Review of Futures Markets (RFM)
ISSN: 1933-7116
Volume 34 Issue 2 (2026)
Website: https://fra.st

Business Ethics and Sustainable Competitive Advantage: The Sequential Mediating Role of Artificial Intelligence Capabilities and Organizational Innovation – A Field Study at Condor Electronics in Algeria

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Received: 18/12/2025 ; Accepted: 15/06/2026 ; Published: 01/07/2026

Abstract:
Purpose: This study aims to examine the effect of business ethics on achieving sustainable competitive advantage, and to uncover the serial mediating role of AI capability and organizational innovation in this relationship, drawing on the Dynamic Capabilities View (DCV). The study seeks to clarify how business ethics can move beyond a mere commitment to values and norms to become a strategic resource that contributes to developing technical and innovative capabilities, thereby enhancing sustainable competitive advantage.
Design/methodology/approach: The study adopted a quantitative empirical design based on serial mediation analysis, conducted among employees of Condor Electronics in Algeria, with a sample of 95 respondents. Data were collected through a questionnaire and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.1. After confirming the reliability and validity of the measurement model, the structural model was tested using the bootstrapping technique to assess the significance of path coefficients and indirect effects.
Findings: The results revealed a positive and significant effect of business ethics on AI capability ($\beta = 0.495$, $T = 6.272$, $p < 0.001$) and on sustainable competitive advantage ($\beta = 0.473$, $T = 6.778$, $p < 0.001$). AI capability was also found to have a positive and significant effect on organizational innovation ($\beta = 0.463$, $T = 5.255$, $p < 0.001$), and organizational innovation on sustainable competitive advantage ($\beta = 0.517$, $T = 6.785$, $p < 0.001$). Furthermore, the results confirmed a significant serial mediating effect of AI capability and organizational innovation on the relationship between business ethics and sustainable competitive advantage ($\beta = 0.145$, $T = 3.419$, $p = 0.001$).
Originality/value: This study contributes to the literature by proposing an integrative model that explains the mechanism through which business ethics is translated into sustainable competitive advantage, enriching both the theoretical and practical understanding of this relationship within the context of industrial firms in emerging economies.
Keywords: Business Ethics; AI Capability; Organizational Innovation; Sustainable Competitive Advantage; Serial Mediation; SmartPLS.
JEL Classification: M14; O32; O33; L25.

1. Introduction:

The world is witnessing a rapid transformation in the adoption of artificial intelligence technologies within organizations. Artificial intelligence represents one of the revolutionary technologies shaping the modern business and industrial environment, and its use within organizations has expanded considerably due to the opportunities it provides for improving processes and developing innovative solutions (Gama & Magistretti, 2025). This transformation has contributed to reshaping the sources of competitive advantage, as organizations' ability to deploy and leverage artificial intelligence technologies has become an important factor in achieving growth and sustainability in a business environment characterized by dynamism and rapid change (Zhou, 2025). However, the increasing reliance on artificial intelligence technologies has not been without ethical, social, and organizational challenges, making ethical considerations increasingly prominent in discussions concerning the deployment of these technologies and their long-term implications for organizations and society (Khogali & Mekid, 2023).

Against this backdrop, the success of artificial intelligence initiatives is no longer dependent solely on the availability of technological infrastructure and technical resources; rather, it has become closely associated with an organization's ability to establish an integrated ethical framework governing the design, development, and use of these technologies. The absence of ethical principles may lead to unfair decision-making and weaken levels of organizational transparency and accountability (Madanchian & Taherdoost, 2025). Such shortcomings may also undermine stakeholders' trust in the organization and its intelligent systems, in addition to exacerbating legal and regulatory risks resulting from the absence of clear governance frameworks. Ultimately, this may constrain the organization's ability to realize the strategic value and organizational outcomes expected from artificial intelligence applications (Xinzi, 2026). In contrast, business ethics contribute to establishing the principles of integrity, transparency, and accountability (Isseki & Ferhani, 2026), while promoting fairness and reducing bias in dealing with employees and customers, respecting privacy and protecting data, complying with applicable laws and regulations, and supporting sustainability, environmental responsibility, and equal employment opportunities. These practices, in turn, enhance the trust of employees, customers, and other stakeholders (Leal, et al., 2024).

Accordingly, Business Ethics have emerged as one of the fundamental pillars of contemporary management. They are no longer viewed merely as compliance with laws or a set of normative principles; rather, they have become a strategic framework that guides the behavior of individuals and organizations and promotes integrity in decision-making processes (Versteegt, Marius, & Muel, 2025). Recent literature indicates that organizations adopting well-established ethical practices are better positioned to build trust with stakeholders (Van Rietschoten & Van Bommel, 2025), strengthen their corporate reputation, and improve the quality of ethical and managerial decisions, which positively contributes to organizational performance and the sustainability of success in highly competitive business environments (Roy, Newman, Round, & Bhattacharya, 2024). In the context of accelerating digital transformation, business ethics are no longer merely a supporting element; rather, they have become an essential component for ensuring the responsible deployment of advanced technologies, particularly artificial intelligence, in a manner that contributes to creating sustainable value for both the organization and its stakeholders (Amarolinda, 2022) .

In this context, recent literature indicates that realizing the strategic value of artificial intelligence does not depend merely on adopting its technologies; rather, it is associated with organizations' possession of organizational capabilities that enable them to integrate, develop, and effectively deploy these technologies across various activities and processes (Weber, Engert, Schaffer, Weking, & Krcmar, 2023). **AI Capability** is viewed as a set of organizational and technological resources and skills that enable organizations to leverage data, algorithms, and digital infrastructure to support decision-making, improve performance, and enhance innovation (Mikalef & Gupta, 2021). Conversely, building such capabilities requires an organizational environment based on trust, transparency, accountability, and integrity, which represent core values of business ethics. This suggests that ethical practices do not merely affect performance directly but also contribute to developing the capabilities necessary for the sustainable utilization of artificial intelligence technologies (Cao, Duan, & Edwards, 2026).

Despite the growing importance of AI capabilities, the literature emphasizes that possessing such capabilities does not, in itself, guarantee the realization of strategic value for an organization unless they are translated into innovative practices that generate tangible improvements in products, services, processes, and business models (Pavitra & Surajit, 2021). From this perspective, **Organizational Innovation** is viewed as a mechanism through which organizations can transform technological and knowledge-based potential into innovative solutions that enhance operational efficiency, improve decision quality, and increase their ability to respond to environmental changes (Mikalef & Gupta, 2021). Recent studies also indicate that organizations with advanced AI capabilities are better positioned to develop organizational innovation through improved data processing, support for organizational learning, and enhanced collaboration among different organizational units, thereby creating an environment more conducive to value creation and sustainable growth (Han, Zhang, Zhang, & Lin, 2025).

Organizational innovation represents a key link in this chain, as it contributes to translating the organizational resources and capabilities accumulated by an organization into **Sustainable Competitive Advantage**, which is difficult for competitors to imitate (Yildiz & Aykanat, 2021), as will be elaborated later in the theoretical framework. In this regard, the literature confirms that organizations capable of fostering a culture of innovation and continuously developing organizational solutions are better able to build sustainable competitive advantage by improving operational efficiency, enhancing the value offered to customers, and supporting continuous organizational learning. Therefore, achieving sustainable competitive advantage is not merely a direct outcome of adopting business ethics or artificial intelligence technologies; rather, it results from an integrated interaction among the organization's ethical environment, its AI capabilities, and the level of organizational innovation it succeeds in achieving (Zhang, Chu, Ren , & Xing, 2023).

Despite the considerable progress in the literature addressing business ethics, artificial intelligence, and organizational innovation, previous studies still provide a fragmented picture of the relationships among these variables. Some studies have focused on the effect of business ethics on organizational performance (Souissi & Chauaibi, 2025), while others have examined the role of AI capabilities in improving innovation or operational efficiency (Salman, Marco, & Qamar, 2023). Other studies, meanwhile, have addressed organizational innovation as an avenue for achieving sustainable competitive advantage (Riaz & Hadi, 2024). However, the literature still lacks an integrated model explaining the mechanism through which the effects of business ethics are transmitted toward achieving sustainable competitive advantage through the sequential mediating role of AI capabilities and organizational innovation. This research gap becomes particularly significant in the context of Algerian industrial organizations operating in the home-appliance manufacturing sector, thereby calling for further empirical investigation and analysis.

Building on this research gap, the present study aims to develop and test a conceptual model explaining how business ethics contribute to achieving sustainable competitive advantage through the sequential mediating role of AI capabilities and organizational innovation, based on field data collected from **Condor Electronics in Algeria**. The study seeks to contribute to the literature by providing an integrated framework linking business ethics, artificial intelligence technology management, and organizational innovation within a single causal chain, thereby clarifying the mechanisms through which ethical principles are transformed into sustainable strategic value. From a practical perspective, the study provides a set of managerial implications that can assist managers and decision-makers in the organization under investigation in strengthening ethical practices, developing AI capabilities, and fostering organizational innovation, thereby supporting the development of sustainable competitive advantage in contemporary business environments.

This article is structured into **five main sections**. The first section presents the introduction, while the second reviews the theoretical framework and develops the research hypotheses. The third section presents the study methodology, and the fourth reports the statistical results and hypothesis testing. Finally, the fifth section concludes the study by presenting the main findings and recommendations addressed to the organization under investigation.

2. Theoretical Framework and Hypothesis Development

2.1. Theoretical Foundation

This study is grounded in the Dynamic Capability Theory proposed by (Teece , Pisano , & Shuen, 1997), which posits that achieving sustainable competitive advantage does not depend on the mere possession of resources, but rather on an organization's ability to integrate, reconfigure, and continuously develop its resources in response to the rapid changes in the business environment (Dukhaykh & Alangri, 2026). Amid accelerating digital transformation, this theory has become one of the most widely used frameworks for explaining how emerging technologies, particularly artificial intelligence, can be leveraged to build organizational capabilities that support innovation and enhance long-term performance (Weber, Engert, Schaffer, Weking, & Krcmar, 2023). Building on this perspective, the present study posits that business ethics do not merely represent a set of normative principles, but constitute an organizational resource that contributes to fostering an institutional environment based on trust, transparency, and accountability, thereby enhancing the organization's ability to develop AI capabilities and direct them toward organizational innovation, which is ultimately reflected in the achievement of sustainable competitive advantage. Accordingly, Dynamic Capability Theory provides a coherent theoretical framework for explaining the causal relationships proposed in the research model, illustrating how organizational resources and values are transformed into capabilities, how these capabilities are translated into organizational innovation, and how this, in turn, leads to sustainable competitive advantage.

2.2. Business Ethics and AI Capability

Business ethics constitute a governing framework for organizational behavior, providing the principles and values that guide decision-making processes and enhance transparency, accountability, and integrity within the organization. Amid the growing reliance on artificial intelligence technologies, these principles are no longer confined to regulating relationships among stakeholders; rather, they have come to play a pivotal role in fostering an organizational environment that supports the responsible adoption and management of digital technologies (Madanchian & Taherdoost, 2025). The literature indicates that organizations adopting well-established ethical practices are better positioned to build trust among employees, encourage knowledge sharing, and foster a culture of learning and experimentation (Roy, Newman, Round, & Bhattacharya, 2024), all of which are factors that contribute to developing AI Capability, defined as an organization's ability to integrate data, algorithms, digital infrastructure, and human skills to leverage artificial intelligence in supporting decision-making, improving processes, and creating value (Mikalef & Gupta, 2021). From the perspective of Dynamic Capability Theory, business ethics represent an intangible organizational resource that contributes to building new strategic capabilities, as they provide an institutional climate that helps develop and effectively leverage technical capabilities, rather than merely possessing the technology itself (Knapp, Namada, & Dougan, 2025). Accordingly, organizations with a high level of business ethics are better able to develop AI capabilities sustainably, leading to the following hypothesis:

H1: Business ethics have a positive and significant effect on AI capability at a significance level of ($\alpha \leq 0.05$).

2.3. Business Ethics and Sustainable Competitive Advantage

The relationship between Business Ethics and Sustainable Competitive Advantage has received growing attention in the strategic management literature, as business ethics are no longer viewed merely as a legal obligation or a form of social responsibility, but rather as a strategic asset that contributes to creating long-term value for the organization (Ghauri, Elg, & Melen, 2023). Organizations that adopt well-established ethical practices are better able to build trust-based relationships with customers, employees, suppliers, and other stakeholders, which is reflected in enhanced customer loyalty (Crossley, Taylor, Liden , Wo , & Piccolo, 2024). Recent studies indicate that these effects not only improve current performance but also help organizations develop resources and capabilities that are difficult for competitors to imitate, which represents the core of sustainable competitive advantage (Asa, Nautwima, & Villet , 2024). From the perspective of Dynamic Capability Theory, business ethics represent an intangible organizational resource that contributes to developing the organization's ability to adapt to environmental changes and reconfigure its resources in a way that supports the maintenance of its long-term competitive superiority (Knapp, Namada, & Dougan, 2025). Building on the above, the second hypothesis is formulated as follows:

It is worth noting that testing the direct effect of business ethics on sustainable competitive advantage (H2) does not contradict the logic of Dynamic Capability Theory adopted in this study; rather, it constitutes a necessary methodological step within the serial mediation analysis. It allows for determining whether the effect of business ethics remains significant after introducing AI capability and organizational innovation as mediators (partial mediation), or vanishes entirely (full mediation), in accordance with the criterion adopted in contemporary mediation analyses (Andrew, 2022), which further strengthens the interpretation of the results later in light of the adopted theoretical framework.

