

Unlocking Sustainable Performance through AI Assimilation and Green Ambidexterity

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Abstract

This study explores how AI assimilation (AIA) drives sustainable business performance (SBP) through green ambidexterity (GAX) and cybersecurity awareness (CSA). Using the Resource-Based View and data from 199 UK supply chain managers, the research reveals that AIA enhances GAX—balancing green innovation and practices—which then improves SBP. CSA further amplifies the positive effect of AIA on GAX. However, SBP negatively impacts SCR, suggesting that resource-efficient, sustainability-focused strategies may reduce supply chain adaptability to disruptions. The findings indicate that AIA alone does not directly boost SBP but requires integration with GAX to foster sustainability. Practically, organizations should align AI adoption with sustainability goals and cybersecurity measures. Therefore, managers should prioritize AI-enabled analytical frameworks that identify high-impact green initiatives while embedding real-time security monitoring, ensuring eco-efficiency gains are achieved without increasing cyber-risk exposure across the supply chain.

Keywords: AI, Green ambidexterity, Sustainability, Cyber security awareness.

Word Count: 6740 words

1. Introduction

The convergence of the sustainability imperative—which extends the focus beyond mere profit to encompass people and the planet—and the digital imperative, characterized by digital transformation, and the continuous evolution of technology landscape, presents supply chain organizations with significant opportunities to achieve their sustainability objectives (Pan & Nishant, 2023; Kotlarsky et al., 2023; Pan et al., 2022). In this context, AI technology has emerged as both a powerful technological tool and a strategic asset, capable of driving progress towards achieving sustainable development goals (Appio et al., 2024; Kar et al., 2022; Govindan, 2022; Wynsberghe, 2021; Qureshi et al., 2021). In the sustainability literature, research has suggested that AI driven insights play a pivotal role to drive sustainability practices in various areas such as sustainable manufacturing systems (Bag et al., 2021), waste management (Wilts et al., 2021), and reverse logistics (Schluter, 2021). Additionally, AI-driven intelligent applications also contribute to cost reduction through resource optimization (Wang & Zhang, 2020) and carbon footprint reduction (Płoszaj-Mazurek et al., 2020), optimizing waste management (Rosecký et al., 2020) and climate change tracking (Leal Filho et al., 2022) in pursuit of achieving sustainability goals.

However, as digitalization accelerates and AI technologies continue to evolve, the risks and vulnerabilities associated with cybersecurity are also on the rise (Park, 2023; OpenAI, 2023; Ben-Sasson & Greenberg, 2023; IBM, 2023). In this context, if security of AI systems and corresponding information flows from these systems is compromised, it could lead to incorrect conclusions, poor strategic choices, or even major operational disruptions (Humphreys et al., 2024; IBM, 2023). Organizations must therefore balance the opportunities offered by AI technology with the need to protect their systems from cyber threats (IBM, 2023). This requires not only robust cybersecurity measures but also a proactive approach to cyber security awareness (CSA) within the organization (Humphreys et al., 2024; IBM, 2023).

Existing research has primarily focused on AI adoption and capability related constructs and their impact on firm performance, particularly profitability and economic outcomes (Sullivan & Fosso-Wamba, 2024; Fosso-Wamba et al., 2020). While economic performance is crucial for supply chain organizations to sustain their daily operations and build competitiveness, achieving sustainability is equally important, given the growing emphasis on environmental and social responsibilities in today's business landscape (World Economic Forum, 2022). The literature across multiple disciplines has acknowledged and provided empirical evidence on the transformative potential of AI to create business value through automation and augmentation (Fosso-Wamba et al., 2024; Kemp, 2024; Gupta et al., 2022). In this context, AI assimilation (AIA) has emerged as a new theme that emphasizes the integration of AI technologies into organizational processes, enabling firms to enhance their capabilities, drive innovation, and achieve sustained competitive advantage (Priksht et al., 2023; Fosso-Wamba, 2022). In this vein, an existing study has highlighted that while AI technologies have significant potential, their mere adoption does not automatically lead to better performance outcomes for organizations (Olan et al., 2022). In line with this perspective, ongoing research across various disciplines continues to support the notion that the effective integration of AI tools within organizations plays a crucial role in promoting green practices and fostering sustainability-oriented innovation (Pan & Nishant, 2023; Nishat et al., 2020).

Despite these theoretical narratives, there is limited empirical evidence addressing three critical areas. The first area is the extent to which AIA directly contributes to SBP. Without robust evidence, the connection between AIA and sustainable outcomes remains largely speculative, leaving a gap in our understanding. The second area is understanding why leveraging AIA leads to SBP (Akhter et al., 2021). This involves exploring the underlying mechanisms that enable AI to positively influence sustainability performance outcomes. Without this empirical exploration, the rationale behind AI's potential to foster sustainability remains unclear, hindering the ability of supply chain organizations to fully

harness AI's capabilities for achieving sustainability (Krakowski et al., 2023). When empirical evidence is limited, organizations face uncertainty regarding the potential benefits and risks associated with integrating AI into their operations, which becomes an uncharted territory (Chowdhury et al., 2022). This uncertainty can lead to either hesitation or cautious approaches in adopting AI technologies, as decision-makers may struggle to justify investments in AI without clear evidence of its impact on sustainability performance. This gap in knowledge can result in missed opportunities, suboptimal AIA, and overall failure to capitalize on AIA's potential to drive sustainable growth. Therefore, the following research questions will guide this research.

How does AI assimilation in supply chain organizations influence sustainable business performance?

Understanding the connection between AIA and sustainable business performance (SBP) is particularly crucial in supply chain organizations, where efficiency and sustainability often intersect. Effective AI assimilation could enable these organizations to achieve a balance between reducing operational costs and minimizing environmental impact, thus contributing to long-term business viability and social responsibility.

We answer the research question by developing a conceptual model drawing from resource-based view (RBV) theoretical perspective. According to RBV, a firm's resources and capabilities are the primary drivers to achieve competitive advantage and performance (Barney, 2001). Additionally, possessing resources and capabilities that are valuable, rare, difficult to imitate, and non-substitutable (VRIN) will help organizations to achieve a sustainable competitive advantage over an extended period compared to its competitors (Priem & Butler, 2001). This theoretical perspective is used to justify AIA and CSA as critical resources within organizations that can be leveraged to develop green ambidexterity (GAX) capability, which would subsequently lead to SBP.

