect was:

$$\mathbf{AI \rightarrow FP = 0.124502}$$

while the total effect was:

$$\mathbf{AI \rightarrow FP = 0.287739}$$

This difference is highly important for interpreting the model.

The total effect of artificial intelligence on FP exceeds its direct effect due to the presence of indirect pathways, including pathways through BMI and SCA, as well as other relationships included in the model. This indicates that a substantial part of the value generated by AI emerges through its effects on mediating variables and organizational capabilities rather than through a direct effect alone.

Accordingly, the study provides support for the idea that investment in artificial intelligence should form part of a broader organizational transformation rather than merely involve the acquisition of separate digital technologies.

Sixteenth: General Conclusion of the Empirical Study

Based on the results of the analysis using PLS-SEM and Bootstrapping, a number of key findings can be drawn.

First, the measurement model demonstrated high levels of reliability and validity, as all Cronbach's Alpha and Composite Reliability values exceeded the acceptable thresholds, while all AVE values exceeded 0.50, supporting the quality of the measurement model.

Second, the HTMT results confirmed discriminant validity among the constructs, while no substantial multicollinearity problem was identified according to the VIF results.

Third, the results demonstrated a positive and statistically significant direct effect of artificial intelligence on FP, confirming the importance of AI in explaining organizational outcomes.

Fourth, AI demonstrated positive and significant effects on BMI and SCA, while both BMI and SCA demonstrated relatively strong effects on FP.

Fifth, the indirect-effect results highlighted the importance of the mediating pathways. The indirect effect of AI on FP through BMI was approximately 0.0833, while the indirect effect through SCA was approximately 0.0799.

Sixth, the results confirmed a statistically significant moderating effect of the AI × SCA interaction on FP, whereas the AI × BMI interaction was not statistically significant.

Seventh, the model explained 43.8% of the variance in FP, reflecting an important explanatory capacity.

Eighth, the overall findings indicate that the strategic value of artificial intelligence does not originate from technology alone, but rather from the organization's ability to integrate AI within a system of organizational and strategic capabilities.

Conclusion: This study aimed to analyze the role of intelligent quality management as a strategic capability, with a particular focus on the impact of artificial intelligence and predictive analytics on continuous improvement and the achievement of competitive outcomes for firms.

Using field data comprising 325 observations, analyzed through PLS-SEM and Bootstrapping with 5,000 subsamples, the results demonstrated that the proposed model possesses satisfactory levels of reliability and validity and that artificial intelligence represents an important factor in strengthening organizational capabilities and improving outcomes.

Study Results: Based on the foregoing analysis, the following results were obtained:

- There is a positive and statistically significant effect of artificial intelligence on BMI, with $\beta = 0.200$.
- There is a positive direct effect of artificial intelligence on FP, with $\beta = 0.125$.
- There is a positive effect of artificial intelligence on SCA, with $\beta = 0.249$.
- There are relatively strong effects of BMI on FP ($\beta = 0.417$) and SCA on FP ($\beta = 0.321$).
- There are indirect effects of artificial intelligence on FP through BMI and SCA, confirming the importance of mediating roles in transforming technology into organizational outcomes.
- There is a statistically significant moderating effect of AI × SCA on FP ($\beta = 0.123$), whereas the AI × BMI interaction was not statistically significant.
- The explanatory power of the model for FP reached approximately 43.8% ($R^2 = 0.438$), reflecting an important explanatory capacity of the model.

Overall, the findings confirm that the strategic value of artificial intelligence is not achieved through technology alone, but through its integration with organizational and strategic capabilities and continuous improvement mechanisms.

Recommendations: Based on the above findings, the following recommendations can be proposed:

- Integrate artificial intelligence into corporate strategy rather than treating it merely as a technological tool.
- Strengthen strategic and organizational capabilities that enable organizations to transform the outputs of artificial intelligence and predictive analytics into actual decisions and improvements.
- Develop predictive analytics systems to identify quality problems and risks before they occur and to support proactive quality management.

- Link artificial intelligence with continuous improvement rather than using intelligent technologies independently from the quality management system.
- Invest in human resource training in artificial intelligence, data analytics, and evidence-based decision-making.
- Improve data quality and governance, considering them fundamental prerequisites for effective predictive analytics and intelligent decision-making.
- Develop indicators for measuring the return on artificial intelligence investment, including process quality, cost reduction, response speed, innovation, and competitive performance.

The study confirms that achieving sustainable competitive advantage in the era of artificial intelligence does not depend solely on possessing technology, but rather on firms' ability to integrate artificial intelligence and predictive analytics within an integrated system of strategic capabilities, intelligent quality management, and continuous improvement.

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