H2: Business ethics have a direct, positive, and significant effect on sustainable competitive advantage at a significance level of ($\alpha \leq 0.05$).

2.4. AI Capability and Organizational Innovation

Recent literature indicates that the true value of artificial intelligence for organizations lies not merely in possessing its technologies or adopting its applications, but rather in the organization's ability to develop AI Capability, which enables it to absorb these technologies and integrate them effectively into its operations and strategic activities. These capabilities encompass digital infrastructure, data resources, human expertise, and analytical skills, in addition to the organization's ability to deploy algorithms to support decision-making, improve performance, and create organizational knowledge. (Cao, Duan, & Edwards, 2026)

In this context, organizational innovation is viewed as one of the most important strategic outcomes of AI capability, as these capabilities contribute to improving information flow, accelerating data processing, enhancing organizational learning, and discovering new opportunities, thereby supporting the development of more innovative products, services, processes, and business models. Studies also confirm that organizations with high levels of AI capability are better able to respond to environmental changes, which positively reflects on their innovative capacity (Fuller, Hutter , Wahl, Bilgram, & Tekic, 2022).

From the perspective of Dynamic Capability Theory, AI capability represents a dynamic organizational capability that enables the organization to sense and seize opportunities and threats through the deployment of digital technologies, and to continuously reconfigure its resources and capabilities (Cao, Duan, & Edwards, 2026). Consequently, organizations that invest in developing AI capability benefit not only from improved operational efficiency but also from enhanced organizational innovation as a key mechanism for achieving growth and adapting to a changing business environment (Fuller, Hutter , Wahl, Bilgram, & Tekic, 2022). Despite the growing number of studies addressing artificial intelligence and innovation, evidence concerning the effect of AI capability, as an integrated organizational capability, on organizational innovation still requires further investigation, particularly within Algerian industrial organizations operating in the home-appliance manufacturing sector. Building on the above, the third hypothesis is formulated as follows:

H3: AI capability has a positive and significant effect on organizational innovation at a significance level of ($\alpha \leq 0.05$).

2.5. Organizational Innovation and Sustainable Competitive Advantage

Organizational innovation is one of the most important strategic factors that enable organizations to enhance their ability to adapt to rapid changes in the business environment and achieve superior long-term performance. Organizational innovation is not limited to developing new products or services; it also encompasses redesigning organizational structures, improving administrative processes, developing work methods, and strengthening learning and knowledge-sharing mechanisms within the organization, thereby contributing to raising its operational efficiency and increasing its strategic flexibility (Lopez & Oliver, 2025).

A recent literature review concluded that organizations that continuously adopt organizational innovation are better able to efficiently utilize their resources, respond rapidly to market requirements, and develop innovative solutions that meet customer needs, which leads to improved organizational performance and enhances the ability to maintain a competitive position that is difficult for competitors to imitate (El Moudden & Balhadj , 2024). Organizational innovation also contributes to building dynamic capabilities that support continuous learning, stimulate creativity, and increase the organization's ability to confront challenges and environmental disruptions, thereby enhancing the sustainability of its competitive superiority (Garcia, Jacobo , & Flores, 2023).

From the perspective of Dynamic Capability Theory, organizational innovation represents one of the key outcomes of the process of reconfiguring organizational resources and capabilities, as well as the mechanism through which tangible and intangible resources are transformed into sustainable strategic value. Accordingly, organizations that succeed in establishing a culture of innovation and developing innovative organizational practices are better able to achieve and maintain sustainable competitive advantage amid a continuously changing business environment (Dukhaykh & Alangri, 2026). Despite the considerable number of studies addressing the relationship between innovation and organizational performance, evidence regarding the role of organizational innovation in building sustainable competitive advantage within Algerian industrial organizations, particularly in the home-appliance manufacturing sector, still requires further empirical investigation.

Building on the above, the fourth hypothesis is formulated as follows:

H4: Organizational innovation has a positive and significant effect on sustainable competitive advantage at a significance level of ($\alpha \leq 0.05$)

2.6. The Serial Mediating Role of AI Capability and Organizational Innovation

Recent literature indicates that achieving sustainable competitive advantage does not result directly from possessing distinctive organizational resources, but rather depends on the organization's ability to transform these resources into organizational capabilities, and subsequently into innovative practices capable of creating sustainable value. In this context, a recent systematic literature review showed that integrating ethical practices within AI-driven organizations enhances their legitimacy and stakeholder trust, and that adopting clear governance mechanisms and ethical practices contributes to reducing information asymmetry between the organization and external parties, while reinforcing perceptions of reliability and long-term sustainability (Basharat, 2026). On the other hand, AI capability is considered one of the modern organizational resources whose role in enhancing organizational performance and innovation has been demonstrated by applied studies, not only directly, but also through activating the mechanisms of sensing, seizing, and reconfiguring resources that translate these capabilities into tangible outcomes. A recent study, grounded in the Dynamic Capabilities perspective, showed that AI adoption enhances an organization's innovative capacity by reinforcing the mechanisms of sensing and seizing technological opportunities and reconfiguring organizational resources accordingly, implying that the positive effect of AI capability on performance and strategic value is realized more fully when translated into actual innovative practices within the organization (Cao, Duan, & Edwards, 2026). Accordingly, it can be argued that organizations' adoption of AI capability fosters a supportive environment for developing organizational innovation, which subsequently contributes to redesigning their processes and business models more efficiently.

Building on the relationships addressed in the previous literature between business ethics and AI capability, between AI capability and organizational innovation, and between organizational innovation and sustainable competitive advantage, the present study proposes that these relationships can be viewed within a single serial pathway, whereby AI capability may represent a first mediating link, followed by organizational innovation as a second mediating link, in the relationship between business ethics and sustainable competitive advantage. This proposition is grounded in the logic of Dynamic Capability Theory, which views the achievement of strategic outcomes as a process involving the development and reconfiguration of resources and capabilities in a manner that allows their transformation into value-creating outcomes. From this perspective, it can be assumed that business ethics may provide a favorable organizational environment for developing AI capability, and that this capability may, in turn, be associated with enhanced organizational innovation, which may ultimately be reflected in the organization's ability to achieve sustainable competitive advantage. However, the existence of this serial pathway and its explanatory power remain an empirical matter that must be verified and cannot be assumed a priori, which leads the present study to test whether AI capability and organizational innovation actually function as serial mediators in the relationship between business ethics and sustainable competitive advantage.

Building on the above, the main mediation hypothesis is formulated as follows:

H5: AI capability and organizational innovation serially mediate the relationship between business ethics and sustainable competitive advantage.

3. Study Methodology

3.1. Research Design and Rationale

This study adopted a Quantitative Empirical Explanatory Approach, based on the collection of field data through a questionnaire and its statistical analysis to test the causal relationships among the study variables (Saunders & Thornhill, 2019). This approach is considered the most suitable for the nature of the present study for the following reasons: first, it aligns with the nature of the proposed conceptual model, which encompasses direct relationships and serial mediation among four variables (business ethics, AI capability, organizational innovation, and sustainable competitive advantage). Second, it enables the testing of pre-specified hypotheses grounded in a clear theoretical framework (Dynamic Capability Theory), consistent with the explanatory, rather than exploratory, nature of the study. Third, it is compatible with the analytical technique adopted (PLS-SEM), which requires quantitative data measurable through Likert-type scales.

3.2. Study Population and Sample

Company Profile

This study was conducted at Condor Electronics, the flagship company and most prominent brand of the Benhamadi Group, an Algerian family-owned business conglomerate whose origins trace back to 1954. Condor Electronics was formally established on 9 February 2002 by Abderrahmane Benhamadi and is headquartered in Bordj Bou Arréridj. The company began by assembling televisions from imported components before progressively expanding into the manufacturing of computers, smartphones, household appliances, and solar panels, thereby becoming today Algeria's largest privately held company, with a broad product portfolio encompassing televisions, refrigerators, freezers, washing machines, ovens, and air conditioners, alongside after-sales services. In recent years, the company has expanded its export activities into African, European, and Asian markets through distribution agreements in several countries, in addition to international industrial partnerships aimed at establishing advanced manufacturing units within Algeria. This accelerating expansion, coupled with the company's growing reliance on artificial intelligence technologies and digital transformation in its industrial operations, makes Condor Electronics a suitable research setting for examining how ethical practices are translated into technical and innovative capabilities that support sustainable competitive advantage within a dynamic and competitive industrial context.

Study Population

Condor Electronics employs a total of 4,700 employees (as of 2026), who constitute the target population of the study. Given the scale of operational activity and production requirements at the company, management imposes an internal limit on the number of questionnaires that may be distributed to employees for academic and field research purposes. Accordingly, a maximum of 100 questionnaires was adopted for this study.

Sample and Sampling Technique

The study employed a stratified sampling technique, whereby the study population was divided into three main functional strata: administration, production, and marketing, and questionnaires were distributed across each stratum in a manner that broadly reflects its representation within the company's functional structure. Questionnaires for the administration and production departments were distributed in person to employees at the company's headquarters in Bordj Bou Arréridj, in coordination with the Human Resources Department, whereas questionnaires for the marketing department were distributed across the company's showrooms located in three different provinces (Bordj Bou Arréridj, Algiers, and Djelfa), thereby adding geographic diversity to the representation of this stratum within the sample. Distribution and collection were conducted directly and in person during official working hours, which accounts for the high response rate achieved.

After collecting and screening the returned questionnaires, 95 were deemed complete and valid for statistical analysis, corresponding to a response rate of 95%. Of the final sample, 40 respondents (42.1%) were drawn from the administration department, 35 (36.8%) from the production department, and 20 (21.1%) from the marketing department. Although this sample size (n = 95) falls below the threshold recommended by conventional sample-size determination tables for broad statistical generalization to a population of 4,700 (Krejcie & Morgan, 1970), it meets the statistical adequacy criteria specific to PLS-SEM, which are based on the rule of ten times the largest number of paths directed at any single construct within the structural model (Hair, et al., 2021), and it constituted the empirical basis for testing the proposed research model.

3.3. Data Collection Instrument

To collect diverse and reliable data on the phenomenon under investigation, several approaches were considered, including observation, interviews, and document analysis. However, the primary instrument employed was a structured questionnaire, carefully designed based on multiple academic sources and refined through expert consultation to ensure its validity and reliability. A closed-ended questionnaire was adopted, divided into two sections: the first covering demographic data, and the second comprising the items measuring the study variables, using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with intermediate values of 2 (disagree), 3 (neutral), and 4 (agree). The scale items were adapted from well-established and internationally recognized peer-reviewed literature, as follows:

- Business Ethics Scale (IV)

Business ethics was measured as an intangible organizational resource representing the ethical climate governing the organization. The scale was developed based on the Corporate Ethical Virtues Model (CEVM) proposed by Kaptein (2008), one of the most widely used and recognized conceptual frameworks in specialized international journals. The scale comprised eight dimensions, considered representative of the core organizational virtues that ensure the effective implementation of ethics within the Condor Electronics Group. A shortened version of the original scale was adopted, consisting of three items per dimension (24 items in total), in line with the overall length of the questionnaire and the number of variables measured in the model. The items were formulated using a five-point Likert scale, and the eight dimensions are as follows:

- **Clarity:** the extent to which ethical standards and expectations are clearly communicated to employees.
- **Congruency of Senior Management:** the extent to which senior management adheres to and practices ethical behavior.
- **Congruency of Supervisors:** the extent to which immediate supervisors adhere to ethical behavior in front of their subordinates.
- **Supportability:** the extent to which the organization provides support and incentives for compliance with ethical standards.
- **Feasibility:** the availability of conditions, time, and resources that enable employees to comply with ethical values without undue pressure.
- **Transparency:** the degree of clarity and visibility of employees' and management's actions and their outcomes within the organization.
- **Discussability:** the opportunities available for freely discussing ethical dilemmas and issues.
- **Sanctionability:** the existence of rewards for ethical behavior and penalties for violations. (Kaptein, 2008)

- AI Capability Scale (M_1)

This variable was measured using eight items adapted from the scale developed by Mikalef and Gupta (2021), based on the Resource-Based View (RBV), to capture three core dimensions of organizational AI capability: Tangible Resources, Human Skills, and Intangible Resources. The first dimension encompasses data, technology, and basic resources; the second covers employees' technical and managerial skills; while the third addresses inter-departmental coordination, organizational change capacity, and calculated risk-taking propensity (Mikalef & Gupta, 2021).