For this study, data was collected from 199 supply chain managers across various sectors in the UK in a three-wave longitudinal survey. The responses obtained from the survey were analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique.

This study advances the theoretical discourse on AIA by highlighting its role not just as a technological tool but as a vital component of a broader strategic framework that supports sustainability. The research offers a fresh perspective on how organizations can effectively manage and optimize their sustainability efforts through the lens of GAX by leveraging AIA. Finally, our study broadens the theoretical framework surrounding AIA by integrating CSA, which has been discussed in isolation from sustainability efforts.

2. Literature Review and Knowledge Gaps

AIA is an emerging yet increasingly pivotal topic in the field of supply chain management, given its profound potential to transform business operations and drive significant business value (Priksht et al., 2023; Fosso-Wamba, 2022). Similar to IT assimilation (Armstrong & Sambamurthy, 1999), AIA involves integration of AI technologies across all facets of an organization's workflows and business processes, ensuring that these AI tools are not merely isolated applications but are embedded within the broader operational and decision-making processes (Fosso-Wamba, 2022). This holistic integration is crucial for maximizing the impact of AI, as it facilitates AI-driven insights and automation into everyday decision-making and execution (Priksht et al., 2023).

Current research highlights that AIA influences firm performance by enhancing both organizational and customer agility (Fosso-Wamba, 2022). This agility allows firms to respond more swiftly and effectively to market changes, customer demands, and operational challenges (Vokurka & Flidner, 1998).

Studies have demonstrated that AIA enhances an organization's absorptive capacity, thereby enhancing overall firm performance (Wahab & Radmehr, 2024). According to the framework presented in (Priksht et al., 2023) AIA is not merely about adoption; it encompasses the routinization and subsequent extension of AI capabilities throughout the organization. Therefore, AIA equips firms with the necessary capabilities to achieve outcomes that are valued organizationally, such as improved efficiency, innovation, and competitiveness.

In parallel, the concept of GAX has gained attention as a vital organizational capability (Martínez-Falcó et al., 2024; Chen et al., 2022). GAX refers to an organization's ability to balance and integrate both exploratory and exploitative activities focusing on environmental sustainability (Ubeda-Garcia, 2022). Specifically, it involves the pursuit of new, innovative green practices (exploration) alongside the optimization and refinement of existing sustainable practices (exploitation) (Peter & Buijs, 2022). This dual capability is essential for firms that aim to maintain a competitive edge while simultaneously fulfilling sustainability goals (Kumar et al., 2024).

The literature has mostly treated GAX as a higher-order reflective construct and found that it contributes to superior environmental performance and offers sustained competitive advantages (Martínez-Falcó et al., 2024; Chen et al., 2022; Ubeda-Garcia, 2022). However, organizations often exhibit a tendency to favor a more conservative, exploitation-based strategy, which is perceived as less risky and uncertain compared to exploration, which is typically more financially intensive and complex (Peters & Buijs, 2022). Despite this, recent research (Martínez-Falcó et al., 2024) conducted in Spanish wineries, has demonstrated that green human resource and supply chain management practices will positively influence GAX strategies.

By leveraging theoretical perspectives like the natural-resources-based view and the intellectual capital-based view, the study showed that GAX will lead to sustainable business performance. Collectively, these studies reveal that GAX is a capability for organizations to achieve sustainability.

However, it is worth noting that the body of literature on innovation ambidexterity (Chen et al., 2023; Chatterjee & Mariani, 2022; Bustinza et al., 2020; Rialti et al., 2019) is far more extensive compared to GAX. Research on innovation ambidexterity has consistently shown the positive influence of analytical decision support systems, which provide business intelligence capabilities, on innovation ambidexterity and, consequently, on firm performance (Chen et al., 2023; Bustinza et al., 2020) and research and development performance (Kumar et al., 2024). Furthermore, existing studies have also identified the moderating role of environmental dynamism in the relationships between digital capabilities, innovation ambidexterity, and firm performance, suggesting that external factors play a significant role in shaping these outcomes (Kumar et al., 2024; Sivarajah et al., 2024; Akhter et al., 2021). In this context, CSA has emerged as a critical moderator in the relationship between digital capabilities, innovation ambidexterity, and firm performance, particularly given the increasing reliance on digital technologies and the associated risks (Garcia-Perez et al., 2023). As organizations adopt and integrate digital technologies, their exposure to cyber risks increases, making CSA essential for safeguarding digital transformation efforts, particularly in dynamic and unpredictable environments (Tagarey et al., 2021). In summary, while environmental dynamism influences the need for adaptive capabilities like innovation ambidexterity, CSA ensures that these capabilities can be safely and effectively leveraged (Asif et al., 2024). However, role of CSA in sustainability initiatives, practices and processes is yet to be examined in the supply chain management literature (Melnik et al., 2022), irrespective of the exponentially growing number of cyber security incidents over the past few years.

Based on our review, it is evident that the current literature has predominantly focused on the relationship between AI capabilities, business model innovation (Jorzik et al., 2023) and firm performance (Wamba et al., 2024; Mikalef et al., 2023; Chatterjee & Mariani, 2022; Lennerts et al., 2020). However, the role of GAX—a critical capability that enables organizations to balance and integrate sustainable practices—remains significantly underexplored. Furthermore, there is a noticeable gap in research regarding the role of CSA in achieving sustainable business performance, particularly within a highly digitalized business environment (Pan et al., 2022).

While recent studies have highlighted the potential of AI capabilities to enhance research and development performance, as well as the mediating effects of explorative and exploitative innovations (Kumar et al., 2024), the broader implications for sustainable practices and sustainability-oriented outcomes are still largely unknown (Kotlarsky et al., 2023; Pan et al., 2022). This gap indicates a need for further investigation into how these elements interact and contribute to sustainable business performance. Therefore, the aim of this research is to bridge this knowledge gap by exploring the interplay between AIA, GAX, CSA, SBP, and SCR. By doing so, we seek to provide organizations with actionable strategic insights that can transform AI-driven resources into GAX strategic capabilities, ultimately leading to sustainable outcomes, valued by both the organization and its stakeholders.

3. Conceptual Model and Hypotheses

The conceptual model is presented in Figure 1

3.1 AIA and SBP

AI systems can analyse vast amounts of heterogeneous data in real-time, enabling organizations to make more informed decisions, improve efficiency, agility and low carbon management (Dey et al., 2024; Roux et al., 2023).

