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# Artificial Intelligence Capabilities and the Development of a Smart and Sustainable Auditing Ecosystem: The Moderating Role of Cyber Forensic Accounting Intelligence

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## ABSTRACT

This study examines how Artificial Intelligence Capabilities (AIC) contribute to the development of a Smart and Sustainable Auditing Ecosystem (SSAE) within public sector organizations (PSOs). The study also investigates the moderating role of Cyber Forensic Accounting Intelligence (CFAI) in strengthening this relationship. Data were collected from employees working in Vietnamese PSOs using a structured questionnaire survey. The model was examined through Covariance-Based Structural Equation Modeling using IBM AMOS 28. The findings indicate that AIC significantly supports the development of SSAE. Moreover, CFAI strengthens the influence of AIC on SSAE, suggesting that accountants' cyber forensic competencies enhance the effectiveness of AI-enabled auditing systems. These results provide implications for policymakers, auditing authorities, and PSOs seeking to modernize auditing practices. Integrating AI technologies with cyber forensic expertise can facilitate more transparent, data-driven, and sustainable auditing systems that better respond to the challenges of digital governance.

**Keywords:** Auditing ecosystem, Cyber security, Digitalization capabilities and Forensic Accounting.

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## 1. Introduction

Public sector organizations (PSOs) increasingly face pressures related to climate change, limited financial resources, declining public trust, and growing expectations for transparency and accountability. Addressing these challenges requires governance mechanisms capable of managing complex societal demands. As a result, PSOs have become increasingly dependent on digital technologies, including integrated information systems, digital auditing infrastructures, and cybersecurity mechanisms that support transparency and accountability in digital environments. Rapid technological advancement has also encouraged organizations to continuously adapt to their operational practices. However, many governance challenges cannot be addressed by individual organizations alone. Instead, collaborative technology-enabled environments have gained increasing attention. In this context, the concept of a smart and sustainable auditing ecosystem (SSAE) has emerged as an important framework that integrates multiple actors and technological infrastructures to improve auditing effectiveness and oversight. Artificial Intelligence (AI) enables organizations to process large volumes of data, improve decision-making processes, and support innovation across organizational activities [1]. Within accounting and auditing, AI applications are increasingly used to automate analytical procedures, detect anomalies, and strengthen financial oversight [2]. In this context, Artificial Intelligence capabilities (AIC) refer to an organization's ability to deploy advanced technologies to generate insights and support decision-making processes [3].

Despite these benefits, the adoption of AI in the public sector also introduces several challenges, including concerns related to privacy, transparency, and algorithmic bias [4]. Therefore, organizations require professionals who possess strong analytical and investigative capabilities to identify financial irregularities within digital environments. In this study, cyber forensic accounting intelligence (CFAI) refers to accountants' ability to analyze digital financial data, detect suspicious patterns, and interpret complex financial information within technology-driven environments. Although previous research has explored AI adoption in auditing, most studies focus primarily on technological implementation or operational efficiency. Limited attention has been given to how AIC contributes to the development of collaborative and sustainable auditing ecosystems. In addition, the role of CFAI in strengthening AI-driven auditing systems remains insufficiently explored. This gap limits the understanding of how technological capabilities and professional expertise jointly enhance transparency and accountability in modern auditing systems. To address this gap, this study examines the impact of AIC on the development of SSAE and investigates the moderating role of CFAI in this relationship. The current investigation addresses the research questions as follows:

- *RQ1. What is the effect of AIC on SSAE?*
- *RQ2. Does CFAI moderate the relationship between AIC and SSAE?*

This study contributes to the literature by providing empirical evidence from the public sector. While prior academic works largely focus on digital transformation in private organizations, limited research has examined how technological capabilities support sustainable auditing practices in public sector. By examining the relationship between AIC and SSAE, this study enhances understanding of how advanced technologies can support collaborative auditing environments in PSOs. Furthermore, this research contributes to the growing discussion on AI-driven governance in the public sector. AI technologies are increasingly recognized as drivers of administrative digitalization and service innovation in public sector [5]. Their integration can enhance organizational adaptability and improve service efficiency [6]. Within auditing, AI is considered a transformative technology that can significantly improve auditing effectiveness [7].

In addition to examining technological capabilities, this study also highlights the importance of professional expertise. The effectiveness of AI-driven auditing systems depends not only on technology but also on accountants' ability to interpret complex financial data and detect irregularities in digital environments. CFAI therefore plays an important role in strengthening the interaction between technological capabilities and auditing practices. The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 presents the research methodology. Section 4 presents the empirical results and implications, while Section 5 concludes the study with limitations and future research directions.

## 2. Literature Review and Hypothesis Development

### *2.1 Theoretical backgrounds*

Dynamic capabilities theory (DCT) provides a useful framework for explaining how organizations respond to rapidly changing environments. In PSOs, these capabilities are reflected in the ability to integrate technological infrastructure, knowledge resources, and organizational processes to enhance service delivery and organizational performance [8]. When AI technologies are embedded within organizational processes, they become part of a broader capability set that supports data-driven decision-making and innovation. These capabilities are often conceptualized as AIC [9]. From the perspective of auditing and financial governance, forensic accounting practices can also be interpreted through the lens of dynamic capabilities. Activities such as identifying financial risks, conducting investigations, and strengthening control mechanisms reflect processes of sensing, seizing, and reconfiguring resources [10]. This perspective highlights how technological capabilities and professional expertise can jointly support adaptive governance mechanisms.

### *2.2 Conceptual frameworks*

Artificial Intelligence capabilities (AIC). AI has attracted increasing attention in both academic research and organizational practice. Within organizations, AI technologies enable the processing of large volumes of information and support decision-making across various operational activities. These systems can analyze data, identify patterns, and generate insights that assist managers in addressing complex problems [11]. Building on this perspective, AIC describe an organization's ability to utilize AI-based technologies such as machine learning, cognitive computing, and advanced analytics to enhance decision-making and operational performance [3]. Through these capabilities, organizations can interpret complex datasets, generate actionable insights, and strengthen data-driven managerial decisions. Previous studies indicate that AIC contribute significantly to organizational outcomes. AI technologies can improve analytical capabilities, increase operational efficiency, and stimulate innovation across business functions [12]. Likewise, AIC can strengthen competitive advantage by supporting organizational learning and innovation processes ([1]; [8]).