Given that the original scale comprises more than twenty items distributed across these dimensions and their sub-dimensions, it was condensed in the present study to eight items (two to three items per dimension) in order to reduce respondent burden and improve completion rates — a practice adopted by prior studies employing the same scale

- Organizational Innovation (M_2)

This variable was measured using seven items adapted from the scale developed by Yildiz and Aykanat (2021), which was originally used to measure the mediating role of organizational innovation in the relationship between strategic agility and firm performance. This scale was selected specifically for the following methodological reasons:

- The scale was developed and statistically tested within a mediation model structurally similar to the model of the current study, in which organizational innovation served as the mediating variable between a prior organizational capability (strategic agility) and a subsequent performance outcome (firm performance); this makes it methodologically consistent with the role played by the M_2 variable in the current model.
- The scale is theoretically grounded in the classical typology developed by Damanpour (1991) for organizational innovation, which distinguishes between technical innovation and administrative innovation, the latter being associated with organizational structures, policies, and management practices. In the process of scale construction, this dichotomous typology was operationalized into three distinct measurement dimensions: two dimensions falling under technical innovation (product innovation and process innovation), and a third dimension corresponding to administrative innovation.
- In its original study, the scale demonstrated high internal consistency, with an overall Cronbach's alpha coefficient of 0.94, in addition to satisfying convergent and discriminant validity tests within confirmatory factor analysis, thereby reinforcing confidence in its use for quantitative measurement purposes.

  The scale covers three main dimensions:
- **Product Innovation:** the extent to which the organization introduces new or substantially improved products or services.
- **Process Innovation:** the extent to which the organization adopts new or improved production or service delivery methods.
- **Administrative Innovation:** the extent to which the organization develops new organizational structures, policies, or management practices that support and facilitate the implementation of innovation. (Yildiz & Aykanat, 2021)

- Sustainable Competitive Advantage

This variable was measured using six items selected from two previous scales: **Dukhaykh & Alangri (2026)** and **Zhang et al. (2023)**. The selection of these sources was intended to achieve broader conceptual coverage of the sustainable competitive advantage construct and to draw on measures that have previously been examined in empirical studies.

- **First: Consistency with the conceptual model of the present study.** The selection of these two sources is consistent with the theoretical model of the present study, as both studies conceptualize sustainable competitive advantage as a final organizational outcome influenced by a set of organizational capabilities and intermediary processes. In the study by (Dukhaykh & Alangri, 2026) the relationship between dynamic capabilities and sustainable competitive advantage was examined with innovation serving as a mediating mechanism. In contrast, (Zhang, Chu, Ren , & Xing, 2023), examined the relationship between open innovation and sustainable competitive advantage, with particular emphasis on the mediating role of organizational learning.
- **Second: Recency and measurement properties of the sources.** The scale employed by (Dukhaykh & Alangri, 2026) represents a recent measure of sustainable competitive advantage and was used within an empirical model based on structural equation modeling to

Review of Futures Markets (RFM)
ISSN: 1933-7116
Volume 34 Issue 2 (2026)
Website: https://fra.st

examine the relationships among dynamic capabilities, innovation, and sustainable competitive advantage. The scale developed by (Zhang, Chu, Ren , & Xing, 2023), was employed in an empirical study published in *Technological Forecasting and Social Change*, which examined sustainable competitive advantage as a strategic outcome of open innovation and organizational learning, based on data collected from 269 Chinese high-tech firms.

- **Third: Integration in the conceptual coverage of the construct.** The concept of sustainable competitive advantage is grounded in the **Resource-Based View (RBV)** and the **VRIN framework** developed by (Barney, 1991), which associates sustainable competitive advantage with the possession of resources and capabilities that are valuable, rare, difficult to imitate, and non-substitutable. Accordingly, the items selected from the two sources were intended to capture different aspects of this construct. Some items focus on the difficulty of imitating organizational resources and capabilities and the sustainability of competitive superiority over time, whereas others reflect relative competitive superiority, differentiation, and the value offered to customers compared with competitors. Therefore, combining the selected items from the two sources aims to provide broader conceptual coverage of sustainable competitive advantage rather than relying on a single source that may not fully encompass all the dimensions addressed by the conceptual model of the present study.

Table (01): Final Version of the Questionnaire for the Study Variables, Dimensions, and Items

Variables / Dimensions	Items	Respondents' Responses				
		Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
Business Ethics						
1. Clarity	The organization clearly defines the ethical standards and rules that employees are expected to follow.					
	I clearly understand what is ethically expected of me when performing my daily tasks.					
	The organization translates its ethical principles into clear and practical guidelines that are easy to apply at work.					
2. Congruency of Senior Management	Senior management in the organization consistently acts in accordance with the ethical principles it promotes.					

	Senior management's actions are consistent with its statements regarding ethical values.					
	Senior management sets a good example of ethical behavior for employees.					
3. Congruency of Supervisors	My immediate supervisor consistently demonstrates ethical behavior in different situations.					
	My immediate supervisor's actions are consistent with the ethical guidelines that employees are expected to follow.					
	My immediate supervisor does not overlook ethical violations when they occur in their presence.					
4. Supportability	The organization provides the necessary support to employees who adhere to ethical behavior in their work.					
	The organization provides incentives or recognition to employees who act with integrity.					
	I feel that the organization genuinely encourages me to adhere to ethical standards rather than merely mentioning them formally.					
5. Feasibility	I have sufficient time to perform my work according to the required ethical standards without being rushed into compromising them.					

	I have the necessary resources to apply ethical values in my work without unreasonable constraints.					
	My working conditions do not impose pressures that push me to act contrary to what I believe is ethically right.					
6. Transparency	The actions of employees and management within the organization are sufficiently clear and visible to be evaluated.					
	Employees can easily understand the outcomes of decisions and procedures taken within the organization.					
	The organization does not conceal information that may affect the evaluation of employees' or management's behavior.					
7. Discussability	The organization provides genuine opportunities to openly discuss ethical dilemmas with colleagues or supervisors.					
	I feel safe raising ethical questions or concerns without fear of being criticized.					
	Open discussion of ethical issues related to work is welcomed in our organization.					
8. Sanctionability	Employees who adhere to ethical behavior are rewarded in our organization.					

	Actual and clear sanctions are applied to those who violate the organization's ethical standards.					
	The organization treats ethical misconduct seriously regardless of the offender's position or rank.					
	AI Capability					
1. Tangible Resources	Our organization possesses the necessary technological infrastructure (hardware and software) to implement artificial intelligence solutions.					
	Our organization possesses sufficient and high-quality data to support artificial intelligence applications.					
	Our organization provides the essential financial resources required for artificial intelligence investments.					
2. Human Skills	Our IT employees possess sufficient technical skills to develop and operate artificial intelligence solutions.					
	Our managers have sufficient understanding of how to leverage artificial intelligence to achieve business objectives.					
3.Intangible Resources	Our organization continuously trains its employees in artificial intelligence skills.					
	Our organization demonstrates a readiness for effective coordination					

Review of Futures Markets (RFM)
ISSN: 1933-7116
Volume 34 Issue 2 (2026)
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	among departments when adopting artificial intelligence projects.					
	Our management demonstrates a willingness to undertake calculated risks associated with adopting artificial intelligence technologies.					
Organizational Innovation						
1. Product Innovation	Our organization introduces new products/services frequently compared with its competitors.					
	Our organization substantially improves the features of its existing products/services.					
	Our organization responds rapidly to new customer needs by developing innovative offerings.					
2. Process Innovation	Our organization adopts new production or service delivery methods that improve operational efficiency.					
	Our organization continuously adopts new technologies to improve its internal processes.					
3.Administrative Innovation	Our organization introduces new organizational structures or administrative policies that support innovation.					
	Our senior management encourages the adoption of new managerial approaches					

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	to improve organizational performance.					
Sustainable Competitive Advantage	Our organization possesses resources and capabilities that are difficult for competitors to imitate.					
	Our organization maintains its competitive advantage over time despite changes in the market.					
	Our organization's products/services outperform competitors in terms of the value provided to customers.					
	Our organization holds a distinctive competitive position that is difficult for competitors to attain.					
	Our organization consistently achieves performance above the average performance of competitors in the sector.					
	Our organization is able to sustain its competitive superiority over the long term.					

Source: Prepared by the researchers based on the relevant literature and measurement scales adopted in the study

3.4. Psychometric Properties

- **Expert Judgment (Face and Content Validity):** This was assessed by presenting the questionnaire to a group of specialized academic experts for review and evaluation.
- **Construct Validity:** This was assessed using:
  - Convergent Validity, through Outer Loadings and Average Variance Extracted (AVE).
  - Discriminant Validity, through the Fornell–Larcker Criterion and Heterotrait–Monotrait Ratio (HTMT).

3.5. Statistical Analysis Methods

This section includes the following:

- **Measurement Model Assessment**
  - Assessment of Outer Loadings.
  - Assessment of Convergent Validity using AVE.
  - Assessment of Reliability using Cronbach's Alpha, rho_A, and Composite Reliability.
  - Assessment of Discriminant Validity using the Fornell–Larcker Criterion and HTMT.
- **Structural Model Assessment**
  - Assessment of Multicollinearity using Inner VIF.
  - Assessment of the Coefficient of Determination (R^2) and Adjusted R^2.
  - Assessment of **Path Coefficients**.

3.5. Direct Hypothesis Testing

The direct hypotheses H1–H4 were tested using Path Coefficients (β), T-statistics, and P-values obtained through the Bootstrapping procedure.

- **Sequential Mediation Analysis:**

Hypothesis H5, which assumes a sequential mediating effect of AI Capability and Organizational Innovation on the relationship between Business Ethics and Sustainable Competitive Advantage, was tested using the Specific Indirect Effects obtained through the Bootstrapping procedure.

3.6. Research Ethical Considerations

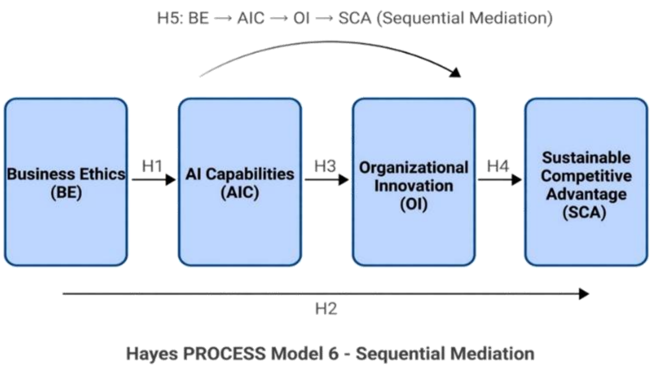
The study adhered to the following ethical considerations:

- Maintaining the confidentiality of the information and data obtained from the respondents.
- Using the collected data exclusively for scientific research purposes.
- Ensuring that the identities of the participants were not disclosed.
- Obtaining the participants' consent to complete the questionnaire.

3.7. The Model to Be Tested

The proposed model was developed to examine the direct relationships among the study variables, as well as the sequential mediating role of AI Capability and Organizational Innovation in the relationship between Business Ethics and Sustainable Competitive Advantage. The model was tested using PLS-SEM through SmartPLS 4.1, with Bootstrapping employed to assess the statistical significance of the direct and indirect effects.

Figure 1: The Study Model



Source: Prepared by the researchers based on previous studies.

Figure 1 presents the proposed study model based on **sequential mediation according to Hayes' PROCESS Model 6**. The model assumes that **Business Ethics (BE)**, as the independent variable, has a direct effect on **Sustainable Competitive Advantage (SCA)** (H2), as well as an indirect effect through two sequential mediators.

- **Business Ethics** contributes to the development of **AI Capability (AIC)** (H1) by providing the ethical framework and governance mechanisms necessary for responsible AI adoption.
- **AI Capability** enables the organization to achieve **Organizational Innovation (OI)** (H3), which, in turn, represents a key driver of **Sustainable Competitive Advantage (SCA)** (H4). Hypothesis **H5** examines the sequential indirect effect **BE → AIC → OI → SCA**, suggesting that ethical principles are translated into competitive advantage when they are embodied in technological capabilities and tangible organizational innovations.

3.8. Face Validity (Content Validity)

A distinction should be made between **Face Validity** and **Construct Validity**. Based on the questionnaire used in the present study, there is a clear correspondence between the measurement items and their underlying theoretical dimensions.

Table 2: Face Validity of the Study Variables

Variable	Dimensions	Number of Items
Business Ethics	8 CEVM dimensions	**24**
AI Capability	Tangible, Human, and Intangible Resources	**8**
Organizational Innovation	Product, Process, and Administrative Innovation	**7**
Sustainable Competitive Advantage	Unidimensional scale	**6**
Total	—	**45**

Source: Prepared by the researchers.