In this context, AIA can optimize supply chain management, enhance supply chain agility, and predict market trends, leading to cost savings and revenue growth (Toorajipour et al., 2021). The existing literature has highlighted that AI-driven automation and analytics significantly improve productivity and profitability in various industries, underscoring its positive impact on economic performance (Mishra et al., 2022). AIA as a result of adopting AI tools (such as analytical decision support systems) can also contribute to environmental sustainability by improving risk management (Baryannis et al., 2019), resource efficiency, adoption of circular economy practices and reducing carbon footprints (Appio et al., 2024; Nishant et al., 2020). AI can optimize energy usage in manufacturing processes, reduce emissions through predictive maintenance, and help organizations monitor and reduce their environmental impact (Wang & Zhang, 2020; Kohtamaki et al., 2019). AIA can also contribute to socially responsible practices by improving workplace safety, enhancing customer experiences, and fostering (Alkire et al., 2024; Rakova et al., 2021). Additionally, AI tools can be employed to promote diversity and inclusion within organizations by mitigating biases in recruitment and human resource- centric decision-making processes (Daugherty et al., 2020).

AIA will empower firms to not only keep pace with but also pre-emptively react to evolving market conditions, customer expectations, industry competition and regulatory changes, ensuring they remain at the forefront of innovation and market responsiveness (Zong et al., 2024; Richey et al., 2023). Therefore., organizations that can successfully integrate AI into their operations and decision-making processes gain a distinct competitive advantage, making AIA a rare resource. The successful assimilation of AI often requires a combination of advanced technological infrastructure, skilled personnel, and organizational culture that fosters innovation, which are difficult for competitors to replicate (Mikalef et al., 2023).

AI's analytical and computational capabilities resulting from AIA to provide actionable insights is unparalleled compared to other technologies making it a non-substitutable resource (Jarrahi et al., 2023). Therefore, from the RBV perspective, AIA represents a strategic resource that can enhance a firm's sustainable business performance by providing value, rarity, inimitability, and non-substitutability (Helfat et al., 2023), which leads us to the following hypothesis.

Hypothesis 1: AIA will positively influence SPB in supply chain organizations.

3.2 AIA and GAX

AIA has the potential to significantly enhance an organization's capacity for green exploration by facilitating the discovery and development of new, environmentally friendly technologies and low carbon management practices (Dey et al., 2024). AI can process and analyze large datasets related to environmental impacts, resource consumption, and sustainable practices, thereby enabling organizations to identify novel opportunities for both green and sustainability-oriented innovation (Shinde et al., 2022; Nishant et al., 2020). On the exploitative side, AI tools can streamline operations, reduce waste, and improve the efficiency of resource utilization, thereby refining an organization's current green strategies (Roux et al., 2023; Javaid et al., 2022). Wamba et al. (2020) demonstrated that organizations leveraging AI see significant improvements in the efficiency and effectiveness of their sustainability initiatives, supporting the notion that AI enhances exploitative green practices. AI can support decision-making by predicting the environmental impacts of different strategies, helping organizations to allocate resources optimally between developing new green innovations and enhancing existing (Wankhede et al., 2024; Al-Surmi et al., 2022). This balancing act is crucial for achieving long-term sustainability goals without compromising immediate operational efficiency (Kumar et al., 2024).

From the RBV perspective, AIA provides decision-making capabilities that can help organizations adapt to changing environmental demands and opportunities (Yarosan et al., 2024). This is rooted in AI's analytical ability to serve as a rare and inimitable resource that supports innovation (Jarrahi et al., 2023). Moreover, AI's data processing power and predictive abilities will allow organizations to identify and develop new green strategies that competitors may not easily replicate (Bag et al., 2021). Based on these arguments we formulate the following hypotheses.

Hypothesis 2: AIA will positively influence GAX in supply chain organizations

3.3 AIA, CSA and GAX (moderating relationship)

CSA refers to the knowledge and understanding that individuals and organizations possess about the potential risks and threats to their information systems, data, and digital operations from cyber-attacks (Hasan et al., 2023). It is the recognition of various cyber threats (such as phishing, malware, and hacking), understanding the potential impact of these threats, and adopting best practices to prevent, detect, and respond to cyber incidents (Rohan et al., 2023). As organizations increasingly rely on AI systems and infrastructure, these systems become more susceptible to cyber threats, which can compromise both the integrity of AI-driven processes and the data that AI systems rely on (Chowdhury et al., 2024).

CSA will ensure that organizations can protect its AIA assets (Schreiber & Schreiber, 2024), thereby maintaining the value, rarity, inimitability, and non-substitutability of these resources. Such measures will safeguard the effectiveness of AIA, particularly in GAX context, where the reliability, accuracy and trustworthiness of data and information flow are vital for making well-informed decisions that can drive both ecological and business outcomes (Bruijn & Janssen, 2017).

CSA helps to implement practices that will protect the integrity of data from potential threats (Kim, 2022), ensuring that AI systems resulting from AIA can function effectively without being compromised (Akhter et al., 2022). This, in turn, supports reliable data analysis, robust infrastructure and trustworthy decision-making processes, which are essential for achieving the delicate balance between environmental, social and financial objectives (Akhter et al., 2022). Therefore, CSA ensures that AIA's role in promoting GAX is not compromised by security breaches, which could otherwise lead to data loss, operational disruptions, reputational damage, and faulty innovations that might not meet environmental standards and cause financial damage (Peltier, 2016). This will be critical for sustaining GAX capabilities over time, as it enables the organization to continuously innovate and optimize in a secure, reliable and trustworthy digital environment by leveraging AIA. Based on these arguments, we derive the following hypothesis.

Hypothesis 3: CSA moderates the relationship between AIA and GAX

3.4 AIA, GAX and SBP (mediating relationship)

AIA requires the right set of capabilities to translate its potential into tangible sustainability outcomes (Al-Surmi et al., 2022). The existing research has shown that AI adoption influences circular economy practices, green supply chain management, low carbon management and supply chain agility, which subsequently leads to sustainable business performance (Dey et al., 2024; Bag et al., 2021). GAX is about being ambidextrous—effectively managing both the exploitation of existing resources for immediate gains (such as efficiency improvements) and the exploration of new strategies that support long-term sustainability (Martinez-Falco et al., 2024; Ubeda-Garcia et al., 2022). Through its exploratory function, green ambidexterity enables organizations to use AI to identify and pursue new opportunities for sustainability (Chen et al., 2022).