Smart and sustainable auditing ecosystem (SSAE). In recent years, researchers have increasingly examined how technological ecosystems can support sustainable governance and organizational practices. Within the auditing field, the notion of an audit ecosystem describes a network that integrates technological infrastructures, governance mechanisms, and organizational actors to improve auditing processes and oversight [13]. These ecosystems have evolved alongside the development of digital auditing technologies, including advanced audit analytics and computer-assisted auditing tools [14]. Building on this perspective, SSAE can be understood as a technology-enabled environment in which multiple actors collaborate to enhance auditing effectiveness and transparency. Such ecosystems facilitate coordination among stakeholders, allowing organizations to integrate technological resources and auditing expertise more efficiently. Through collaborative interactions and shared technological infrastructures, SSAEs support innovation in auditing practices and promote data-driven decision-making. As a result, these ecosystems can strengthen governance mechanisms while improving transparency and accountability in auditing activities.

Accountants' cyber forensic accounting intelligence (CFAI). Traditionally, forensic accountants are expected to possess knowledge of accounting, auditing, legal procedures, and financial investigation [15]. With the increasing digitalization of financial systems, forensic accounting practices now require additional competencies related to digital forensics, cybersecurity, and data analytics. Modern forensic accountants therefore need analytical reasoning skills, investigative expertise, and knowledge of accounting information systems in order to analyze digital financial evidence [16]. The concept of forensic intelligence further extends traditional forensic practices by focusing on the analysis of patterns and information that support proactive decision-making ([17];[18];[19]). Recent studies also emphasize the integration of cyber forensics with intelligence-based approaches to address cyber-related threats in digital environments [20]. At the same time, cybersecurity has become an important component of organizational resilience and digital infrastructure protection [21]. Based on these perspectives, CFAI can be conceptualized as a multidimensional capability that integrates technological knowledge, analytical reasoning, and professional judgment. These competencies enable accountants to analyze digital financial information, identify irregular patterns, and interpret financial activities within technology-driven environments.

### *2.3 Research hypothesis development*

AI-based systems enable organizations to process large datasets, automate analytical procedures, and support complex decision-making processes [22]. Through these capabilities, AI technologies can generate insights that extend beyond traditional human analytical capacities [23]. In the accounting and auditing domain, AI technologies are increasingly transforming traditional auditing practices. AI-driven systems allow auditors to process large volumes of financial data, automate repetitive procedures, and identify potential risks in financial systems [2]. As a result, the integration of AI technologies can improve the efficiency and effectiveness of auditing activities [24]. AI technologies also facilitate collaboration within organizational ecosystems by supporting data sharing and knowledge exchange among participating actors [25]. From an organizational perspective, AIC enables organizations to manage complex information environments and strengthen collaboration across networks [3]. In auditing ecosystems, these capabilities may enhance coordination among ecosystem participants and improve auditing processes. Therefore, the following hypothesis is proposed:

- *H1: AIC positively influences the development of SSAE.*

SSAE can be viewed as networks of interconnected actors who collaborate to improve auditing practices and governance mechanisms. Within these ecosystems, participants combine technological capabilities, knowledge resources, and organizational expertise to generate value and deliver improved auditing services. Although AI technologies enhance collaboration and decision-making, digital environments also introduce new vulnerabilities. Technological infrastructures may be exploited by malicious actors seeking unauthorized access to sensitive information or attempting to disrupt organizational operations [26]. Consequently, organizations must develop capabilities that enable them to detect and mitigate risks in digital environments. From a governance perspective, organizations are expected to maintain transparency and reliability in financial reporting [27]. However, fraudulent activities may still occur even when financial statements are subject to external auditing processes [28]. As a result, organizations often rely on complementary governance mechanisms and specialized expertise to strengthen fraud detection. Forensic accounting provides analytical techniques that support the detection and investigation of fraudulent activities [29]. Empirical evidence also indicates that forensic accounting practices can help reduce fraud risks in PSOs [30]. CFAI enables accountants to interpret complex financial information, detect irregularities, and strengthen control mechanisms within digital environments. Accordingly, the following hypothesis is proposed:

- *H1A: CFAI positively moderates the relationship between AIC and SSAE.*

The model that is proposed, which highlights the impact of AIC on SSAE and illustrates a single CFAI moderator that moderates the relationship, is shown in Figure 1.

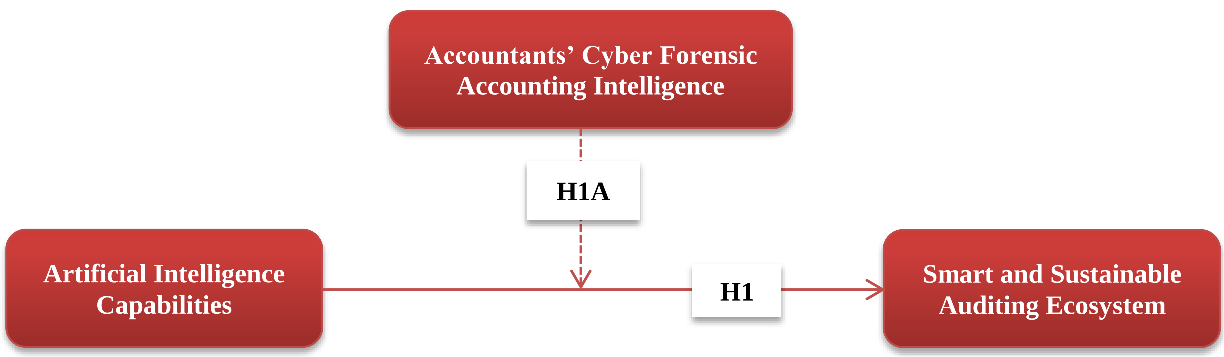


**Figure 1**. The hypothesized model

## 3. Research Methodology

### *3.1. Sampling procedure and data collection*

Data were collected from employees working in PSOs in Southern Vietnam using a structured questionnaire survey. Convenience sampling combined with snowball sampling was applied to reach respondents with relevant professional experience. Structural equation modeling (SEM) has been widely applied in sustainability-related studies to test relationships among latent constructs [31]. SEM enables researchers to estimate multiple relationships simultaneously within complex models [32]. When the objective is to test theoretically grounded relationships and evaluate a confirmatory conceptual framework, covariance-based SEM (CB-SEM) is considered appropriate [33]. Accordingly, this study employed CB-SEM using AMOS 28 to evaluate the proposed model. A total of 930 questionnaires were distributed between June 2024 and May 2025. After incomplete and invalid responses were removed, 812 valid questionnaires were retained for analysis. Previous studies suggest that a minimum sample size of 200 is generally sufficient for SEM analysis [34]. Therefore, the final sample size exceeded the recommended threshold for CB-SEM model estimation.