The face and content validity of the questionnaire were assessed through expert review, involving university professors and practitioners from Condor Electronics, to ensure the clarity, comprehensibility, and contextual appropriateness of the measurement items.

4. Statistical Tests and Examination of the Study Hypotheses

4.1. Construct Validity

Assessing the quality of the measurement model is an essential step before proceeding to the evaluation of the structural model and testing the hypothesized relationships among the study variables. This assessment aims to ensure that the indicators used measure the intended theoretical constructs in a reliable and valid manner. Convergent Validity is one of the fundamental aspects of assessing a reflective measurement model, as it reflects the extent to which indicators associated with the same latent construct converge in measuring the same concept, thereby ensuring that these indicators share a sufficient proportion of common variance.

Within the framework of Partial Least Squares Structural Equation Modeling (PLS-SEM), convergent validity is primarily assessed based on the Average Variance Extracted (AVE), together with an examination of the reliability and consistency of the measurement indicators using Cronbach's Alpha, Composite Reliability, and rho_A. An AVE value above 0.50 is generally recommended, indicating that the latent construct explains more than half of the variance in its measurement indicators. Meanwhile, reliability values exceeding 0.70 are generally considered indicative of acceptable internal consistency (Hair, et al., 2021).

Construct validity in PLS-SEM was assessed using the following indicators:

- **Outer Loadings:**

Table 3: Results of the Measurement Indicator Validity Assessment Using Outer Loadings

Dimensions	Outer Loadings	Dimensions	Outer Loadings
AIC_HS_1 <- AIC_HS	0.919	BE_SP_2 <- BE_SP	0.907
AIC_HS_2 <- AIC_HS	0.874	BE_SP_3 <- BE_SP	0.890
AIC_HS_3 <- AIC_HS	0.863	BE_SU_1 <- BE_SU	0.910
AIC_IR_1 <- AIC_IR	0.930	BE_SU_2 <- BE_SU	0.917
AIC_IR_2 <- AIC_IR	0.916	BE_SU_3 <- BE_SU	0.922
AIC_TR_1 <- AIC_TR	0.904	BE_TR_1 <- BE_TR	0.923
AIC_TR_2 <- AIC_TR	0.914	BE_TR_2 <- BE_TR	0.904
AIC_TR_3 <- AIC_TR	0.918	BE_TR_3 <- BE_TR	0.904
BE_CL_2 <- BE_CI	0.914	OI_AI_1 <- OI_AI	0.937
BE_CL_3 <- BE_CI	0.917	OI_AI_2 <- OI_AI	0.893
BE_DI_1 <- BE_DI	0.910	OI_PI_1 <- OI_PI	0.884
BE_DI_2 <- BE_DI	0.881	OI_PI_2 <- OI_PI	0.910
BE_DI_3 <- BE_DI	0.876	OI_PI_3 <- OI_PI	0.903
BE_FE_1 <- BE_FE	0.904	OI_PRI_1 <- OI_PRI	0.918
BE_FE_2 <- BE_FE	0.904	OI_PRI_2 <- OI_PRI	0.917
BE_FE_3 <- BE_FE	0.933	SCA_1 <- Sustainable Competitive Adva...	0.873

BE_SA_1 <- BE_SA	0.916	SCA_2 <- Sustainable Competitive Adva...	0.883
BE_SA_2 <- BE_SA	0.880	SCA_3 <- Sustainable Competitive Adva...	0.824
BE_SA_3 <- BE_SA	0.938	SCA_4 <- Sustainable Competitive Adva...	0.843
BE_SM_1 <- BE_SM	0.917	SCA_5 <- Sustainable Competitive Adva...	0.829
BE_SM_2 <- BE_SM	0.928	SCA_6 <- Sustainable Competitive Adva...	0.863
BE_SM_3 <- BE_SM	0.912	BE_CL_1 <- BE_CI	0.916
BE_SP_1 <- BE_SP	0.897		

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results presented in **Table 3** show that all **Outer Loadings** of the indicators of the measurement model dimensions fall within statistically acceptable limits, with values ranging from **0.824 to 0.938**, all of which exceed the commonly accepted threshold of **0.70**. This indicates a strong association between each indicator and the latent construct it measures. The indicator **BE_SA_3** recorded the highest outer loading, with a value of **0.938**, followed by **OI_AI_1**, with a value of **0.937**, while **SCA_3** recorded the lowest value of **0.824**, which nevertheless remains clearly above the acceptable threshold. These results indicate that the measurement indicators have a good ability to explain the latent constructs to which they belong, thereby supporting the adequacy of the measurement model in terms of indicator quality. Moreover, none of the items recorded an outer loading below **0.70**, indicating that there is no statistical justification for deleting any indicator at this stage. Accordingly, all measurement indicators were retained in the **Stage 1 model**, and the analysis proceeded with the remaining assessments of the validity and reliability of the measurement model.

It is also worth noting that the relatively high outer loading values, all exceeding **0.80**, reflect a strong contribution of the indicators to the measurement of their respective constructs, without any excessively high values that might indicate a potential problem of redundancy or substantial overlap of information among the indicators.

- **Convergent Validity:**

Table 4: Results of the Convergent Validity and Internal Consistency Reliability Assessment of the Study Dimensions

Dimensions	Cronbach's alpha	Composite realibility (rho_a)	Composite realibility (rho_a)	Average variance extracted (AVE)
AIC-HS	0.862	0.866	0.916	0.785
AIC-IR	0.826	0.831	0.920	0.852
AIC-TR	0.899	0.900	0.937	0.832
BE-CI	0.904	0.906	0.940	0.838
BE-DI	0.867	0.868	0.919	0.791
BE-FE	0.902	0.917	0.938	0.835
BE-SA	0.899	0.925	0.937	0.831
BE-SM	0.908	0.910	0.942	0.844
BE-SP	0.880	0.882	0.926	0.807
BE-SU	0.905	0.909	0.940	0.840
BE-TR	0.897	0.897	0.936	0.829
OI-AI	0.809	0.846	0.911	0.837
OI-PI	0.881	0.884	0.927	0.808
OI-PRI	0.812	0.813	0.914	0.842
Sustainable Competitive Advantage	**0.925**	**0.931**	**0.941**	**0.727**

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results presented in **Table 4** show that all study dimensions achieved acceptable to high levels of **convergent validity and internal consistency reliability**. The **Average Variance Extracted (AVE)** values ranged from **0.727 to 0.852**, all of which exceed the recommended threshold of **0.50**. This confirms that each dimension explains a sufficient proportion of the variance in its indicators and, consequently, that the convergent validity requirements of the measurement model are satisfied.

The **Composite Reliability (rho_c)** values ranged from **0.911 to 0.942**, while the **rho_A** values ranged from **0.813 to 0.931**. All these values exceed the acceptable threshold of **0.70**, indicating a high level of reliability and internal consistency. Likewise, **Cronbach's Alpha** values ranged from **0.809 to 0.925**, which are also above the recommended threshold of **0.70**, confirming the internal consistency of the items measuring each latent construct. Accordingly, the results demonstrate that all study dimensions satisfy the requirements for **convergent validity and internal consistency reliability**, with no indication that any dimension should be excluded at this stage of the analysis.

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ISSN: 1933-7116
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4.2. Discriminant Validity

Discriminant Validity is one of the fundamental criteria used to assess the quality of the measurement model. It aims to determine the extent to which each latent construct is distinct from the other latent constructs in the model, such that each dimension measures a theoretically different concept from those measured by the other dimensions. Assessing discriminant validity is particularly important in models involving a large number of variables and dimensions, as a high degree of similarity among dimensions may lead to conceptual and statistical overlap, thereby weakening the ability to accurately interpret the structural relationships among them.

Within the framework of **Partial Least Squares Structural Equation Modeling (PLS-SEM)**, discriminant validity can be assessed using several criteria, most notably the **Fornell–Larcker Criterion**, **Cross Loadings**, and the **Heterotrait–Monotrait Ratio (HTMT)**. The HTMT has become an important and recommended criterion in contemporary assessments of discriminant validity because of its ability to detect potential overlap between latent constructs. In general, HTMT values are expected to remain below the established threshold values, thereby supporting sufficient discriminant validity among the dimensions and confirming that each latent construct represents a distinct concept from the others (Henseler, Ringle, & Sarstedt, 2014).

Table 5: Discriminant Validity among the Study Constructs

	AIC_HS	AIC_IR	AIC_TR	BE_CI	BE_DI	BE_FE	BE_SA	BE_SM	BE_SP	BE_SU	BE_TR	OI_AI	OI_PI	OI_PRI
AIC_HS														
AIC_IR	1.020													
AIC_TR	1.025	0.996												
BE_CI	0.510	0.521	0.513	0.510										
BE_DI	0.438	1.027	0.477	0.453	0.438									
BE_FE	0.530	1.034	1.012	0.546	0.551	0.530								
BE_SA	0.521	1.016	1.010	1.001	0.548	0.518	0.521							
BE_SM	0.509	0.971	1.012	1.005	0.992	0.548	0.569	0.509						
BE_SP	0.517	1.007	1.003	1.026	1.018	1.002	0.533	0.547	0.517					
BE_SU	0.473	0.998	0.998	0.973	0.992	1.024	1.012	0.490	0.508	0.473				
BE_TR	0.494	1.007	1.008	0.964	0.995	1.011	1.017	1.023	0.476	0.505	0.494			
OI_AI	0.569	0.467	0.475	0.536	0.452	0.429	0.446	0.451	0.517	0.548	0.587	0.569		
OI_PI	0.621	1.019	0.417	0.439	0.459	0.403	0.401	0.412	0.414	0.473	0.569	0.600	0.621	
OI_PRI	0.659	1.034	0.994	0.461	0.475	0.536	0.418	0.470	0.453	0.454	0.539	0.623	0.655	0.659
Sustainable Competitive Advantage	0.502	0.658	0.625	0.457	0.488	0.523	0.440	0.493	0.512	0.452	0.507	0.553	0.462	0.502

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results of the **Heterotrait–Monotrait Ratio (HTMT)** test presented in **Table 5** indicate some variation in the levels of discriminant validity among the dimensions of the measurement model. Although the majority of the relationships between the dimensions yielded relatively acceptable values, some pairs of dimensions exhibited high values exceeding the reference threshold of **0.90**, indicating a high degree of similarity or potential overlap between certain latent constructs.

The HTMT values ranged from **0.401 to 1.034**. The highest value was recorded between **BE-DI** and **BE-FE**, at **1.034**. Other relatively high values were also observed, including the relationship between **OI-PI** and **OI-PRI**, with a value of **1.034**, between **BE-CI** and **BE-DI**, with a value of **1.027**, and between **BE-SM** and **BE-FE**, with a value of **1.026**. These results indicate the possibility of a degree of overlap among some dimensions.

4.3. Structural Model

After verifying the quality of the measurement model by examining convergent validity and discriminant validity, the analysis proceeded to assess the issue of collinearity within the structural model using the Inner Variance Inflation Factor (Inner VIF). This test aims to ensure that there is no high degree of linear correlation among the independent variables used to explain the dependent variables, as the presence of high collinearity may distort the estimates of the path coefficients, increase their standard errors, and consequently affect the accuracy of hypothesis testing. The VIF is one of the indicators used to assess this issue in Partial Least Squares Structural Equation Modeling (PLS-SEM), where low values indicate the absence of a substantial collinearity problem, whereas high values require further examination (Saima, Qazi, Rizwan, Vveinhardt, & Streimikiene , 2019).

In the present study, Inner VIF values were used to verify that the proposed structural relationships were free from substantial collinearity before proceeding to evaluate the structural relationships and paths and test the study hypotheses.

Table 6: Results of the Collinearity Assessment among the Latent Variables Using the Inner VIF

	AIC_HS	AIC_IR	AIC_TR	BE_ CI	BE_ DI	BE_ FE	BE_ SA	BE_ SM	BE_ SP	BE_ SU	BE_ TR	OI_AI	OI_PI	OI_PRI	Sustainable Competitive Advantage
AIC_HS												5.449	5.449	5.449	
AIC_IR												5.944	5.944	5.944	
AIC_TR												6.727	6.727	6.727	
BE_CI	10.914	10.914	10.914									11.051	11.051	11.051	
BE_DI	8.938	8.938	8.938									9.606	9.606	9.606	
BE_FE	12.037	12.037	12.037									12.249	12.249	12.249	
BE_SA	8.498	8.498	8.498									8.929	8.929	8.929	
BE_SM	8.906	8.906	8.906									9.331	9.331	9.331	
BE_SP	8.479	8.479	8.479									8.511	8.511	8.511	
BE_SU	9.462	9.462	9.462									9.506	9.506	9.506	
BE_TR	9.538	9.538	9.538									10.001	10.001	10.001	
OI_AI															**3.390**
OI_PI															**5.999**
OI_PRI															**4.490**

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results of the **collinearity assessment** using the **Inner Variance Inflation Factor (Inner VIF)** indicate variation in the levels of collinearity among the latent variables in the structural model. The recorded **Inner VIF** values ranged from **3.390 to 12.249**, with some relationships showing values exceeding the commonly accepted reference thresholds, indicating a high degree of linear overlap among certain explanatory variables.