On the other hand, the exploitative function of GAX ensures that the organization uses AI to optimize and refine its existing sustainable practices (Ubeda-Garcia et al., 2022). Therefore, GAX provides the necessary capability to channel AI-centric resources towards sustainable development outcomes (Birkinshaw & Gupta, 2013). This ensures that AI is not merely a tool for efficiency but also a strategic source that drives long-term sustainability (Akhter et al., 2021; Nishant et al., 2020). From an RBV perspective, GAX is the capability that allows firms to effectively utilize AIA as a resource to achieve SBP (Pan et al., 2022). Based on these arguments we frame the following hypothesis.

Hypothesis 4: GAX will positively mediate the relationship between AIA and SBP.

Insert Figure 1: Conceptual model

4. Methodology

4.1 Sample and authenticity checks

We carried out a longitudinal three-wave survey to empirically validate the proposed conceptual model (refer to Figure 1). At Time 1 (T1), respondents rated statements related to AIA and CSA. One week later, at Time 2 (T2), the same participants rated statements related to GAX and SBP, followed by SCR at Time 3 (T3), one week after T2. The survey was conducted via the Prolific platform. The data was gathered from 199 supply chain managers based in the UK, representing a diverse array of sectors and industries. The UK served as a suitable setting for this study due to its recognized leadership in both AI innovation and sustainability efforts. The UK government has consistently taken a forward-thinking approach, implementing policies that actively promote sustainable business practices through its net zero strategy (UK Net Zero, 2022), and the widespread adoption of AI technologies, as outlined in the UK AI Strategy (UK National AI Strategy, 2021). Additionally, the UK's high ranking on the Digital Economy and Society Index (DESI) highlights advanced technological

capabilities (European Commission, 2022). The UK also excels in global sustainability rankings, on green index (Yale Center for Environmental Law & Policy, 2022).

4.2 Pilot testing and screening criteria

The initial version of the instrument was pilot tested with fifteen managers who were not included in the final sample. This step was essential to ensure that the survey was effective, easy to understand, and clear in its questions (Kumar et al., 2024). The selection criteria of respondents were as follows: (1) they had to be based in the UK and hold a managerial role (e.g., C-level executive, president/VP, director, or manager), as these positions typically involve decision-making responsibilities and a comprehensive understanding of their organization's strategic initiatives, including those related to AIA and GAX; (2) they needed to work for organizations that had implemented AI technologies and adopted green practices or innovation; (3) they had to be involved in or possess knowledge about their organization's AI, sustainability performance; (4) they were required to have at least three years of experience in their current role ensuring they had sufficient expertise and insight into both operational and strategic aspects of their organization; (5) they should not have participated in similar studies recently to avoid potential bias in their responses.

Control variables were gathered, including organization size (measured by the number of employees), the industry sector in which it operates, the number of years the firm has been utilizing AI, and the duration of its green initiatives within business operations, aligned with previous research in related contexts.

5 Measures

All items were rated on a 5-point Likert-type scale (1 = strongly disagree 5 = strongly agree), unless indicated otherwise. *AIA* was assessed using the three-item scale reported in Fosso-Wamba et al. (2022). *GAX* is a higher order reflective construct comprising of green exploration (4 items) and green exploitation (4 items) derived from Ubeda-Garcia et al. (2022). *CSA* awareness was assessed using a 5-item scale derived from Flores & Ekstedt (2016). *SBP* is a higher order reflective construct comprising of three dimensions – economic performance (ECO), environmental performance (ENV) and social performance (SOC). *ECO* was measured using a five-item scale reported in Mikalef & Gupta (2021). *ENV* was measured using a five-item scale reported in Paulraj (2011). *SOC* were measured using a five-item scale both derived from Paille et al. (2014). *SCR* was measured using a 4-item scale derived from Queiroz et al. (2022).

5. Findings

5.1 Model Structure.

To determine the appropriate model structure for the higher-order constructs, GAX and SBP, we conducted Confirmatory Tetrad Analysis (CTA) using SmartPLS4 using 19000 bootstrap subsamples. CTA enables us to statistically assess whether the data aligns more accurately with a reflective or formative model structure, thereby guiding our modeling decisions (Hair et al., 2024). In CTA, the 80-20 rule for p-values serves as a guideline: if fewer than 80% of the p-values are significant, it indicates that the construct should be modeled as reflective (Hair et al., 2024; Gundergan et al., 2008). Our results showed that in both the GAX and SBP constructs, less than 80% of the p-values were significant, confirming that these higher-order constructs are best represented as reflective models.

5.2 Sample adequacy.

G* power tool is used to test the sample adequacy for the model (Figure 1) by executing an F-test for a liner multiple regression Fixed Model with R2 deviation to zero (Dey et al., 2024). The test returned a sample size of 119 for effect size (medium = 0.15), for alpha 0.05, power set as 0.95, given three outcome variables in the model, showing the sample size (199) is sufficient to validate the findings. Moreover, we also used the Kaiser-Meyer-Olkin (KMO) test to measure the sampling adequacy. The KMO statistic was 0.88, indicating a meritorious level of sampling adequacy.

Insert Table I: Factor loadings of lower order construct

Insert Table II: Sample characteristics

5.3 Measurement model (lower order and reflective higher order)

We employed Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair et al., 2021 & 2019), which has been applied across various disciplines, including AI, business analytics and CE research (Kristoffersen et al., 2021). PLS-SEM is particularly suitable for exploratory research (as in this study, i.e., testing a theoretical model from a prediction perspective) compared to co-variance-based SEM (Dash & Paul, 2021). PLS-SEM is preferred due to its ability to handle relatively small sample sizes, non-normal data, and complex models (Henseler et al., 2016).

Our model is comprised of two reflective second order constructs (GAX and SBP), therefore the lower order measurement model is tested first, followed by the higher order measurement model. We considered the individual items loadings above 0.7, the minimum cutoff values as recommended by Hair et al. (2021), as shown in Table 1. The sample characteristics are reported in Table 2. The results of the lower order measurement model testing are reported in Table 3. The Cronbach's alpha and composite reliability for each construct (shown in Table 2) are found to be more than the cut-off of 0.70 recommended in the literature (Hair et al., 2021 & 2019). Convergent validity of the constructs is measured using the average variance extracted (AVE), with values higher than the 0.50 cut-off (Hair et al., 2021 & 2019), indicating that each construct accounts for over half of the variation observed in the items associated with it (Table 2).