### *3.2. Measurement of the model's constructs*

Measurement items for all constructs were adapted from prior studies. Before the main survey was conducted, a pilot test was performed with 30 participants to evaluate the clarity and reliability of the measurement items. Cronbach's alpha was calculated using SPSS 29 to assess internal consistency. A value above 0.70 was considered acceptable for scale reliability. All constructs were measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The AIC construct was conceptualized as comprising three dimensions: perceptive capabilities, predictive capabilities, and prescriptive capabilities. The measurement items were adapted from [35] and contextualized for Vietnamese PSOs. The CFAI measurement scale was constructed based on adaptations from previous studies examining forensic accounting competencies and intelligence capabilities, particularly those of [16]; [36]; [28]; [37]. The items were modified to ensure relevance to digital financial environments within Vietnamese PSOs. The SSAE construct was operationalized through three dimensions: innovation resource decentralization, dynamism of co-innovation, and open collaboration. Its measurement items were adapted from prior research on innovation ecosystems and collaborative governance, particularly [14]; [38]; [39].

**Table 1**. Demographic information

| Respondent's Demographic Profile | Variables | Usable Responses | Weight (%) |
|---|---|---|---|
| Gender of respondent | | | |
| | Female | 483 | 59.48 |
| | Male | 329 | 40.52 |
| Age of respondent | | | |
| | 20 – under 30 | 53 | 6.53 |
| | 30 – under 40 | 228 | 28.08 |
| | 40 – under 50 | 520 | 64.04 |
| | 50 – under 60 | 11 | 1.35 |
| | | | |
| Experience of respondent (years) | | | |
| | Under 10 | 66 | 8.13 |
| | 10 - under 20 | 337 | 41.50 |
| | 20 - under 30 | 390 | 48.03 |
| | 30 - under 40 | 19 | 2.34 |
| Education | | | |
| | Undergraduate | 797 | 98.15 |
| | Postgraduate | 15 | 1.85 |

**Table 2.** Summary of constructs with corresponding scale items

| Construct | | Indicator |
|---|---|---|
| **Artificial Intelligence Capabilities (AIC)** | | |
| | **Perceptive Capabilities (PERC)** | **PERC1**: Our organization uses Artificial Intelligence to continuously monitor organizational processes and operational performance. |
| | | **PERC2**: Artificial Intelligence systems in our organization can detect real-time activity patterns and operational anomalies. |
| | | **PERC3**: Artificial Intelligence enables our organization to extract meaningful insights from large volumes of organizational data. |
| | **Predictive Capabilities (PRED)** | **PRED1**: Our organization uses Artificial Intelligence to anticipate potential operational changes and emerging trends. |
| | | **PRED2**: Artificial Intelligence enables our organization to forecast future outcomes based on historical and real-time data. |
| | | **PRED3**: Artificial Intelligence helps our organization predict potential risks and operational disruptions. |
| | **Prescriptive Capabilities (PRES)** | **PRES1:** Artificial Intelligence provides recommendations to support organizational decision making. |
| | | **PRES2:** Artificial Intelligence helps our organization optimize actions in response to operational conditions. |

| | | |
|---|---|---|
| | | **PRES3:** Artificial Intelligence systems help identify data-driven opportunities for improving organizational performance. |
| **Cyber forensic accounting intelligence (CFAI)** | | **CFAI1:** The accountant is capable of communicating forensic and cyber-related financial findings effectively in digital interactions. |
| | | **CFAI2:** The accountant is able to develop risk management procedures and support the effective implementation of cybersecurity controls. |
| | | **CFAI3:** The accountant is capable of formulating policies and procedures that promote ethical behavior in digital financial practices. |
| | | **CFAI4:** The accountant is capable of analyzing real-time data collected from digital systems to support forensic accounting assessments. |
| | | **CFAI5:** The accountant is able to understand and apply data protection and encryption-related controls in digital financial environments. |
| | | **CFAI6:** The accountant demonstrates strong critical thinking when evaluating complex digital financial information. |
| | | **CFAI7:** The accountant is capable of developing solutions to complex and unstructured problems in digital financial environments. |
| | | **CFAI8:** The accountant is capable of coordinating with relevant stakeholders to resolve cyber-related financial issues. |
| | | **CFAI9:** The accountant is capable of conducting economic damage calculations in cases involving financial misconduct or cyber incidents. |
| | | **CFAI10:** The accountant is capable of addressing cyber-related financial risks by using digital technologies in an ethical and responsible manner. |
| **Smart and sustainable auditing ecosystem (SSAE)** | | |
| | **Innovation resource decentralization (IRD)** | **IRD1:** Innovation resources related to auditing practices within the ecosystem originate from multiple sources. |
| | | **IRD2:** Innovation resources related to auditing practices are accessible and distributed across different actors within the auditing ecosystem. |
| | | **IRD3:** Actors within the auditing ecosystem share innovation resources through innovation chains, innovation networks, and digital innovation platforms. |
| | **Dynamism of co-innovation (DCI)** | **DCI1:** The participation of actors in the auditing ecosystem changes the composition of actors involved in innovation activities. |
| | | **DCI2:** The participation of actors in the auditing ecosystem changes collaboration patterns and knowledge flows within the innovation network. |
| | | **DCI3:** The withdrawal of actors from the auditing ecosystem leads to the reconfiguration of roles and connections within the innovation network. |
| | **Open collaboration (OC)** | **OC1:** Open collaboration creates benefits through both competition and cooperation in auditing practices. |
| | | **OC2:** Open collaboration aligns focal organizations and key stakeholders around shared audit-related goals. |
| | | **OC3:** Open collaboration improves communication and interaction among relevant actors within the public-sector auditing ecosystem. |

## 4. Result and Discussion

### *4.1. Common method bias*

To evaluate potential common method bias (CMB), Harman's single-factor test was conducted using SPSS 29. This procedure was undertaken to determine whether a single underlying factor accounted for a substantial proportion of the variance across the measurement items. The results suggested that CMB was not a serious threat to the validity of the study. The extracted factors collectively explained 56.549% of the total variance, while the first factor accounted for only 19.309%.