The highest value was **12.249** for the relationship associated with the **BE-DI** dimension. Other dimensions also recorded relatively high values, including **AIC-TR**, with a value of **11.051**, **BE-CI**, with a value of **9.606**, **BE-SU**, with a value of **10.001**, and **BE-SP**, with a value of **9.506**, in addition to other values exceeding **5**. In contrast, some values were comparatively lower, such as **3.390** for **BE-TR** and **4.490** for **OI-PI**.

Accordingly, the results indicate the presence of a **relatively high degree of collinearity in several relationships**, which should be taken into consideration when proceeding to evaluate the structural model and test the path coefficients. Therefore, the assessment of model quality should not rely solely on the measurement-model indicators, but should also take into account the potential effects of collinearity on the estimation and interpretation of the structural relationships.

4.4. R^2 of the Model

After verifying the quality of the measurement model and examining the issue of collinearity among the explanatory variables, the analysis proceeded to assess the explanatory power of the structural model using the **coefficient of determination (R^2)**. The coefficient of determination is one of the fundamental indicators used in evaluating structural equation models, as it represents the proportion of variance in the dependent variable that can be explained by the independent variables included in the model. Accordingly, this indicator makes it possible to assess the explanatory power of the model for each endogenous variable, with higher **R^2** values indicating a greater ability of the explanatory variables to account for variations in the dependent variable.

The **adjusted coefficient of determination (Adjusted R^2)** was also considered, as it takes into account the number of explanatory variables and the sample size, thereby providing a more conservative estimate of the model's explanatory power. Accordingly, both **R^2** and **Adjusted R^2** were used to assess the explanatory power of the structural model before proceeding to evaluate effect sizes and test the hypothesized relationships among the study variables (Ocktavia, Marenza, Al Ayubi , & Maulana, 2024).

Table 7: Results of the Coefficient of Determination (R^2) and Adjusted Coefficient of Determination (Adjusted R^2) for the Structural Model

Dimensions	R -square	R-square adjusted
AIC_HS	0.268	0.200
AIC_IR	0.293	0.228
AIC_TR	0.297	0.232
OI_AI	0.368	0.284
OI_PI	0.378	0.296
OI_PRI	0.457	0.385
Sustainable Competitive Advantage	0.394	0.374

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results presented in **Table 7** indicate variation in the explanatory power of the structural model across its different dimensions and endogenous variables. The **coefficient of determination (R^2)** values ranged from **0.268 to 0.457**, while the **Adjusted R^2** values ranged from **0.200 to 0.385**. The **AIC_HS** dimension recorded an R^2 value of **0.268** and an Adjusted R^2 value of **0.200**, while the corresponding values for **AIC_IR** were **0.293** and **0.228**, and for **AIC_TR**, **0.297** and **0.232**, respectively.

Regarding the dimensions of **Organizational Innovation**, **Administrative Innovation (OI_AI)** recorded an R^2 value of **0.368**, with an Adjusted R^2 of **0.284**, whereas **Product Innovation (OI_PI)** recorded an R^2 of **0.378**, compared with an Adjusted R^2 of **0.296**. **Process Innovation (OI_PRI)** showed the highest explanatory power among the Organizational Innovation dimensions, with an R^2 value of **0.457** and an Adjusted R^2 value of **0.385**.

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ISSN: 1933-7116
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With respect to **Sustainable Competitive Advantage**, the R^2 value was **0.394**, while the Adjusted R^2 value was **0.374**, indicating that the explanatory variables included in the model account for a substantial proportion of the variance in Sustainable Competitive Advantage. Overall, these results reflect **varying levels of explanatory power, ranging from relatively weak to moderate depending on the endogenous construct**, with the highest explanatory power observed for **Process Innovation**, followed by **Sustainable Competitive Advantage**. The relatively small difference between the R^2 and Adjusted R^2 values for Sustainable Competitive Advantage also supports the stability of the model's explanatory power for this construct.

4.5. Effect Size (f^2) Assessment

After confirming the quality of the measurement model, verifying its reliability and validity, and assessing the explanatory power of the model using the coefficient of determination (R^2), the analysis proceeds to assess the **effect size (f^2)** to determine the relative importance of each independent variable in explaining the variation in the dependent variable. This indicator complements the R^2 value by showing the extent to which the explanatory power of an endogenous variable changes when a particular exogenous variable is omitted from the model.

According to **Cohen (1988)**, f^2 values of **0.02, 0.15, and 0.35** are generally interpreted as indicating **small, medium, and large effect sizes**, respectively, whereas values below **0.02** indicate that the effect has little or no practical significance. Accordingly, the f^2 assessment makes it possible to evaluate the **practical importance** of the hypothesized effects rather than merely determining their statistical significance (Cohen, 1988).

Table 8: Results of the Effect Size (f^2) Assessment of the Independent Variables in Explaining the Dependent Variables

	AIC_HS	AIC_IR	AIC_TR	BE_CI	BE_DI	BE_FE	BE_SA	BE_SM	BE_SP	BE_SU	BE_TR	OI_AI	OI_PI	OI_PRI	Sustainable Competitive Advantage
AIC_HS												0.006	0.034	0.017	
AIC_IR												0.010	0.008	0.022	
AIC_TR												0.001	0.000	0.000	
BE_CI	0.004	0.000	0.004									0.042	0.037	0.083	
BE_DI	0.046	0.056	0.022									0.001	0.003	0.002	
BE_FE	0.014	0.016	0.010									0.013	0.007	0.012	
BE_SA	0.013	0.001	0.021									0.019	0.008	0.001	
BE_SM	0.003	0.026	0.014									0.013	0.016	0.072	
BE_SP	0.002	0.003	0.001									0.058	0.017	0.064	
BE_SU	0.000	0.000	0.000									0.002	0.006	0.003	
BE_TR	0.000	0.000	0.010									0.002	0.007	0.018	
OI_AI															0.004
OI_PI															0.015
OI_PRI															0.040

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results presented in **Table 8** indicate that the **f^2 effect sizes** vary across the relationships among the constructs in the model, with the recorded values ranging from **0.000 to 0.083**. According to **Cohen (1988)**, f^2 values of **0.02, 0.15, and 0.35** indicate **small, medium, and large effects**, respectively. Accordingly, the results reveal small effects for some relationships, while the majority of the values fall below the **0.02** threshold, indicating that the contribution of some constructs to explaining the variance in the endogenous constructs is limited in terms of effect size.

The highest recorded value was **0.083**, corresponding to the effect of **AIC_TR on OI_PRI**, followed by **0.072** for the effect of **BE_SA on OI_PRI**, and **0.064** for the effect of **BE_SM on OI_PRI**. All of these values fall within the **small-effect range**. Some values were also close to the **0.02** threshold, such as **0.022** and **0.021**, indicating small effects, whereas several relationships recorded values approaching zero, suggesting limited practical effects in explaining the endogenous constructs.

Overall, the **f^2 results** indicate that the practical direct effect of most constructs in the model is limited, although some relationships make relatively greater contributions than others. Therefore, the assessment should be complemented by examining the **Path Coefficients** and conducting **Bootstrapping** to determine the statistical significance of the hypothesized relationships.

4.6. Path Coefficients

After confirming the quality of the measurement model by assessing convergent validity and discriminant validity, as well as ensuring that there is no substantial collinearity among the latent constructs, the analysis proceeded to evaluate the structural model and determine the significance of the hypothesized relationships among the study variables.

In this context, the Bootstrapping technique implemented in SmartPLS 4.1 was employed as a resampling procedure that enables the estimation of the stability of path coefficients and the assessment of their statistical significance through repeated resampling from the original dataset. The significance of the structural paths was primarily assessed based on the T-statistics and P-values. A relationship was considered statistically significant at the 0.05 significance level when $P \leq 0.05$, while the sign of the path coefficient (β) was considered to determine the direction of the relationship, whether positive or negative (Jorg, Ringle, & Rudolf, 2009).

The following table presents the results of the structural path analysis among the dimensions of the study.

Table 9: Results of Testing the Relationships among the Study Variables Using the Bootstrapping Technique

Dimensions	O	M	SD	T	P	Dimensions	O	M	SD	T	P
AIC_HS -> OI_AI	0.432	0.786	0.190	0.132	0.149	**BE_FE -> AIC_TR**	0.341	0.953	0.305	0.326	0.291
AIC_HS -> OI_PI	0.068	1.822	0.187	0.334	0.341	**BE_FE -> OI_AI**	0.419	0.808	0.390	-0.278	-0.315
AIC_HS->OI_PRI	0.209	1.258	0.180	0.222	0.226	**BE_FE -> OI_PI**	0.520	0.643	0.361	-0.196	-0.232
AIC_IR -> OI AI	0.420	0.806	0.243	0.192	0.196	**BE_FE -> OI_PRI**	0.454	0.749	0.381	-0.246	-0.286
AIC_IR -> OI_PI	0.442	0.769	0.221	0.163	0.170	**BE_SA -> AIC_HS**	0.272	1.099	0.254	0.287	0.279

ISSN: 1933-7116
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AIC_IR -> OI_PRI	0.185	1.326	0.202	0.263	0.269	**BE_SA -> AIC_IR**	0.730	0.346	0.264	0.095	0.091
AIC_TR -> OI_AI	0.723	0.355	0.215	0.095	0.076	**BE_SA -> AIC_TR**	0.127	1.525	0.234	0.368	0.357
AIC_TR -> OI_PI	0.997	0.004	0.212	0.015	0.001	**BE_SA -> OI_AI**	0.186	1.323	0.248	- 0.350	- 0.329
AIC_TR->OI_PRI	0.910	0.113	0.216	0.034	0.024	**BE_SA -> OI_PI**	0.382	0.875	0.244	- 0.232	- 0.214
BE_CI -> AIC_HS	0.510	0.659	0.278	0.179	0.183	**BE_SA -> OI_PRI**	0.791	0.264	0.259	- 0.091	- 0.069
BE_CI -> AIC_IR	0.903	0.121	0.285	0.022	0.035	**BE_SM-> AIC_HS**	0.629	0.483	0.275	0.122	0.133
BE_CI -> AIC_TR	0.536	0.619	0.272	0.161	0.168	**BE_SM-> AIC_IR**	0.155	1.424	0.286	0.407	0.408
BE_CI -> OI_AI	0.109	1.603	0.337	0.553	0.540	**BE_SM->AIC_TR**	0.352	0.931	0.314	0.271	0.292
BE_CI -> OI_PI	0.080	1.748	0.290	0.513	0.506	**BE_SM -> OI_AI**	0.445	0.764	0.360	- 0.307	- 0.275
BE_CI -> OI_PRI	0.022	2.286	0.308	0.716	0.704	**BE_SM -> OI_PI**	0.322	0.990	0.303	- 0.319	- 0.300
BE_DI -> AIC_HS	0.082	1.740	0.316	- 0.521	- 0.549	**BE_SM-> OI_PRI**	0.077	1.767	0.341	- 0.631	- 0.602
BE_DI -> AIC_IR	0.057	1.907	0.311	- 0.563	- 0.594	**BE_SP-> AIC_HS**	0.702	0.382	0.277	0.081	0.106
BE_DI -> AIC_TR	0.169	1.374	0.273	- 0.349	- 0.375	**BE_SP -> AIC_IR**	0.577	0.558	0.252	0.126	0.141
BE_DI -> OI_AI	0.782	0.276	0.236	0.059	0.065	**BE_SP -> AIC_TR**	0.743	0.328	0.282	0.069	0.092
BE_DI -> OI_PI	0.607	0.514	0.259	0.124	0.133	**BE_SP -> OI_AI**	0.025	2.245	0.250	0.576	0.560
BE_DI -> OI_PRI	0.717	0.363	0.246	0.086	0.089	**BE_SP -> OI_PI**	0.201	1.279	0.232	0.306	0.297
BE_FE -> AIC_HS	0.300	1.037	0.339	0.380	0.352	**BE_SP -> OI_PRI**	0.015	2.427	0.223	0.560	0.542
BE_FE->AIC_IR	0.252	1.145	0.322	0.388	0.369	**BE_SU-> AIC_HS**	0.928	0.090	0.298	- 0.052	- 0.027

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices.

The results presented in the above table reveal variation in the statistical significance of the **path coefficients** across the dimensions of the study. The **P-values** were used to assess the statistical significance of the relationships at the **$\alpha \leq 0.05$** significance level, while the **T-statistics** were considered to determine the strength of the statistical evidence. The path coefficient **(O)** indicates the direction of the relationship.