We used the Fornell and Larcker criterion as the item loadings in our study range between 0.753-0.922 (Hair et al., 2019). Table 2 also shows that the square root of the AVE is greater than all the inter-construct correlations, providing evidence of sufficient discriminant validity. We also checked for multicollinearity employing the variance inflation factor (VIF) technique and found that the value for VIF is less than 3.3 for all the constructs (Hair et al., 2021), indicating no multicollinearity issues. After validating the lower order measurement model, the higher order measurement model was tested using the same process. The results of the higher order measurement model testing are presented in Table 3. The results for GAX and SBP are found to be reliable, convergent and discriminant validity is established, and there are no multicollinearity issues.

Insert Table III: Descriptive statistics and construct validity

5.4 Model fit and Indices

Before testing our hypotheses, we conducted a series of confirmatory factor analyses (CFAs) to examine the fit of our proposed five-factor model (Figure 1). The results showed that the model fit the data well: $\chi^2(549) = 888.440$, CFI = 0.921 (> 0.9), TLI = 0.915 (> 0.9), RMSEA = 0.056, SRMR = 0.061 (< 0.008), satisfying the threshold fit criteria (Dash & Paul, 2021; Henseler et al., 2016) and performed better than alternative models, including the six-factor model with GET and GEX as distinct constructs: $\chi^2(549) = 1105.016$, CFI = 0.871, TLI = 0.860, RMSEA = 0.071, SRMR = 0.118; six-factor model with ECO as a distinct construct and combining, ENV and SOC into a single construct: $\chi^2(513) = 861.797$, CFI = 0.907, TLI = 0.867, RMSEA = 0.068, SRMR = 0.065. Additionally, we followed the procedures outlined in (Hair et al., 2021) to test the model fit in the PLS-SEM (structural model having higher order constructs). The standardized root-mean-square residual (SRMR) was found to be 0.065 which is below the threshold value 0.08 (Kumar et al., 2024; Paulraj, 2011), and normed fit index (NFI) was 0.769, i.e., less than 0.90 (Kumar et al., 2024), which shows that the model has a good fit for structural analysis. We found the control variables (firm size, sector, duration of AI use and duration of green practices use) did not significantly impact GAX and SBP in the model. We employed a longitudinal design, where data on the independent and dependent variables was collected at different points in time. This temporal separation of data collection helped to mitigate the risk of common methods bias (CMB) (Podsakoff et al., 2003).

Insert Table IV: Hypothesis testing results (model 1)

Insert Figure 2: PLS-SEM Hypothesis testing (model 1)

5.5 Structural model analysis and hypothesis testing

We employed bootstrapping 5000 subsample procedure (Hair et al., 2021) to test the structural model presented. The results of bootstrapping are summarized in Table 4 and presented in Figure 2. Our findings showed that AIA positively and significantly influences SBP ($\beta = 0.141$, $SD = 0.056$, $t = 2.367$, $p = 0.018$), and GAX ($\beta = 0.232$, $SD = 0.071$, $t = 3.258$, $p = 0.001$), supporting hypotheses 1 and 2 respectively. The moderating effect of CSA on the relationship between AIA and GAX was found to be significant ($\beta = 0.134$, $SD = 0.060$, $t = 2.220$, $p = 0.026$), supporting Hypothesis 3. The simple slope analysis (Figure 3) indicates that high levels of CSA strengthen the positive relationship between AIA and GAX, i.e. the impact of AIA on GAX is more pronounced because of CSA. The mediating effect of GAX between AIA and SBP was examined by looking at the indirect effect which was found to be significant ($\beta = 0.148$, $SD = 0.044$, $t = 3.220$, $p = 0.001$). Therefore, we accept Hypothesis 4, for a complementary partial mediation because the p-values for all the direct and indirect effects is significant and positive.

Insert Figure 3: Moderation simple slope analysis

6. Discussion

Regarding **Hypothesis 1**, we found that AIA has a positive impact on SBP, consistent with existing literature on AI adoption, big data analytics capabilities, and AI-driven capabilities (Pan & Nishant, 2023; Pan et al., 2022; Nishant et al., 2020; Wamba et al., 2024).

This finding is attributed to AIA's ability to generate actionable insights empowering the managers to make informed decisions and develop strategies that drive sustainability-oriented outcome (Yaroson et al., 2024). In supplementary analysis, we found that AIA significantly influences ECO, but not ENV and SOC. This finding is both novel and intriguing, as previous research has rarely examined the impact of AIA—or AI-related constructs—on the distinct dimensions of sustainable performance. AI is often leveraged to optimize operations, enhance efficiency, and drive economic outcomes, which naturally aligns more closely with improving ECO (Wamba et al., 2024; Jorzik et al., 2023). ENV, for example, often involves reducing carbon footprints, managing resources sustainably—areas where AI might play a supportive role but not a direct, measurable impact (Nishant et al., 2020). Similarly, SOC, includes factors like employee welfare, and ethical practices, may not be immediately influenced by AIA without a strategic effort to apply AI technologies in these domains (Chowdhury et al., 2023).

In relation to **Hypothesis 2**, we found that AIA significantly influences GAX, which is a novel contribution to the existing literature and aligns with Kumar et al. (2024). While previous research has extensively explored the role of AI and big data analytics capabilities to enhance supply chain ambidexterity (Fosso-Wamba, 2022), circular economy practices (Yaroson et al., 2024), supply chain agility and robustness (Dey et al., 2024), and resource orchestration (Kristoffersen et al., 2021), the direct relationship between AIA and GAX has not been examined until now. AIA fosters GAX by enabling organizations to better identify environmental threats and seize sustainable opportunities (Kumar et al., 2024), thereby supporting both explorative (innovation-driven) and exploitative (efficiency-driven) green strategies. Moreover, AIA extends the scope of data-driven decision-making by integrating various forms of data—from environmental metrics to market trends and consumer behavior—into a cohesive framework (Akhter et al., 2021). This enables firms to develop a

nuanced understanding of their operational environment, fostering a more responsive approach to emerging market needs related to sustainability.