Given that the variance explained by the first factor was substantially below the commonly recommended 50% threshold, these results indicated that the measurement items were not dominated by a single underlying factor.

### *4.2. Assessment of construct reliability and convergent validity*

The measurement model was evaluated using CB-SEM in AMOS 28, as illustrated in Figure 2. Indicator loadings, Cronbach's alpha, composite reliability, and average variance extracted (AVE) were examined to assess indicator reliability, internal consistency reliability, and convergent validity, as reported in Table 3. According to [40], standardized factor loadings above 0.50 were considered indicative of adequate indicator reliability. All measurement items met this criterion, suggesting acceptable indicator reliability. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability, with values exceeding the recommended threshold of 0.70 [40]. The results showed that all constructs satisfied this requirement. Convergent validity was evaluated using AVE, where values above 0.50 indicated that a construct explained more than half of the variance in its indicators [40]. All AVE values exceeded this threshold. In addition, the overall model fit indices indicated a good fit between the measurement model and the data ($\chi^2/df = 2.242$; CFI = 0.958; GFI = 0.937; TLI = 0.951; RMSEA = 0.039).

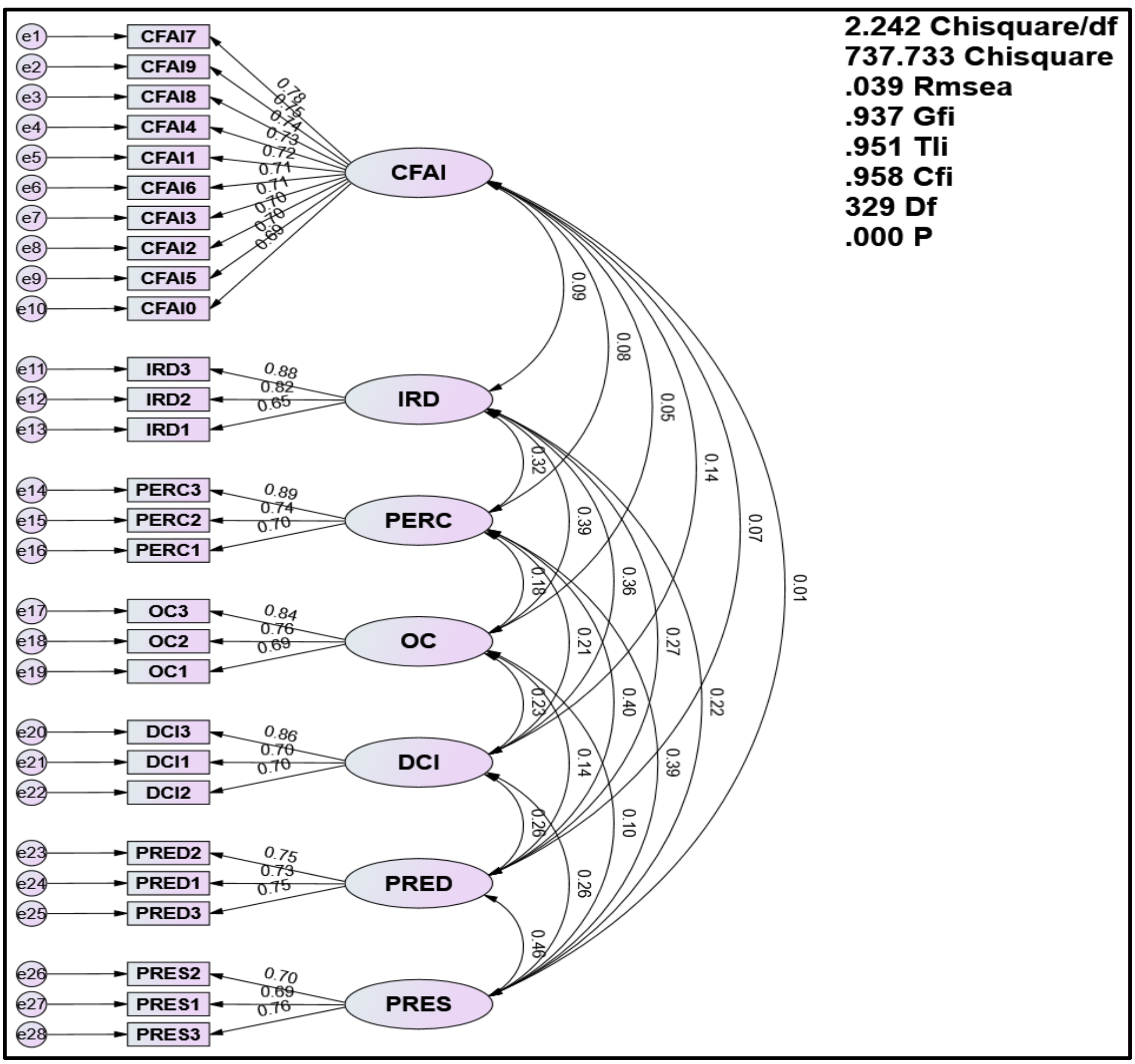


**Figure 2**. CFA result

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**Table 3**. Results summary of Convergent validity and Construct reliability

| Construct | Item acronyms | Convergent validity | | Construct reliability | | Inference |
|---|---|---|---|---|---|---|
| | | Factor Loadings Ranges | AVE | Cronbach's Alpha | Composite Reliability | |
| **Artificial Intelligence Capabilities** | **AIC** | | | | | |
| Perceptive Capabilities | PERC | 0.611 - 0.966 | 0.612 | 0.815 | 0.824 | Retained |
| Predictive Capabilities | PRED | 0.732 - 0.739 | 0.551 | 0.785 | 0.786 | Retained |
| Prescriptive Capabilities | PRES | 0.707 - 0.720 | 0.516 | 0.762 | 0.762 | Retained |
| **Smart and sustainable auditing ecosystem** | **SSAE** | | | | | |
| Innovation resource decentralization | IRD | 0.595 - 0.890 | 0.624 | 0.819 | 0.830 | Retained |
| Dynamism of co-innovation | DCI | 0.640 - 0.909 | 0.572 | 0.793 | 0.799 | Retained |
| Open collaboration | OC | 0.639 - 0.896 | 0.590 | 0.807 | 0.811 | Retained |
| **Cyber forensic accounting intelligence** | **CFAI** | 0.693 - 0.777 | 0.524 | 0.915 | 0.917 | Retained |