The results indicate several statistically significant relationships, with some paths recording **P-values below 0.05**. For example, the relationship **BE_SM → OI_PI** recorded a path coefficient of **0.704**, with **T = 2.286** and **P = 0.022**, indicating a positive and statistically significant effect. Similarly, the relationship **BE_DI → OI_AI** recorded a path coefficient of **0.560**, with **T = 2.245** and **P = 0.025**, while **BE_DI → OI_PRI** recorded a coefficient of **0.542**, with **T = 2.427** and **P = 0.015**. Both relationships are positive and statistically significant.

Some relationships also showed negative effects, but were not statistically significant. For instance, **BE_SP → AIC_HS** recorded a path coefficient of **−0.594**, with **T = 1.907** and **P = 0.057**. Therefore, although the direction of the relationship is negative, it is **not statistically significant at the 0.05 level** and should not be interpreted as a significant relationship. Similarly, **BE_CI → OI_PRI** recorded a negative coefficient of **−0.602**, with **P = 0.077**, and is therefore not statistically significant at the 5% level.

Conversely, other relationships also failed to reach statistical significance. For example, **AIC_IR → OI_AI** recorded a **P-value of 0.272**, indicating a non-significant relationship, while **AIC_HS → OI_PI** recorded a **P-value of 0.068**, which is likewise non-significant at the 5% level. Accordingly, statistical significance should not be determined solely by the magnitude of the path coefficient; rather, it should be assessed based on the **T-statistics and P-values**, with **P ≤ 0.05** adopted as the primary criterion for establishing the statistical significance of a structural path.

4.7. Testing the Study Hypotheses

After confirming the quality of the measurement model by assessing **reliability, convergent validity, and discriminant validity**, and ensuring that the structural model is free from substantial **collinearity** problems, the analysis proceeds to test the study hypotheses and evaluate the hypothesized relationships among its constructs based on the results of the **Bootstrapping** procedure.

The structural model was developed by considering **Business Ethics (BE)** as the independent variable and **Sustainable Competitive Advantage (SCA)** as the dependent variable, while **Artificial Intelligence Capability (AIC)** and **Organizational Innovation (OI)** serve as mediating variables in the relationship between them. Accordingly, the model hypothesizes a direct effect of Business Ethics on both Artificial Intelligence Capability and Sustainable Competitive Advantage, an effect of Artificial Intelligence Capability on Organizational Innovation, and a direct effect of Organizational Innovation on Sustainable Competitive Advantage. In addition, the model proposes an **indirect sequential effect** of Business Ethics on Sustainable Competitive Advantage through Artificial Intelligence Capability and subsequently Organizational Innovation.

Figure 2: Structural Model of the Hypothesized Relationships among Business Ethics, Artificial Intelligence Capability, Organizational Innovation, and Sustainable Competitive Advantage

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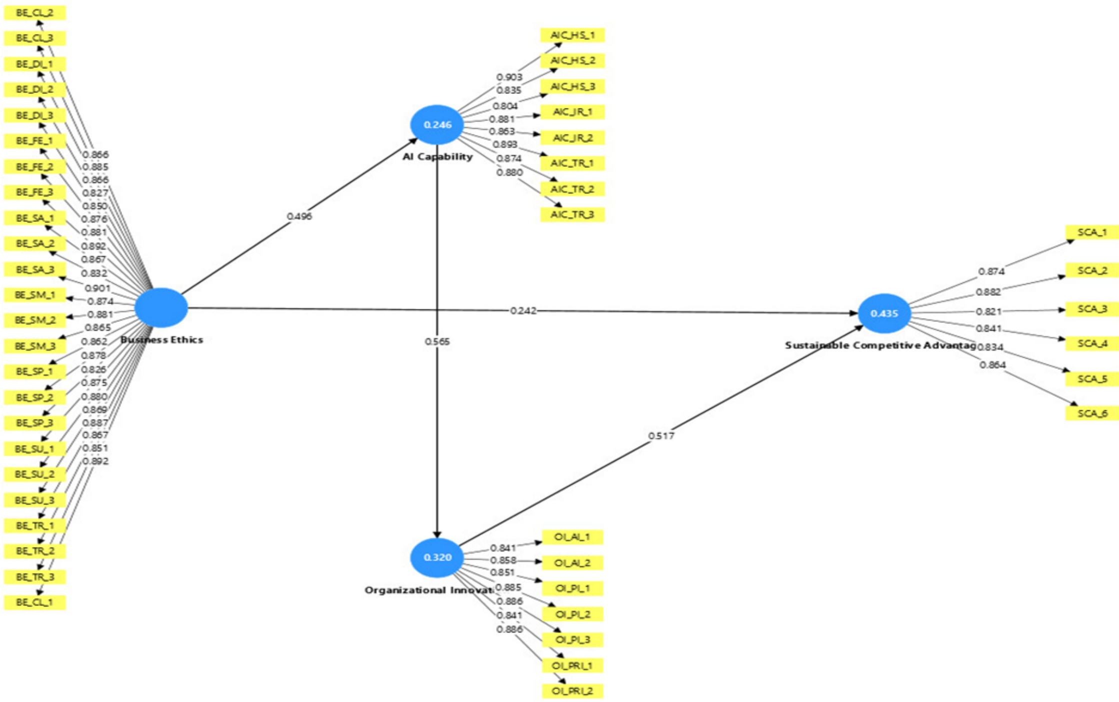

Source: Prepared by the researchers based on SmartPLS 4.1

To achieve this, the **direct hypotheses (H1–H4)** will first be tested based on the **path coefficients (β)** and the **T-statistics and P-values** obtained from the **Bootstrapping** procedure. The analysis will then proceed to test **H5**, which concerns the sequential mediation effect, through the analysis of **Specific Indirect Effects**, allowing the extent to which the effect of Business Ethics on Sustainable Competitive Advantage is transmitted sequentially through Artificial Intelligence Capability and Organizational Innovation to be determined.

- **Testing Hypothesis H1:**

To determine the extent to which **Business Ethics affects Artificial Intelligence Capability**, the first hypothesis was tested based on the **Bootstrapping** results within the **PLS-SEM** framework, using the **path coefficient (β)**, **T-statistic (T)**, and **statistical significance level (P)**.

BE → AIC

Table 10: Results of Testing Hypothesis H1 on the Effect of Business Ethics on Artificial Intelligence Capability

β	p-value	T
0.496	0.000	6.305

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results show that the **path coefficient (β)** was **0.496**, which is positive, indicating a positive effect of **Business Ethics on Artificial Intelligence Capability**. The **T-statistic was 6.305**, which exceeds the critical value of **1.96** at the **α ≤ 0.05** significance level, while the **p-value was < 0.001**, which is below 0.05, confirming that this effect is statistically significant. Accordingly, **Hypothesis H1 is supported**, stating that: *"Business Ethics has a positive and statistically significant effect on Artificial Intelligence Capability at the α ≤ 0.05 significance level."* This finding indicates that a higher level of adoption of Business Ethics within the organization is associated with stronger Artificial Intelligence Capabilities.

- **Testing Hypothesis H2:**

BE → SCA

Table 11: Results of Testing Hypothesis H2 on the Effect of Business Ethics on Sustainable Competitive Advantage

β	p-value	T
0.242	0.004	2.865

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results show that the **path coefficient (β)** was **0.242**, which is positive, indicating a positive effect of **Business Ethics on Sustainable Competitive Advantage**. The **T-statistic was 2.865**, which exceeds the critical value of **1.96** at the **α ≤ 0.05** significance level, while the **p-value was 0.004**, which is below 0.05, confirming that the effect is statistically significant. Accordingly, **Hypothesis H2 is supported**, stating that: *"Business Ethics has a direct, positive, and statistically significant effect on Sustainable Competitive Advantage at the α ≤ 0.05 significance level."* This finding indicates that strengthening Business Ethics practices within the organization contributes positively to supporting and achieving Sustainable Competitive Advantage.

- **Testing Hypothesis H3:**

AIC → OI

Table 12: Results of Testing Hypothesis H3 on the Effect of Artificial Intelligence Capability on Organizational Innovation

β	p-value	T
0.565	0.000	8.022

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results presented in **Table 12** show that the **path coefficient (β)** was **0.565**, which is positive, indicating a positive effect of **Artificial Intelligence Capability on Organizational Innovation**. The **T-statistic was 8.022**, which exceeds the critical value of **1.96** at the **α ≤ 0.05** significance level, while the **p-value was < 0.001**, which is below 0.05, confirming that this effect is statistically significant. Accordingly, **Hypothesis H3 is supported**, stating that: *"Artificial Intelligence Capability has a positive and statistically significant effect on Organizational Innovation at the α ≤ 0.05 significance level."* This finding indicates that strengthening the organization's Artificial Intelligence Capabilities is associated with a greater ability to adopt and develop Organizational Innovation practices.

- **Testing Hypothesis H4:**

OI → SCA

Table 13: Results of Testing Hypothesis H4 on the Effect of Organizational Innovation on Sustainable Competitive Advantage

β	p-value	T
0.517	0.000	6.785

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results show that the **path coefficient (β)** was **0.517**, which is positive, indicating a positive effect of **Organizational Innovation on Sustainable Competitive Advantage**. The **T-statistic was 6.785**, which exceeds the critical value of **1.96** at the **α ≤ 0.05** significance level, while the **p-value was < 0.001**, which is below 0.05, confirming that this effect is statistically significant. Accordingly, **Hypothesis H4 is supported**, stating that: *"Organizational Innovation has a positive and statistically significant effect on Sustainable Competitive Advantage at the α ≤ 0.05 significance level."* This finding indicates that a higher level of Organizational Innovation within the organization contributes positively to strengthening its ability to achieve Sustainable Competitive Advantage.

- **Testing Hypothesis H5: Sequential Mediation**

After establishing the presence of direct effects among the study variables through the preceding hypotheses, it becomes important to examine whether the effect of **Business Ethics on Sustainable Competitive Advantage** extends beyond the direct relationship and is also transmitted indirectly through **Artificial Intelligence Capability** and subsequently **Organizational Innovation**. Accordingly, **Hypothesis H5** was tested as a **sequential mediation hypothesis** by analyzing the **Specific Indirect Effect** using the **Bootstrapping** technique. This analysis was conducted to assess the following sequential path:

Business Ethics → Artificial Intelligence Capability → Organizational Innovation → Sustainable Competitive Advantage.

Table 14: Results of Testing the Sequential Indirect Effect of Business Ethics on Sustainable Competitive Advantage

	β	**p-value**	**T**
Business Ethics → AI Capability → Organizational Innovation → Sustainable Competitive Advantage	0.145	0.001	3.419

Source: Prepared by the researchers based on SmartPLS 4.1; see the appendices**.**

The results presented in the table show that the indirect effect coefficient was **β = 0.145**, which is positive, indicating that business ethics has a positive indirect effect on sustainable competitive advantage through **AI capabilities and organizational innovation in a sequential manner**. The **T-value was 3.419**, exceeding the critical value of 1.96 at the significance level of **α ≤ 0.05**, while the **p-value was < 0.001**, which is below 0.05, confirming that the indirect effect is statistically significant.

Accordingly, **Hypothesis H5 is supported**, stating that: *"AI capabilities and organizational innovation sequentially mediate the relationship between business ethics and sustainable competitive advantage at the significance level of α ≤ 0.05."* This finding indicates that the effect of business ethics on sustainable competitive advantage is not transmitted solely through a direct pathway, but also operates through a sequential mechanism that begins with strengthening the organization's AI capabilities, which in turn contributes to organizational innovation, ultimately enhancing sustainable competitive advantage.

5. CONCLUSION

This study examined the effect of business ethics on achieving sustainable competitive advantage, uncovering the serial mediating role of both AI capability and organizational innovation, drawing on the Dynamic Capability View (DCV). The research was based on a field study conducted among a sample of 95 employees at Condor Electronics in Algeria. The study sought to move beyond the traditional view of business ethics as a mere normative or legal obligation, instead confirming that it constitutes a strategic organizational resource that contributes to building technical and innovative capabilities, which are ultimately translated into a competitive edge that is difficult for rivals to replicate.

The statistical analysis, conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.1, revealed that all five hypothesized relationships were supported, strongly reinforcing the proposed theoretical framework. Business ethics was found to have a positive and significant effect on both AI capability and sustainable competitive advantage. AI capability, in turn, was found to enhance organizational innovation, which positively affected sustainable competitive advantage. Most importantly, the study confirmed a significant serial mediating effect of AI capability and organizational innovation in the relationship between business ethics and sustainable competitive advantage offering a mechanistic explanation of how ethical principles are transformed into tangible strategic value, a gap that prior studies had not addressed in an integrated manner.