In the context of **Hypothesis 3**, the results showed that CSA significantly moderates the relationship between AIA and GAX, which is a new finding. While literature has reported the significance of CSA in risk management and to build trust and reliability of the software systems within business organizations (Akhter et al., 2022), our study extends this understanding by demonstrating that CSA is a critical resource for optimizing the benefits of AIA. Specifically, our findings suggest that CSA enhances the ability of organizations to fully integrate AI technologies into their operations, ensuring that the data and systems supporting AI-driven decision-making are secure and trustworthy. This is crucial because AI systems often rely on large volumes of sensitive data, and any breach or compromise can not only disrupt operations but also erode stakeholder confidence (Chowdhury et al., 2024). Therefore, CSA acts as a foundation that supports the safe and effective AIA, making it possible for organizations to harness AI tool's full potential without exposing themselves to unnecessary risks.

With respect to **Hypothesis 4**, our results reveal that GAX mediates the relationship between AIA and SBP. This finding highlights the critical role of GAX in translating the potential of AIA into tangible sustainability outcomes. While AIA provides the technological capabilities and data-driven insights necessary for innovation and efficiency, GAX enables organizations to develop green capabilities to promote sustainability across economic, environmental, and social dimensions (Sivarajah et al., 2024; Chatterjee & Mariani, 2022). AI-driven insights can often present organizations with numerous opportunities for sustainability improvements, but without the ability to explore and experiment with these opportunities (a key aspect of GAX – Ubeda-Garcia et al., 2022), organizations may fail to realize their full potential. Our supplementary analysis revealed that without the presence of

GAX, AIA does not significantly impact ENV and SOC. In the absence of GAX, AIA alone may lead to improvements in ECO, such as cost reduction and efficiency gains, but it will fall short in driving ENV and SOC. This is because AI, by itself, does not inherently prioritize sustainability (Kotlarsky et al., 2023; Govindan et al., 2022); it is a tool that requires strategic guidance to be applied effectively towards green objectives (Nishant et al., 2020). Moreover, GAX allows organizations to adapt and respond to the dynamic sustainability challenges (Chen et al., 2022; Peters & Buijs, 2022). Environmental and social issues are complex and evolving, and they require a flexible approach that balances the exploration of new opportunities with the exploitation of proven strategies.

7. Research Implications

7.1 Theoretical Implications

Firstly, our study is one of the first to investigate the relationship between AIA, CSA, GAX, SBP and SCR, offering novel insights into the mechanisms by which AIA—recognized as a critical resource—can enhance sustainable outcomes. Therefore, this research provides a nuanced understanding of the pathways through which AIA can be effectively leveraged to achieve not only economic gains but also environmental and social goals.

Secondly, this research reveals that AIA within an organization does not uniformly influence SBP across each of the three triple bottom line dimensions. This finding challenges the assumption that AIA (or AI adoption) inherently drives sustainability (Pan & Nishant, 2023; Kotlarsky et al., 2023; Pan et al., 2022; Nishant et al., 2020). In this context, our research highlights the pivotal role of GAX as a mediating capability, which enables organizations to achieve SBP across all the three distinct sustainability performance dimensions. This contribution advances the theory by suggesting that AIA alone is insufficient to achieve sustainability outcomes. Rather, it should be viewed as a critical

resource that, when combined with GAX enhances informed decision-making and supports sustainable outcomes.

Thirdly, the findings uncover the crucial role of CSA as a critical resource that strengthens the relationship between AIA and GAX. This finding emphasizes the significant impact that the safety and security of information assets and flows have within an organization, particularly in the context of leveraging AI for sustainability. Our study uniquely highlights CSA as a reinforcing mechanism that ensures the integrity and reliability of AI-driven processes. This enhances the organization's ability to utilize AI for both explorative and exploitative green innovation, thereby contributing to overall sustainable business performance. This insight broadens the theoretical framework surrounding AIA (and other AI related constructs) by integrating the dimension of CSA, which has traditionally been discussed in isolation from sustainability efforts.

Fourth, the research demonstrates that GAX serves as a critical mechanism for organizations to achieve SBP across all the triple bottom line dimensions. This highlights the essential role of GAX through which organizations can balance and integrate both explorative and exploitative green practices. This dual focus enables firms not only to innovate in sustainability but also to optimize their existing processes for greater efficiency and sustainable impact. Furthermore, this research expands the theoretical discourse by connecting GAX with SBP in a way that underscores its strategic value. While the concept of ambidexterity has been explored in other contexts, its application to green practices and sustainability performance has not been thoroughly examined. By introducing GAX as a key construct that bridges innovation and efficiency in sustainability, our research provides a new lens through which sustainability strategies can be approached.

7.2 Practical implications

Based on the findings related to *Hypothesis 3*, it is imperative that organizations actively promote CSA both within their own operations and among their supply chain partners. Ensuring the security and protection of information assets is crucial, especially when these assets are integral to making informed green decisions. This proactive approach not only secures critical information but also reinforces trust and collaboration across the supply chain, ultimately supporting the organization's sustainability goals. To effectively increase CSA, organizations should implement a comprehensive program tailored to the needs of all employees and supply chain partners. Moreover, organizations should develop and disseminate clear, easy-to-understand cybersecurity policies and guidelines. These should outline the roles of all employees and partners in maintaining cybersecurity, including the proper handling of sensitive data and the use of secure communication channels.

Considering the results of *Hypothesis 4*, organizations should adjust their expectations regarding the impact of AIA on ENV and SOC. Instead of directly relying on AI to improve these performance outcomes, organizations should strategically leverage AI to support GAX practices. In this context, organizations should create frameworks that use AI-generated insights to guide decisions that balance economic performance with environmental and social considerations. For instance, AI can be used to model the trade-offs between different sustainability initiatives, helping leaders choose strategies that will not only optimize overall performance, but also enhance individual performance of the triple-bottom line dimensions.

8. Conclusion

The findings of the longitudinal three-wave study conducted with supply chain managers in the UK advances the theoretical perspective by positioning AIA and CSA as key VRIN resources to enhance GAX capability within the organization. In this context, our study showed that GAX resulting from AIA drives the success of sustainability initiatives across all the three sustainability performance dimensions. The results also contributes to a more sophisticated understanding of supply chain management by challenging assumptions of inherent compatibility between sustainability.