*4.3. Assessment on discriminant validity*

Discriminant validity was assessed using the Fornell–Larcker criterion [41]. Under this criterion, discriminant validity was supported when the square root of the AVE for each construct exceeded its correlations with other constructs in the model. As reported in Table 4, the square root values of AVE were greater than the corresponding inter-construct correlations for all constructs. These results indicated that the constructs were empirically distinct from one another, thereby supporting the discriminant validity of the measurement model.

**Table 4.** Results summary of Discriminant validity using Fornell–Larcker process

| | CFAI | IRD | PERC | OC | DCI | PRED | PRES |
|---|---|---|---|---|---|---|---|
| **CFAI** | **0.724** | | | | | | |
| **IRD** | 0.085 | **0.790** | | | | | |
| **PERC** | 0.077 | 0.316 | **0.782** | | | | |
| **OC** | 0.048 | 0.387 | 0.181 | **0.768** | | | |
| **DCI** | 0.143 | 0.364 | 0.214 | 0.231 | **0.756** | | |
| **PRED** | 0.067 | 0.272 | 0.400 | 0.135 | 0.263 | **0.742** | |
| **PRES** | 0.011 | 0.217 | 0.395 | 0.100 | 0.260 | 0.459 | **0.718** |

To further strengthen the assessment, the Heterotrait–Monotrait ratio (HTMT) was also examined. According to [42], HTMT values below 0.90 were considered indicative of acceptable discriminant validity. As reported in Table 5, all HTMT values were below the recommended threshold. These findings provided additional evidence that the constructs were empirically distinct, thereby supporting the discriminant validity of the measurement model.

**Table 5.** Results summary for discriminant validity on Heterotrait–Monotrait ratio

| | CFAI | IRD | PERC | OC | DCI | PRED | PRES |
|---|---|---|---|---|---|---|---|
| **CFAI** | | | | | | | |
| **IRD** | 0.068 | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| **PERC** | 0.066 | 0.276 | | | | |
| **OC** | 0.048 | 0.345 | 0.157 | | | |
| **DCI** | 0.130 | 0.317 | 0.197 | 0.205 | | |
| **PRED** | 0.059 | 0.224 | 0.343 | 0.119 | 0.210 | |
| **PRES** | 0.009 | 0.183 | 0.331 | 0.091 | 0.215 | 0.352 |

### *4.4. Assessment of structural model*

Direct effect. The structural model demonstrated satisfactory goodness-of-fit, with Chi-square/df = 1.596, CFI = 0.986, GFI = 0.972, TLI = 0.983, and RMSEA = 0.027. These indices indicated that the model showed a good fit to the data. As shown in Table 6 and Figure 3, the hypothesized direct relationship between AIC and SSAE was positive and statistically significant. The standardized coefficient for this path was β = 0.580, with $p < 0.001$, suggesting that AIC substantially contributes to the development of SSAE. Accordingly, Hypothesis 1 (H1) was supported.

**Table 6**. Results of hypotheses testing

| Hypothesis No. | Hypothesized path | Unstandardized estimate | S.E. | C.R. | P | Standardized | Inference |
|---|---|---|---|---|---|---|---|
| **H1** | AIC ➔ SSAE | 0.792 | 0.103 | 7.717 | 0.000 | 0.580 | Supported |