These findings carry particular significance within the context of Algerian industrial firms operating in the home-appliance manufacturing sector, an industry undergoing rapid digital transformation and expanding adoption of AI technologies. Theoretically, the study enriches the Dynamic Capability View literature by proposing an integrative model that links the ethical, technical, and innovative dimensions within a single causal chain. Practically, it offers decision-makers at the organization under investigation, and at comparable firms, actionable grounds for directing their investments toward embedding ethical practices as a foundation for building effective AI capabilities that support innovation and reinforce sustainable competitiveness.

5.1. Results

Based on the hypothesis-testing results obtained through the Bootstrapping procedure, the main findings can be summarized as follows:

- **Hypothesis H1**: Business ethics was found to have a positive and significant effect on AI capability ($\beta = 0.496$, $T = 6.305$, $p < 0.001$), confirming that an organization's ethical climate provides fertile ground for developing technical and digital capabilities.
- **Hypothesis H2**: Business ethics was found to have a direct, positive, and significant effect on sustainable competitive advantage ($\beta = 0.242$, $T = 2.865$, $p = 0.004$) — a weaker effect compared with the indirect pathway, suggesting that a substantial part of the influence of business ethics operates through mediating variables.
- **Hypothesis H3**: AI capability was found to have a positive and significant effect on organizational innovation ($\beta = 0.565$, $T = 8.022$, $p < 0.001$), the strongest direct effect recorded within the model.
- **Hypothesis H4**: Organizational innovation was found to have a positive and significant effect on sustainable competitive advantage ($\beta = 0.517$, $T = 6.785$, $p < 0.001$).
- **Hypothesis H5**: A significant serial mediating effect of AI capability and organizational innovation was confirmed in the relationship between business ethics and sustainable competitive advantage ($\beta = 0.145$, $T = 3.419$, $p = 0.001$) — meaning that business ethics is translated into sustainable competitive advantage through the sequential pathway: **Business Ethics → AI Capability → Organizational Innovation → Sustainable Competitive Advantage**.
- The proportion of variance explained (R^2) in sustainable competitive advantage was 0.394 (Adjusted $R^2 = 0.374$), an acceptable level reflecting the good explanatory power of the proposed model.
- The effect size (f^2) results showed that most sub-relationships between the dimensions of the variables had small to negligible effect sizes, which calls for caution in interpreting the practical importance of some sub-paths despite their statistical significance at the level of the overall constructs.

5.2. Recommendations and Suggestions

First: Recommendations for Condor Electronics and Firms in the Sector

1. **Embed ethical governance as a strategic priority**: Strengthen the dimensions of business ethics with the greatest influence (such as transparency, accountability, and discussability) by establishing clear codes of conduct and genuine incentive mechanisms for ethical behavior, given that the results confirmed its pivotal role as the starting point of the entire competitive chain.
2. **Invest in building AI capability**: Direct investments toward technical infrastructure, developing the necessary human skills (employee training and staff qualification), and strengthening intangible resources such as inter-departmental coordination and readiness to undertake the calculated risks associated with AI adoption.
3. **Translate technical capabilities into actual innovative practices**: Encourage departments to leverage AI outputs in developing new products, processes, and organizational structures, rather than merely possessing the technology without translating it into tangible innovation.
4. **Strategically link the three pillars**: Design an integrated strategic plan that explicitly connects corporate ethics programs, digital transformation initiatives, and the innovation agenda, rather than treating them as separate tracks, in order to activate the serial pathway confirmed by the study.
5. **Monitor the impact of investments on competitive advantage**: Establish periodic performance indicators to measure the extent to which ethical practices and AI capabilities are translated into actual superiority in customer value and into resources that are difficult for competitors to imitate.

Second: Suggestions for Future Research

1. Conduct comparative studies with larger samples and in other industrial sectors in Algeria or other Maghreb countries, to strengthen the generalizability of the findings, given the relatively small size of the current sample ($n = 95$) and its association with a single organization.
2. Adopt longitudinal research designs to track how the relationship among business ethics, technical capabilities, and innovation evolves over time, rather than relying solely on a cross-sectional approach.
3. Re-examine the content of certain dimensions of the business ethics scale (CEVM), particularly those that showed relatively high HTMT and Inner VIF values (such as BE-DI and BE-FE), which may indicate conceptual overlap requiring item refinement or the merging of certain dimensions.
4. Test additional mediating or moderating variables (such as ethical leadership, organizational culture, or firm size) to deepen understanding of the mechanisms linking ethics to sustainable competitiveness.
5. Broaden the measurement of organizational innovation and AI capability to include objective indicators (such as actual performance data or patents) alongside the perceptual measures based on employee responses.

Bibliography

Amarolinda, K. (2022). Ethical Issues of Digital Transformation. *Organizações & Sociedade Journal, 29*(12), 443-448. doi:https://doi.org/10.1590/1984-92302022v29n0020EN

Andrew, H. (2022). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach* (3 ed.). NY, USA: The Guilford Press.

Asa, A., Nautwima, J., & Villet , H. (2024). An Integrated Approach to Sustainable Competitive Advantage. International Journal of Business and Society. *International Journal of Business and Society, 25*(1), 201-222. doi:https://doi.org/10.33736/ijbs.6907.2024

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management, 17*(1), 99-120. doi:https://doi.org/10.1177/014920639101700108

Basharat, I. (2026). AI-enabled startups, ethical practices and investor decision-making: a systematic literature review. *European Business Review, 38*(4), 640-658. doi:https://doi.org/10.1108/EBR-02-2026-0051

Cao, G., Duan, Y., & Edwards, J. (2026). AI Trustworthiness in Managerial Decision-Making: Ethics, Transparency, and Explainability as Key Drivers: AI Trustworthness in Managerial Decision-MakingG. Cao et al. Journal of Business Ethics. PP1. *Journal of Business Ethics*, 1-21. doi:https://doi.org/10.1007/s10551-026-06400-x

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2 ed.). Routledge. doi:https://doi.org/10.4324/9780203771587

Crossley, C., Taylor, S., Liden , R., Wo , D., & Piccolo, R. (2024). Right From the Start: The Association Between Ethical Leadership, Trust Primacy, and Customer Loyalty. *Journal of Business Ethics, 193*(2), 409-426. doi:https://doi.org/10.1007/s10551-023-05485-y

Dukhaykh, S., & Alangri, N. (2026). Dynamic Capabilities and Sustainable Competitive Advantage in SMEs: The Roles of Innovation and Organizational Learning. *Sustainability, 18*(3), 1-21. doi:https://doi.org/10.3390/su18031320

El Moudden, M., & Balhadj , S. (2024). Organizational innovation: A literature review. *International Journal of Innovation and Applied Studies, 42*(3), 547-554.

Fuller, J., Hutter , K., Wahl, J., Bilgram, V., & Tekic, Z. (2022). How AI revolutionizes innovation management – Perceptions and implementation preferences of AI-based innovators. *Technological Forecasting and Social Change, 178*, 1-22. doi:https://doi.org/10.1016/j.techfore.2022.121598

Gama, F., & Magistretti, S. (2025). Artificial Intelligence in Innovation Management: A Review of Innovation Capabilities and a Taxonomy of AI Applications. *Journal of Product Innovation Management, 42*(1), 76-111. doi:https://doi.org/10.1111/jpim.1269

Garcia, V., Jacobo , H., & Flores, L. (2023). Dynamic Capabilities and Their Effect on Organizational Resilience in Small and Medium-Sized Commercial Enterprises. *Management & Marketing, 18*(4), 496-514. doi:https://doi.org/10.2478/mmcks-2023-0027

Ghauri, P., Elg, U., & Melen, H. (2023). Creating a Sustainable Competitive Position Through Ethical Behaviour. In *Creating a Sustainable Competitive Position: Ethical Challenges for International* (pp. 1-8). Emerald. doi:https://doi.org/10.1108/S1876-066X20230000037001

Hair, J., Hult, T., Ringle , C., Sarstedt, M., Danks, N., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A workbook* (1 ed.). Springer.

Han, S., Zhang, D., Zhang, H., & Lin, S. (2025). Artificial Intelligence Technology, Organizational Learning Capability, and Corporate Innovation Performance: Evidence from Chinese Specialized, Refined, Unique, and Innovative Enterprises. *Sustainability, 17*(6). doi:https://doi.org/2510. 10.3390/su17062510

Henseler, J., Ringle, C., & Sarstedt, M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135. doi:https://doi.org/10.1007/s11747-014-0403-8

Huynh, H., Nguyen, N., & Vo, N. (2024). The influence of knowledge management, green transformational leadership, green organizational culture on green innovation and sustainable performance: The case of Vietnam. *Journal of Open Innovation: Technology, 10*(4). doi:https://doi.org/10.1016/j.joitmc.2024.100436.

Isseki, B., & Ferhani, B. (2026). Organizational Integrity Between Ethics and Performance: A Bibliometric Synthesis of 80 Years and Research Agenda. *Business Ethics*, 1-22. doi:https://doi.org/10.1007/s10551-026-06350-4

Jorg, H., Ringle, C., & Rudolf, S. (2009). The Use of Partial Least Squares Path Modeling in International Marketing. In *Advances in International Marketing.* doi:https://doi.org/10.1108/S1474-7979(2009)0000020014

Kaptein, M. (2008). Developing and testing a measure for the ethical culture of organizations: the corporate ethical virtues model. *Journal of Organizational Behavior, 29*(7), 923-947. doi:https://doi.org/10.1002/job.520

Khogali, H., & Mekid, S. (2023). The blended future of automation and AI: Examining some long-term societal and ethical impact features. *Technology in Society, 73*. doi:https://doi.org/10.1016/j.techsoc.2023.102232.

Knapp, J., Namada, J., & Dougan, W. (2025). Dynamic ethical capabilities in place and in time. *Journal of Management & Organization, 31*(2), 511-532. doi:https://doi.org/10.1017/jmo.2025.1

Krejcie, V., & Morgan, W. (1970). Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*(3), 607-610. doi:https://doi.org/10.1177/001316447003000308

Leal, F., Viera, T., Paulino, P., Simon, R., Anholon , R., Will, M., . . . Bonato, M. (2024). Leal Filho W, Viera Trevisan L, Paulino Pires Eustachio JH, Simon Rampasso I, Anholon R, Platje J, Will M, Doni F, Mazhar M, Borsatto JMLS, Bonato Marcolin C "Assessing ethics and sustainability standards in corporate practices. *Social Responsibility, 20*(5), 880-897. doi:https://doi.org/10.1108/SRJ-03-2023-0116

Lopez, D., & Oliver, M. (2025). Methodology, strategies, and factors for business innovation in large companies. *International Journal of Innovation Studies, 92*(2), 91-115. doi:https://doi.org/10.1016/j.ijis.2025.02.002.

Madanchian, M., & Taherdoost, H. (2025). Ethical theories, governance models, and strategic frameworks for responsible AI adoption and organizational success. *Frontiers Artificial Intelligence, 8*. doi:https://doi.org/10.3389/frai.2025.1619029.

Mikalef, P., & Gupta, M. (2021). Artificial Intelligence Capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(1). doi:https://doi.org/10.1016/j.im.2021.103434

Ocktavia, A., Marenza, S., Al Ayubi , S., & Maulana, H. (2024). Factors Influencing Fashion Consciousness in Muslim Fashion Consumption among Zillennials. *Journal of Islamic Economic Laws, 7*(1), 56-85. doi:https://doi.org/10.23917/jisel.v7i01.3487

Pavitra, D., & Surajit, B. (2021). Role of artificial intelligence in operations environment: a review and bibliometric analysis. *The TQM Journal*, 869-896. doi:https://doi.org/10.1108/TQM-10-2019-0243.

Riaz, A., & Hadi, F. (2024). Responsible innovation and sustainable competitive advantage: is big data the missing link. *30*(4), 1213-1235. doi:https://doi.org/10.1108/BPMJ-11-2022-0619

Roy, A., Newman, A., Round, H., & Bhattacharya, S. (2024). Ethical Culture in Organizations: A Review and Agenda for Future Research. *Business Ethics Quarterly, 34*(1), 97-138. doi:https://doi.org/10.1017/beq.2022.44

Saima, H., Qazi, S., Rizwan, A., Vveinhardt, J., & Streimikiene , D. (2019). Innovative user engagement and playfulness on adoption intentions of technological products: evidence from SEM-based multivariate approach. *Economic Research., 32*(1), 555-577. doi:https://doi.org/10.1080/1331677X.2018.1558086

Salman, B., Marco, C., & Qamar, D. (2023). Artifical intelligence and corporate innovation: A review and research agenda. *Technological Forecasting and Social Change, 188*. doi:https://doi.org/10.1016/j.techfore.2022.122264.

Saunders, L., & Thornhill, A. (2019). *Research methods for business students* (8 ed.). Pearson Education Limited.