8.1 Limitations and Future Research

The study utilized a three-wave longitudinal survey-based methodology, focusing on responses from managers in the UK. While this method provides valuable insights, it also presents limitations regarding the generalizability of the findings. The perspectives and experiences of managers from a single geographic area may not fully capture those from other regions, particularly where economic, cultural, and regulatory contexts differ. Managers in other countries, especially those in developing economies or with varying industrial structures, might have distinct experiences and viewpoints related to AIA, CSA and GAX. Although surveys are effective in gathering a wide range of responses, they may lack the depth and complexity of participants' experiences compared to qualitative methods like interviews and case studies. Therefore, future studies should focus on cross-country and cross-sector comparisons as well as employing qualitative methods building on the findings reported in this study.

In addition to broadening the geographic scope and incorporating qualitative methods, future studies should also focus into the impact of external factors—such as government policies, market dynamics, and cultural influences—on the interplay between AIA, CSA, GAX, SBP and SCR. Future research could examine how different types of government interventions either facilitate or hinder AI usage in promoting sustainable business practices. Cultural factors, including organizational culture, societal values, and norms, can significantly affect how AI is perceived and utilized within organizations. Future research could explore how cultural differences impact the integration of AI in sustainability strategies.

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Table 1. Factor loadings of the lower order constructs [loadings < 0.7 we removed from the analysis]

	AIA	CSA	GET	GEX	ECO	ENV	SOC
AIS_1	0.897						
AIS_2	0.919						
AIS_3	0.932						
CSA_1		0.853					
CSA_2		0.892					
CSA_3		0.712					
CSA_4		0.800					
CSA_5		0.642					
GET_1			0.895				
GET_2			0.867				
GET_3			0.909				
GET_4			0.906				
GEX_1				0.871			
GEX_2				0.774			
GEX_3				0.899			
GEX_4				0.873			
ECO_1					0.847		
ECO_2					0.884		
ECO_3					0.882		
ECO_4					0.867		
ECO_5					0.561		
ENV_1						0.821	
ENV_2						0.871	
ENV_3						0.802	
ENV_4						0.797	
ENV_5						0.801	
SOC_1							0.720
SOC_2							0.835
SOC_3							0.848
SOC_4							0.766
SOC_5							0.642

Table 2. Sample characteristics (control variables)

	0-9 employees [1]	10-50 emp [2]	51-249 emp [3]	250-500 emp [4]	Above 500 [5]
<i>Company size</i>	8	33	66	45	47
	Manufacturing [1]	Construction [2]	Food and Agriculture [3]	Transportation and logistics [4]	
<i>Sector</i>	74	48	53	24	
	0-4 years [1]	5-8 years [2]	9-12 years [3]	More than 12 years [4]	
<i>AI use in firm</i>	104	55	18	22	
	0-4 years [1]	5-8 years [2]	9-12 years [3]	More than 12 years [4]	
<i>Green adoption</i>	54	86	37	7	

Table 3. Descriptive statistics and construct validity

	Variable	Mean	SD		Alpha	CR	AVE	1	2	3	4	5	6	7	8	9
1	AIA	3.591	1.076	Lower order measurement model	0.904	0.940	0.839	0.916								
2	CSA	4.471	0.613		0.883	0.911	0.674	0.232	0.821							
3	GET	3.604	0.920		0.917	0.941	0.801	0.255	0.267	0.894						
4	GEX	3.418	0.928		0.877	0.916	0.732	0.285	0.214	0.834	0.856					
5	ECO	3.724	0.765		0.908	0.931	0.731	0.309	0.186	0.345	0.337	0.855				
6	ENV	3.671	0.823		0.877	0.910	0.670	0.247	0.209	0.590	0.566	0.354	0.819			
7	SOC	3.894	0.674		0.805	0.872	0.630	0.189	0.286	0.508	0.519	0.350	0.642	0.794		
8	GAX	Latent values lower order measurement model		Higher order measurement model	0.910	0.957	0.917	0.282	0.254						0.958	
9	SBP				0.719	0.838	0.637	0.302	0.295						0.639	0.798

Sample size (N)=199. **Values in bold represent square root of AVE.** GAX is a higher order reflective construct having two factors GET and GEX. SBP is a higher order reflective construct having three factors ECO, ENV and SOC. Shaded cells represent higher order constructs

Table 4. Hypothesis testing results [Model 1, Figure 1]

Relationships	B	SD	T stats	p-value	Outcome
AIA → SBP	0.141	0.056	2.367	0.018	Hypothesis 1 accepted
AIA→ GAX	0.232	0.071	3.258	0.001	Hypothesis 2 accepted
Moderation					
AIA*CSA → GAX	0.134	0.060	2.220	0.026	Hypothesis 3 accepted
Mediation					
AIA → GAX → SBP (indirect)	0.148	0.044	3.220	0.001	Hypothesis 4 accepted
GAX → SBP	0.638	0.045	14.177	0.001	
Moderated Mediation					
AIA*CSA → GAX→ SBP	0.069	0.038	1.788	0.037	The impact of AIA on SBP through GAX will vary depending on CSA. (not part of hypothesis)