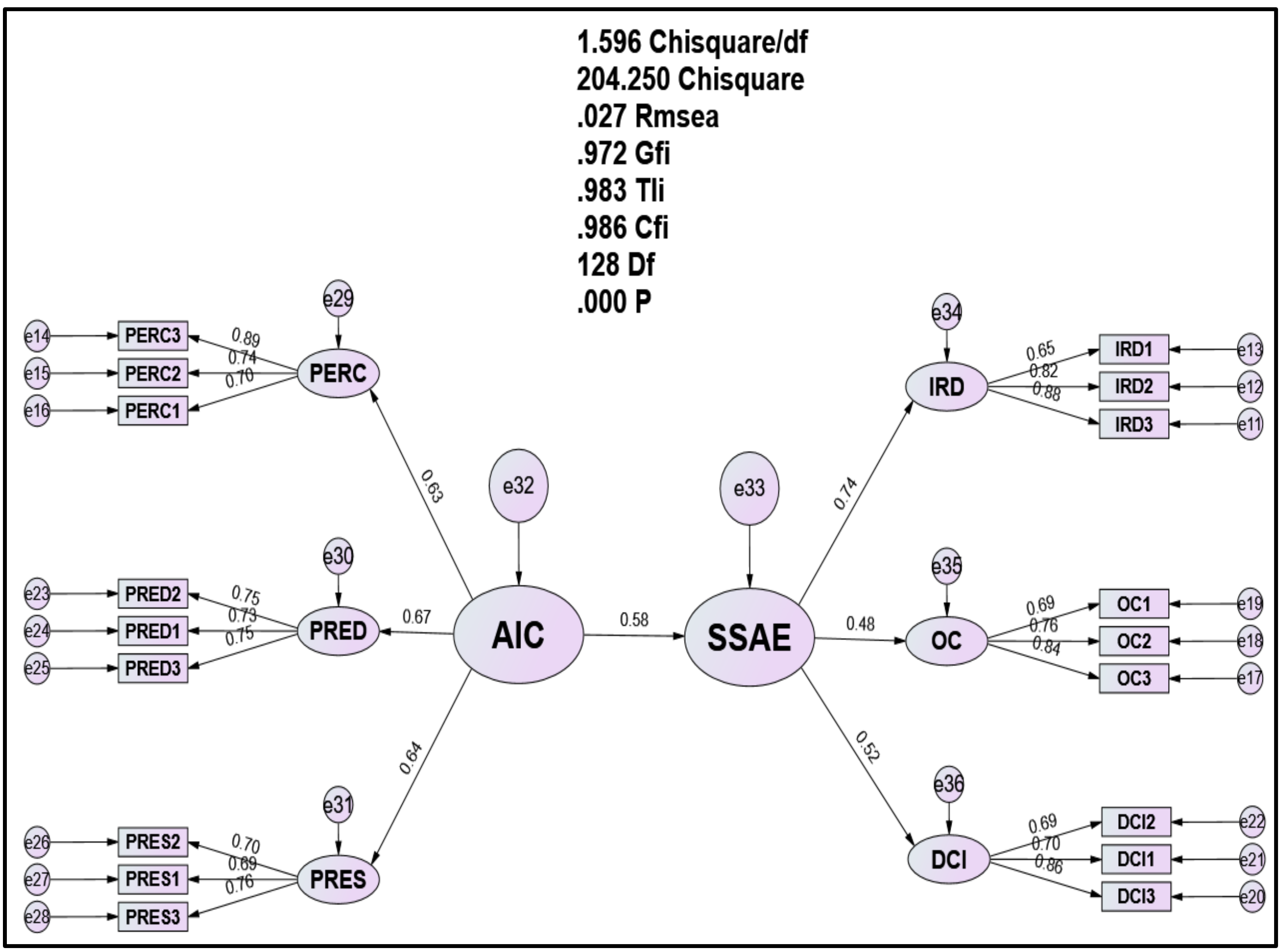


**Figure 3**. The structural model

Moderating effect. To evaluate the moderating role of CFAI in the relationship between AIC and SSAE, a multi-group SEM analysis was conducted. This approach enabled the study to examine whether the structural path from AIC to SSAE differed across groups with different levels of the moderating variable [43]. Respondents were divided into two groups based on the median value of CFAI, resulting in a low-CFAI group and a high-CFAI group. Two competing models were then estimated: an unconstrained model and a constrained model. The comparison between these models revealed a statistically significant difference, with $\Delta\chi^2 = 8.760$ and $\Delta df = 1$. This result indicated that the effect of AIC on SSAE varied significantly between the low- and high-CFAI groups, thereby supporting the moderating role of CFAI. Model fit was further assessed following the recommendations of [44], including TLI, CFI, GFI, and RMSEA.

**Table 7**. Differences in Compatible Indicators between unconstrained structural model and constrained structural model

| Model | Chi-square | df | p-value | TLI | CFI | GFI | RMSEA |
|---|---|---|---|---|---|---|---|
| Unconstrained model | 319.543 | 256 | - | 0.986 | 0.988 | 0.958 | 0.018 |
| Constrained model | 328.303 | 257 | - | 0.984 | 0.987 | 0.957 | 0.019 |
| Differences | 8.760 | 1 | 0.003 | - | - | - | - |

*Note. Difference was calculated as constrained model minus unconstrained model. The chi-square difference test was significant, $\Delta\chi^2 = 8.760$, $\Delta df = 1$, p-value = 0.003.*

As shown in Table 8, the results of the multi-group analysis indicated that the relationship between AIC and SSAE was positive and significant in both the low-CFAI and high-CFAI groups. For the low-CFAI group, the unstandardized estimate was 0.435 (S.E. = 0.138, C.R. = 3.160, p = 0.002), with a standardized estimate of 0.307. For the high-CFAI group, the unstandardized estimate was 1.030 (S.E. = 0.148, C.R. = 6.968, p < 0.001), with a standardized estimate of 0.785. These results showed that the AIC–SSAE relationship was stronger in the high-CFAI group than in the low-CFAI group. Therefore, CFAI strengthens the positive relationship between AIC and SSAE, supporting H1A.

**Table 8**. Results on the moderating effect of level of CFAI

| Hypothesis No. | Hypothesized path | Low CFAI (n=326) | | | | | High CFAI (n=486) | | | | | Inference |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Unstandardized estimate | S.E. | C.R. | p-value | Standardized estimate | Unstandardized estimate | S.E. | C.R. | p-value | Standardized estimate | |
| **H1A** | AIC ➔ SSAE | 0.435 | 0.138 | 3.160 | 0.002 | 0.307 | 1.030 | 0.148 | 6.968 | 0.000 | 0.785 | Supported |

*4.5. Discussion and implication*

**Theoretical implication**. The findings offer important theoretical implications for understanding the development of SSAE. First, the positive effect of AIC on SSAE suggests that AIC should be conceptualized not merely as technological resources, but as enabling organizational capabilities that facilitate ecosystem-level transformation. In PSOs, such capabilities may support the emergence of smarter and more sustainable auditing ecosystems by enhancing data-driven processes, enabling coordination among ecosystem actors, and improving the mobilization of internal and external resources. Second, the findings suggest that the development of SSAE is shaped by the interplay between technological capabilities and collaborative ecosystem mechanisms. This implies that auditing ecosystem development cannot be sufficiently explained by technology adoption alone. Instead, it depends on the extent to which organizations integrate AIC with knowledge exchange, resource sharing, and inter-organizational collaboration. Accordingly, the results highlight the theoretical relevance of viewing auditing ecosystems as dynamic, collaborative systems in which technological and relational capabilities jointly contribute to ecosystem development. Third, the moderating role of CFAI provides further theoretical insight into the enabling conditions under which AIC contributes to SSAE development. The findings suggest that the value of AIC is strengthened when accountants possess the forensic intelligence needed to interpret digital financial information, detect irregularities, and respond to cyber-related risks. Thus, CFAI may be understood as a complementary professional capability that enhances the translation of AI-enabled resources into meaningful improvements in auditing ecosystems.

**Practical implication**. From a practical perspective, the findings offer several implications for policymakers and PSOs. First, PSOs should invest in AIC to support the development of digital auditing systems. Strengthening technological infrastructure can enhance data processing, improve analytical capacity, and increase auditing efficiency. Second, organizations should provide training programs that develop accountants' competencies in digital technologies, cybersecurity, and forensic accounting. These competencies are essential for interpreting financial data, identifying irregularities, and managing risks in digital environments. Third, collaboration among actors within the auditing ecosystem should be encouraged. Greater cooperation among service providers, service users, regulatory institutions, and other key stakeholders can facilitate knowledge exchange, improve audit quality, and support the development of more resilient auditing practices.