Souissi, B., & Chauaibi, S. (2025). The effects of business ethics and corporate social responsibility practices on financial performance: a machine learning prediction and model interpretability approach. *International Journal of Ethics and Systems*. doi:https://doi.org/10.1108/IJOES-05-2024-0127

Teece , D., Pisano , G., & Shuen, A. (1997). Teece, D.J., Pisano, G. and Shuen, A. (1997), Dynamic capabilities and strategic management. *Strategic management Journal, 18*(7), 509-533. doi:https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Van Rietschoten, E., & Van Bommel, K. (2025). van Rietschoten, E., & van Bommel, K. (2025). Toward a contemporary understanding of organizational trust in socio-economic systems: Connecting theoretical perspectives of the management and business ethics literature. *34*, 1592-1620. doi:https://doi.org/10.1111/beer.12725

Versteegt, J., Marius, V., & Muel, K. (2025). The Status of Normative Ethical Decision-Making Models: The Development and Application of an Analytical Framework. *Journal of Business Ethics, 204*(1), 31-49. doi:https://doi.org/10.1007/s10551-02

Weber, M., Engert, M., Schaffer, N., Weking, J., & Krcmar, H. (2023). Organizational Capabilities for AI Implementation Coping with Inscrutability and Data Dependency in AI. *Information Systems Frontiers, 25*(1), 1549-1569. doi:https://doi.org/10.1007/s10796-022-10297-y

Xinzi, L. (2026). Institutionalizing trust in AI governance: from ethical principles to legal design. *AI and Ethics, 6*(2). doi:https://doi.org/10.1007/s43681-026-01009-2

Yildiz, T., & Aykanat, Z. (2021). The Mediating Role of Organizational Innovation on the Impact of Strategic Agility on Firm Performance, World Journal of Entrepreneurship, Management and Sustainable Development. *World Journal of Entrepreneurship, Management and Sustainable Development, 14*(4), 765-786. doi:https://doi.org/10.1108/WJEMSD-06-2020-0070

Zhang, X., Chu, Z., Ren , L., & Xing, J. (2023). Open innovation and sustainable competitive advantage: The role of organizational learning. *Technological Forecasting and Social Change, 186*. doi:https://doi.org/10.1016/j.techfore.2022.122114

Zhou, C. (2025). The Impact of Artificial Intelligence on the Sustainable Development Performance of Chinese Manufacturing Enterprises. *Systems, 13*(1), 1-20. doi:https://doi.org/10.3390/systems13070496

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Construct Realibility and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AIC_HS	0.862	0.866	0.916	0.785
AIC_IR	0.826	0.831	0.920	0.852
AIC_TR	0.899	0.900	0.937	0.832
BE_CI	0.904	0.906	0.940	0.838
BE_DI	0.867	0.868	0.919	0.791
BE_FE	0.902	0.917	0.938	0.835
BE_SA	0.899	0.925	0.937	0.831
BE_SM	0.908	0.910	0.942	0.844
BE_SP	0.880	0.882	0.926	0.807
BE_SU	0.905	0.909	0.940	0.840
BE_TR	0.897	0.897	0.936	0.829
OI_AI	0.809	0.846	0.911	0.837
OI_PI	0.881	0.884	0.927	0.808
OI_PRI	0.813	0.813	0.914	0.842
Sustainable Competitive Advantage	0.925	0.931	0.941	0.727

Outer Loadings

	AIC_HS	AIC_IR	AIC_TR	BE_CI	BE_DI	BE_FE	BE_SA	BE_SM	BE_SP	BE_SU	BE_TR	OI_AI	OI_PI	OI_PRI	Sustainable Competitive Advantage
AIC_HS_1	0.919														
AIC_HS_2	0.874														
AIC_HS_3	0.863														
AIC_IR_1		0.930													
AIC_IR_2		0.916													
AIC_TR_1			0.904												
AIC_TR_2			0.914												
AIC_TR_3			0.918												
BE_CL_2				0.914											
BE_CL_3				0.917											
BE_DI_1					0.910										
BE_DI_2					0.881										
BE_DI_3					0.876										
BE_FE_1						0.904									
BE_FE_2						0.904									
BE_FE_3						0.933									
BE_SA_1							0.916								
BE_SA_2							0.880								
BE_SA_3							0.938								
BE_SM_1								0.917							
BE_SM_2								0.928							
BE_SM_3								0.912							
BE_SP_1									0.897						
BE_SP_2									0.907						
BE_SP_3									0.890						
BE_SU_1										0.910					
BE_SU_2										0.917					
BE_SU_3										0.922					
BE_TR_1											0.923				
BE_TR_2											0.904				
BE_TR_3											0.904				
OI_AI_1												0.937			
OI_AI_2												0.893			
OI_PI_1													0.884		
OI_PI_2													0.910		
OI_PI_3													0.903		
OI_PRI_1														0.918	
OI_PRI_2														0.917	
SCA_1															0.873
SCA_2															0.883
SCA_3															0.824
SCA_4															0.843
SCA_5															0.829
SCA_6															0.863
BE_CL_1				0.916											

ings - Matrix

Discriminant validity (HTMT)

Discriminant validity - Heterotrait-monotrait ratio (HTMT) - Matrix

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	AIC_HS	AIC_IR	AIC_TR	BE_CI	BE_DI	BE_FE	BE_SA	BE_SM	BE_SP	BE_SU	BE_TR	OI_AI	OI_PI	OI_PRI
AIC_HS														
AIC_IR	1.020													
AIC_TR	0.996	1.025												
BE_CI	0.510	0.513	0.521											
BE_DI	0.438	0.453	0.477	1.027										
BE_FE	0.530	0.551	0.546	1.012	1.034									
BE_SA	0.521	0.518	0.548	1.001	1.010	1.016								
BE_SM	0.509	0.569	0.548	0.992	1.005	1.012	0.971							
BE_SP	0.517	0.547	0.533	1.002	1.018	1.026	1.003	1.007						
BE_SU	0.473	0.508	0.490	1.012	1.024	0.992	0.973	0.998	0.998					
BE_TR	0.494	0.505	0.476	1.023	1.017	1.011	0.995	0.964	1.008	1.007				
OI_AI	0.569	0.587	0.548	0.517	0.451	0.446	0.429	0.452	0.536	0.475	0.467			
OI_PI	0.621	0.600	0.569	0.473	0.414	0.412	0.401	0.403	0.459	0.439	0.417	1.019		
OI_PRI	0.659	0.655	0.623	0.539	0.454	0.453	0.470	0.418	0.536	0.475	0.461	0.994	1.034	
Sustainable Competitive Advantage	0.502	0.462	0.553	0.507	0.452	0.512	0.493	0.440	0.523	0.488	0.457	0.625	0.658	0.696

Collinearity statistics (VIF) Inner model

Collinearity statistics (VIF) - Inner model - Matrix

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	AIC_HS	AIC_IR	AIC_TR	BE_CI	BE_DI	BE_FE	BE_SA	BE_SM	BE_SP	BE_SU	BE_TR	OI_AI	OI_PI	OI_PRI	Sustainable Competitive Advantage
AIC_HS												5.449	5.449	5.449	
AIC_IR												5.944	5.944	5.944	
AIC_TR												6.727	6.727	6.727	
BE_CI	10.914	10.914	10.914									11.051	11.051	11.051	
BE_DI	8.938	8.938	8.938									9.606	9.606	9.606	
BE_FE	12.037	12.037	12.037									12.249	12.249	12.249	
BE_SA	8.498	8.498	8.498									8.929	8.929	8.929	
BE_SM	8.906	8.906	8.906									9.331	9.331	9.331	
BE_SP	8.479	8.479	8.479									8.511	8.511	8.511	
BE_SU	9.462	9.462	9.462									9.506	9.506	9.506	
BE_TR	9.538	9.538	9.538									10.001	10.001	10.001	
OI_AI															3.930
OI_PI															5.999
OI_PRI															4.490
Sustainable Competitive Advantage															

Review of Futures Markets (RFM)
ISSN: 1933-7116
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R-square- Overview

R-square - Overview	R-square	R-square adjusted
AIC_HS	0.268	0.200
AIC_IR	0.293	0.228
AIC_TR	0.297	0.232
OI_AI	0.368	0.284
OI_PI	0.378	0.296
OI_PRI	0.457	0.385
Sustainable Competitive Advantage	0.394	0.374

Path Coefficients of all dimensions

Path coefficients - Mean, STDEV, T values, p values

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	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AIC_HS -> OI_AI	0.149	0.132	0.190	0.786	0.432
AIC_HS -> OI_PI	0.341	0.334	0.187	1.822	0.068
AIC_HS -> OI_PRI	0.226	0.222	0.180	1.258	0.209
AIC_IR -> OI_AI	0.196	0.192	0.243	0.806	0.420
AIC_IR -> OI_PI	0.170	0.163	0.221	0.769	0.442
AIC_IR -> OI_PRI	0.269	0.263	0.202	1.326	0.185
AIC_TR -> OI_AI	0.076	0.095	0.215	0.355	0.723
AIC_TR -> OI_PI	0.001	0.015	0.212	0.004	0.997
AIC_TR -> OI_PRI	0.024	0.034	0.216	0.113	0.910
BE_CI -> AIC_HS	0.183	0.179	0.278	0.659	0.510
BE_CI -> AIC_IR	0.035	0.022	0.285	0.121	0.903
BE_CI -> AIC_TR	0.168	0.161	0.272	0.619	0.536
BE_CI -> OI_AI	0.540	0.553	0.337	1.603	0.109
BE_CI -> OI_PI	0.506	0.513	0.290	1.748	0.080
BE_CI -> OI_PRI	0.704	0.716	0.308	2.286	0.022
BE_DI -> AIC_HS	-0.549	-0.521	0.316	1.740	0.082
BE_DI -> AIC_IR	-0.594	-0.563	0.311	1.907	0.057
BE_DI -> AIC_TR	-0.375	-0.349	0.273	1.374	0.169
BE_DI -> OI_AI	0.065	0.059	0.236	0.276	0.782
BE_DI -> OI_PI	0.133	0.124	0.259	0.514	0.607
BE_DI -> OI_PRI	0.089	0.086	0.246	0.363	0.717
BE_FE -> AIC_HS	0.352	0.380	0.339	1.037	0.300
BE_FE -> AIC_IR	0.369	0.388	0.322	1.145	0.252
BE_FE -> AIC_TR	0.291	0.326	0.305	0.953	0.341
BE_FE -> OI_AI	-0.315	-0.278	0.390	0.808	0.419
BE_FE -> OI_PI	-0.232	-0.196	0.361	0.643	0.520
BE_FE -> OI_PRI	-0.286	-0.246	0.381	0.749	0.454
BE_SA -> AIC_HS	0.279	0.287	0.254	1.099	0.272
BE_SA -> AIC_IR	0.091	0.095	0.264	0.346	0.730
BE_SA -> AIC_TR	0.357	0.368	0.234	1.525	0.127
BE_SA -> OI_AI	-0.329	-0.350	0.248	1.323	0.186
BE_SA -> OI_PI	-0.214	-0.232	0.244	0.875	0.382
BE_SA -> OI_PRI	-0.069	-0.091	0.259	0.264	0.791
BE_SM -> AIC_HS	0.133	0.122	0.275	0.483	0.629
BE_SM -> AIC_IR	0.408	0.407	0.286	1.424	0.155
BE_SM -> AIC_TR	0.292	0.271	0.314	0.931	0.352
BE_SM -> OI_AI	-0.275	-0.307	0.360	0.764	0.445
BE_SM -> OI_PI	-0.300	-0.319	0.303	0.990	0.322
BE_SM -> OI_PRI	-0.602	-0.631	0.341	1.767	0.077
BE_SP -> AIC_HS	0.106	0.081	0.277	0.382	0.702
BE_SP -> AIC_IR	0.141	0.126	0.252	0.558	0.577
BE_SP -> AIC_TR	0.092	0.069	0.282	0.328	0.743
BE_SP -> OI_AI	0.560	0.576	0.250	2.245	0.025
BE_SP -> OI_PI	0.297	0.306	0.232	1.279	0.201
BE_SP -> OI_PRI	0.542	0.560	0.223	2.427	0.015
BE_SU -> AIC_HS	-0.027	-0.052	0.298	0.090	0.928
BE_SU -> AIC_IR	0.039	0.005	0.316	0.123	0.902

Hypothesis testing

Path coefficients - Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI Capability -> Organizational Innovation	0.565	0.569	0.070	8.022	0.000
Business Ethics -> AI Capability	0.496	0.501	0.079	6.305	0.000
Business Ethics -> Sustainable Competitive Advantage	0.242	0.245	0.084	2.865	0.004
Organizational Innovation -> Sustainable Competitive Advantage	0.517	0.519	0.076	6.785	0.000

Testing the mediation hypothesis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI Capability -> Organizational Innovation -> Sustainable Competitive Advantage	0.292	0.297	0.062	4.729	0.000
Business Ethics -> AI Capability -> Organizational Innovation	0.280	0.287	0.065	4.325	0.000
Business Ethics -> AI Capability -> Organizational Innovation -> Sustainable Competitive Advantage	0.145	0.150	0.042	3.419	0.001