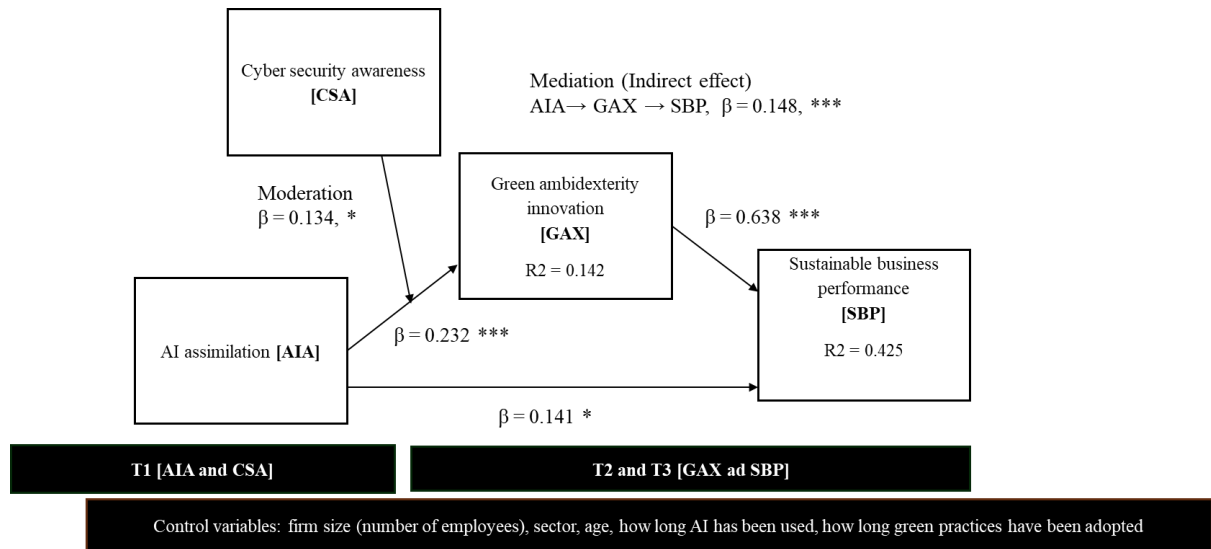


Figure 1. Conceptual Model 1

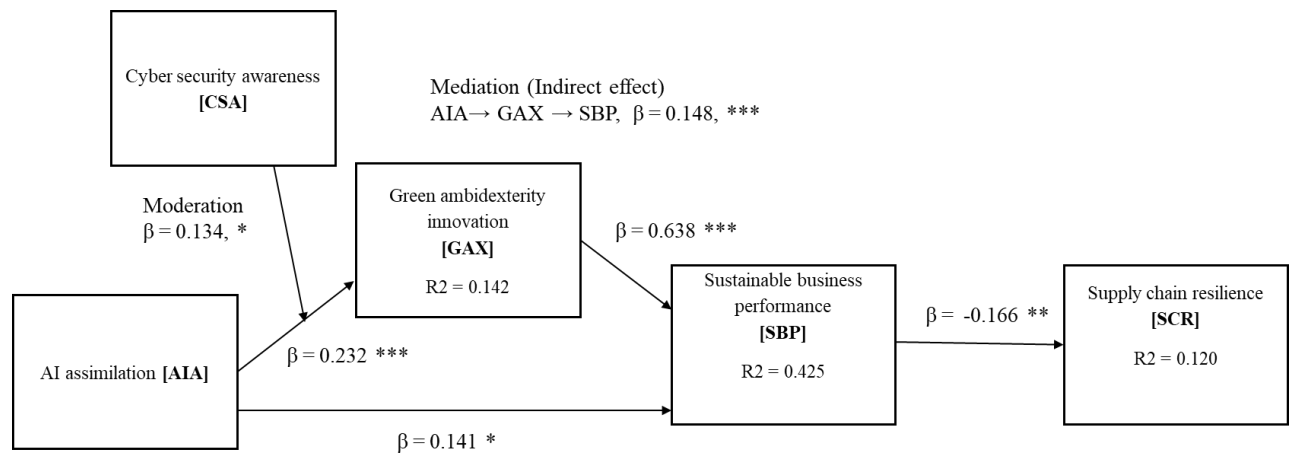


Figure 2. Hypothesis testing results (Conceptual model 1)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

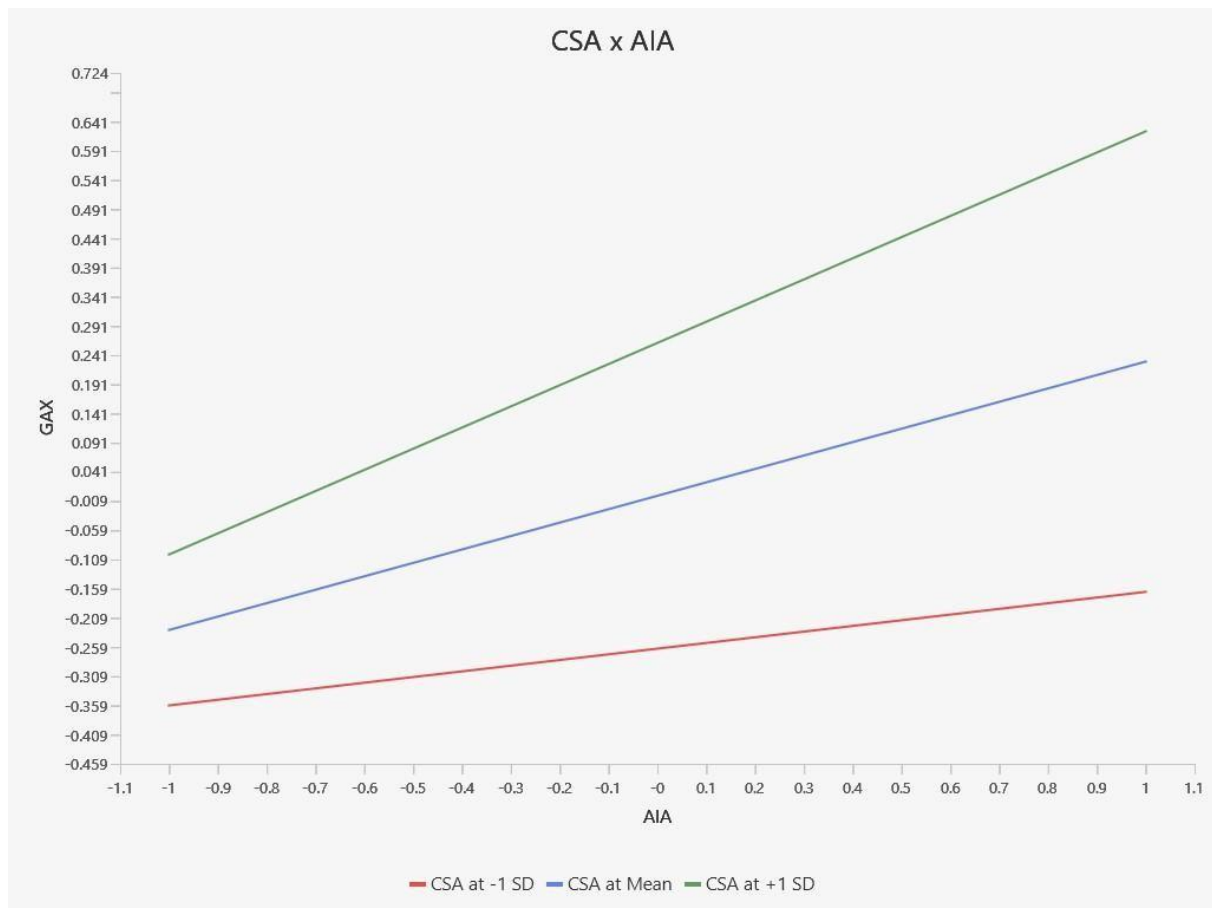


Figure 3. Moderation simple slope analysis