## 5. Conclusion and Future Work

This study examined the impact of AIC on the development of SSAE in PSOs and explored the moderating role of CFAI in this relationship. Based on survey data collected from Vietnamese PSOs and analyzed using CB-SEM, the study provides empirical evidence on the relationship between AIC and the advancement of auditing ecosystems. The findings show that AIC significantly contribute to the development of SSAE by supporting data-driven auditing processes and fostering collaboration among ecosystem actors. CFAI further strengthens this relationship by enhancing accountants' ability to interpret digital financial data, detect irregularities, and respond to emerging risks. This study has several limitations, despite its noteworthy contributions. First and foremost, the data were gathered from PSOs in Southern Vietnam, which may restrict the generalizability of the results to other regions or institutional contexts. Extension of the research setting to other regions of Vietnam or cross-country comparisons are viable options for future research. Secondly, the study's reliance on cross-sectional and self-reported survey data may restrict its capacity to identify changes in AIC, CFAI, and SSAE development over time and may raise concerns about response bias. To mitigate single-source bias and offer more robust evidence of the relationships among the constructs under investigation, future research could implement longitudinal or time-lagged survey designs and gather data from multiple respondent groups within PSOs. Last but not least, this investigation concentrated on the moderating influence of CFAI. Other moderating or mediating factors, such as digital leadership, organizational learning capability, or regulatory pressure, could be investigated in future research.

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This article does not contain any studies with human participants or animals performed by any of the authors.

**Consent for publication**
Not applicable.

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All authors declare no competing interests.

**References**

[1] Zhang, Y., Shi, J., & Huang, Y. (2025). Do artificial intelligence capabilities impact sustainability-oriented innovation performance: exploring the role of green intellectual capital and learning orientation. Journal of Intellectual Capital, 26(4), 946–967. https://doi.org/10.1108/JIC-10-2024-0315

[2] Abdo-Salloum, A. M., & Chehade, S. (2026). The Role of Artificial Intelligence in Transforming Accounting and Auditing Practices: A Systematic Review. SAGE Open, 1–13. https://doi.org/10.1177/21582440251403296.
[3] Sahoo, S., Kumar, S., Donthu, N., & Singh, A.K. (2024). Artificial intelligence capabilities, open innovation, and business performance – empirical insights from multinational B2B companies. Industrial Marketing Management, 117, 28-41. https://doi.org/10.1016/j.indmarman.2023.12.008
[4] Genaro-Moya, D., López-Hernández, A. M., & Godz, M. (2025). Artificial Intelligence and Public Sector Auditing: Challenges and Opportunities for Supreme Audit Institutions. World, 6(2), 1-19. https://doi.org/10.3390/world6020078.
[5] Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjortoft, S.O., Torvatn, H.Y., & Niehaves, B. (2023). Examining how AI capabilities can foster organizational performance in public organizations. Government Information Quarterly, 40(2), 1-14. https://doi.org/10.1016/j.giq.2022.101797
[6] Madan, R., & Ashok, M. (2023). AI adoption and diffusion in public administration: a systematic literature review and future research agenda. Government Information Quarterly, 40(1), 1-18. https://doi.org/10.1016/j.giq.2022.101774
[7] Udrescu, LM. (2025). The Role of Artificial Intelligence in Public Audit: A Case Study of Digitalization in Romania's Public Sector. In: El Khoury, R. (eds) The Future of Work: How Technology is Transforming Jobs and Skills. Studies in Systems, Decision and Control, vol 291 (pp 85–94). Springer, Cham. https://doi.org/10.1007/978-3-031-87372-0_8
[8] Mikalef, P., Conboy, K., & Krogstie, J. (2021). Artificial intelligence as an enabler of B2B marketing: a dynamic capabilities micro-foundations approach. Industrial Marketing Management, 98, 80-92. https://doi.org/10.1016/j.indmarman.2021.08.003
[9] Shao, S., Shao, Z., & Xiong, Y. (2026). The influence of AI capability on enterprise competitive advantage: the mediating effect of business model innovation. Journal of Enterprise Information Management, 1–25. https://doi.org/10.1108/JEIM-08-2024-0453
[10] Awolowo, I. F., Ode, E., Abidoye, A., Ajao, O., & Jogunola, O. (2026). Cybersecurity Assurance for SMEs: A Conceptual Framework Integrating Organizational Culture, Fraud Risk Management and Forensic Accounting. Canadian Journal of Administrative Sciences, 43(1), 1-20. https://doi.org/10.1002/cjas.70051
[11] Rai, A., Constantinides, P., & Sarker, S. (2019). Next generation digital platforms: toward human-AI hybrids. MIS Quarterly, 43(1), iii-ix.
[12] Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. Business Process Management Journal, 26(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411
[13] Kozlowski, S, & Vasarhelyi, MA (2014). An audit ecosystem: A starting point with definitions, attributes and agents. Newark: Working paper, Rutgers Business School.
[14] Kozlowski, S. (2018). An Audit Ecosystem to Support Blockchain-based Accounting and Assurance. In: Chan, D.Y., Chiu, V. and Vasarhelyi, M.A. (Ed.) Continuous Auditing (Rutgers Studies in Accounting Analytics) (pp. 299-313), Emerald Publishing Limited, Leeds.
[15] Renzhou, D. (2011). Research on Legal Procedural Functions of Forensic Accounting. Energy Procedia, 5, 2147–2151. https://doi.org/10.1016/j.egypro.2011.03.371
[16] Crain, M.A., Hopwood, W.S., Gendler, R.S., Young, G.R., & Pacini, C. (2019). Essentials of Forensic Accounting. New York, NY: John Wiley and Sons.
[17] Ribaux, O., Baechler, S., & Rossy, Q. (2022). Forensic intelligence and traceology in digitalised environments: The detection and analysis of crime patterns to inform practice. In: M. Gill (Ed.), The handbook of security (pp. 81–100). Palgrave Macmillan.
[18] Morelato, M., Baechler, S., Ribaux, O., Beavis a, A., Tahtouh, M., Kirkbride, P., Roux, C., & Margot, P. (2014). Forensic intelligence framework—Part I: Induction of a transversal model by comparing illicit drugs and false identity documents monitoring. Forensic Science International, 236, 181-190. https://doi.org/10.1016/j.forsciint.2013.12.045
[19] Taylor, M. L., Turbett, G. R., Lee, J., & Sears, A. (2024). Forensic intelligence in Australia and New Zealand: Status and future directions. Forensic Science International, 1-10. https://doi.org/10.1016/j.forsciint.2024.112207
[20] Sharma, V., Chauhan, P., Vashishth, T. K., Vidyant, S., Sharma, K. K., Chaudhary, K., & Verma, P. K. (2026). A Forensic Intelligence Approach for Profiling and Investigating Human-Driven Cyber Threats. In: Kadry, S., Rai, M., Tripathy, P. Cyber Forensic Frameworks for User-Centric Human Threat Intelligence Analysis (pp. 175-202). IGI Global.
[21] Gazzola, P., Amelio, S., Pavione, E., & Marubini, F. (2026). The centrality of cybersecurity: business models, competitive strategies and sustainability practices. Business Process Management Journal, 1–24. https://doi.org/10.1108/BPMJ-07-2025-1110
[22] Kumar, V., Kumar, S., Chatterjee, S., & Mariani, M. (2024). Artificial intelligence (AI) capabilities and the R&D performance of organizations: The moderating role of environmental dynamism. IEEE Transactions on Engineering Management, 71, 11522–11532. https://doi.org/10.1109/TEM.2024.3423669
[23] Giuggioli, G., & Pellegrini, M. M. (2023). Artificial intelligence as an enabler for entrepreneurs: A systematic literature review and an agenda for future research. International Journal of Entrepreneurial Behavior & Research, 29(4), 816–837. https://doi.org/10.1108/IJEBR-05-2021-0426
[24] Epelbaum & Farrell, 2026; Epelbaum, N., & Farrell, P. J. (2026). Artificial Intelligence and Auditing: A Bibliometric Study. Accounting Perspectives, 1-23. https://doi.org/10.1111/1911-3838.70008
[25] Secundo, G., Spilotro, C., Gast, J., & Corvello, V. (2025). The transformative power of artificial intelligence within innovation ecosystems: a review and a conceptual framework. Review of Managerial Science, 19, 2697–2728. https://doi.org/10.1007/s11846-024-00828-z
[26] Serafim, G.M. (2026). The Role of Artificial Intelligence in Enhancing Cybersecurity: Trends, Challenges, and Ethical Considerations. In: Chakraborty, M., Chakrabarty, S.P., Marsoof, A. (eds) Proceedings of Sixth International Ethical Hacking

Conference. eHaCON 2025. Lecture Notes in Networks and Systems, vol. 1513 (pp. 3–24). Springer, Singapore. https://doi.org/10.1007/978-981-96-8632-2_1
[27] Gray, G. L., Turner, J. L., Coram, P. J., & Mock, T. J. (2011). Perceptions and Misperceptions Regarding the Unqualified Auditor's Report by Financial Statement Preparers, Users, and Auditors. Accounting Horizons, 25(4), 659–684.
[28] Kaur, B., Sood, K., & Grima, S. (2023). A systematic review on forensic accounting and its contribution towards fraud detection and prevention. Journal of Financial Regulation and Compliance, 31(1), 60–95. https://doi.org/10.1108/JFRC-02-2022-0015
[29] Rezaee, Z., Lo, D., Ha, M., & Suen, A. (2016). Forensic accounting education and practice: insights from China. Journal of Forensic and Investigative Accounting, 8(1), 106-119.
[30] Okoye, E.I., & Gbegi, D.O. (2013). An evaluation of forensic accountants to planning management fraud risk detection procedures. Global Journal of Management and Business Research, 13(1), 74-90.
[31] Seelajaroen, R., & Jitmaneeroj, B. (2025). Interdependencies among SDGs: evidence-based insights for sustainable development indicators and policy. Environmental and Sustainability Indicators, 27, 1-14. https://doi.org/10.1016/j.indic.2025.100762
[32] Raman, R., Pattnaik, D., Kumar, C., & Nedungadi, P. (2024). Advancing sustainable energy systems: A decade of SETA research contribution to sustainable development goals. Sustainable Energy Technologies and Assessments, 71, 1-14. https://doi.org/10.1016/j.seta.2024.103978
[33] Nkrumah, S. K., Ledi, K. K., & Peprah-Yeboah, A. (2025). Organisational politics and healthcare supply chain performance. The roles of organisational support and transformational leadership. Cogent Business & Management, 12(1), 1-17. https://doi.org/10.1080/23311975.2025.2553214
[34] Kline, R. B. (2023). Principles and Practice of Structural Equation Modeling. New York, NY: Guilford Publications.
[35] Sjödin, D., Parida, V., & Kohtamäki, M. (2023). Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects. Technological Forecasting and Social Change, 197, 1-15. https://doi.org/10.1016/j.techfore.2023.122903
[36] Umar, B., Ibrahim, U.A., & Eriki, P. (2020). Forensic accounting and incidence of fraud detection. International Journal of Finance and Banking Studies (2147-4486), 9(2), 72-81.
[37] Gardner, H. (1987). The theory of multiple intelligences. Annals of Dyslexia, 37(1), 19–35. https://doi.org/10.1007/BF02648057.
[38] Yin, D., Ming, X., & Zhang, X. (2020). Sustainable and Smart Product Innovation Ecosystem: An integrative status review and future perspectives. Journal of Cleaner Production, 274, 1-19. https://doi.org/10.1016/j.jclepro.2020.123005.
[39] Costa, J., & Matias, J. C. O. (2020). Open Innovation 4.0 as an Enhancer of Sustainable Innovation Ecosystems. Sustainability, 12(19), 1-19. https://doi.org/10.3390/su12198112.
[40] Hair, J. F., Babin, B. J., Anderson, R. E., & Black, W. C. (2019). Multivariate Data Analysis (8th ed.). England: Pearson Prentice.
[41] Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39-50. https://doi.org/10.2307/3151312.
[42] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8.
[43] Byrne, B.M. (2016). Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming. London, UK: Routledge.
[44] Bollen, K., & Long, J. S. (Eds.). (1993). Testing Structural Equation Models. Newbury Park, California: Sage.

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