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BIG DATA ANALYTICS-ARTIFICIAL INTELLIGENCE, AMBIDEXTERITY, AND GREEN SUPPLY CHAIN MANAGEMENT: IMPLICATIONS ON RESPONSIBLE ECONOMY

Análise de Big Data, inteligência artificial, ambidestria e gestão de cadeia de suprimentos verde: Implicações na economia responsável

Análisis de big data, inteligencia artificial, ambidestreza y gestión de la cadena de suministro verde: Implicaciones en la economía responsable

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ABSTRACT

In the current dynamic market, businesses have recognized the pivotal role of data and sustainability technologies in attaining competitive advantage. Big Data Analytics-Artificial Intelligence and Green Supply Chain Management are significant sustainability promotion strategies. The research collected data from 220 employees in the Taiwanese manufacturing sector with the help of a survey methodology. The findings revealed significant impacts of Big Data Analytics-Artificial Intelligence on both green supply chain management and supply chain ambidexterity. Moreover, supply chain ambidexterity significantly influences green supply chain management. Lastly, supply chain ambidexterity was also found to mediate the relationship between Big Data Analytics-Artificial Intelligence and green supply chain management. This study provides several implications for fostering a responsible economy. It elucidates how leveraging Big Data Analytics-Artificial Intelligence enhances supply chain ambidexterity, reinforcing sustainable practices without detectable alterations.
Keywords: *Big Data analytics-artificial intelligence, green supply chain management, supply chain ambidexterity, Partial Least Squares Structural Equation Modeling, responsible economy.*

RESUMO

As empresas reconhecem o papel crucial dos dados no mercado atual, com tecnologias de sustentabilidade cada vez mais adotadas para vantagem competitiva. A análise de Big Data, inteligência artificial e a gestão da cadeia de suprimentos verde (GSCM) são estratégias prevalentes para promover a sustentabilidade. A pesquisa, envolvendo 220 funcionários do setor manufatureiro taiwanês, revela impactos significativos da análise de Big Data e inteligência artificial na gestão verde da cadeia de suprimentos e na ambidestria. Além disso, a ambidestria da cadeia de suprimentos influencia significativamente a gestão verde da cadeia de suprimentos e medeia a relação entre análise de Big Data, inteligência artificial e gestão verde da cadeia de suprimentos. Este estudo destaca a importância crítica da cadeia de suprimentos verde na economia responsável, esclarecendo como alavancar inteligência artificial e Big Data aprimora a ambidestria da cadeia de suprimentos, fortalecendo práticas sustentáveis sem alterações detectáveis.
Palavras-chave: *análise de Big Data-inteligência artificial, gestão de cadeia de suprimentos verde, ambidestria da cadeia de suprimentos, Modelagem de Equações Estruturais de Mínimos Quadrados Parciais, economia responsável.*

RESUMEN

Las empresas valoran los datos en el mercado actual y adoptan tecnologías sostenibles para competir. El análisis de big data, la inteligencia artificial y la gestión de la cadena de suministro verde (GSCM) promueven la sostenibilidad. Una investigación con 220 empleados del sector manufacturero taiwanés muestra el impacto del análisis de big data y la inteligencia artificial en la gestión verde de la cadena de suministro y la ambidestreza. Además, la ambidestreza de la cadena de suministro influye en la gestión verde y media la relación entre el análisis de big data, la inteligencia artificial y la GSCM. Este estudio destaca la importancia crítica de la cadena de suministro verde en una economía responsable. Explica cómo el aprovechamiento de la inteligencia artificial y del big data mejora la ambidestreza, fortaleciendo prácticas sostenibles sin alteraciones detectables.
Palabras clave: *análisis de big data-inteligencia artificial, gestión de la cadena de suministro verde, ambidestreza de la cadena de suministro, modelado de ecuaciones estructurales de mínimos cuadrados parciales, economía responsable.*

INTRODUCTION

In the current dynamic market landscape, businesses recognize data as a pivotal asset, prompting a strategic shift toward sustainability technologies to maintain a competitive edge (Francisco et al., 2020). This paradigm shift is embedded within the broader context of fostering a 'Responsible Economy,' where economic activities harmonize with social and environmental considerations (Brei, 2018; Sharma & Singh, 2023). As conceptualized in this study, a Responsible Economy advocates for business practices that prioritize ecological integrity, societal well-being, and sustainable development (Giannetti et al., 2023; Vieira et al., 2021). Within the ambit of this Responsible Economy framework, the confluence of Big Data Analytics (BDA) and Artificial Intelligence (AI) have extensively influenced the recent advancements in information technology and the corporate world. Both technologies, BDA and AI, have revolutionized many industries and acquired tremendous attention from the research community. Big data refers to excessively large amounts of high-dimensional unstructured data that face challenges of complexity, noise, and dependency (Fan et al., 2014). It is difficult to handle such big data and gain knowledge from it using traditional methods. Therefore, big data analytics, which are very advanced analytical techniques, are utilized to handle these large datasets (Elgendy & Elragal, 2014). Artificial intelligence includes two primary concepts: machine learning and deep learning, which focus on making the machine imitate human-like intelligence (Khan & Adnan, 2018). AI processes data for informed decisions, predicts demand, and optimizes inventory. Automation streamlines tasks and reduces errors. Real-time analysis improves responsiveness. Big Data Analytics-Artificial Intelligence (BDA-AI) boosts competitiveness and innovation. It ensures resilience in dynamic markets. Hence, BDA-AI can enhance the supply chain operations in businesses (Bag et al., 2021).

As mentioned before, businesses consider data an essential asset in the current dynamic market (Albergaria & Jabbour, 2020; Kozjek et al., 2018; Weerakkody et al., 2017). Furthermore, with the advent and employment of digitalization, many organizations are producing large amounts of data (Ivanov et al., 2019). Nevertheless, compared to investments, these large amounts of data do not directly benefit the organization unless they are analyzed with the help of necessary technologies (Aydiner et al., 2019). The data can be leveraged to attain commercial benchmarks (Gamoura, 2019) by practitioners having the greatest understanding and knowledge about the data (Dubey et al., 2020). Big data, with the help of forecasting analysis, can aid organizations in reducing unnecessary costs (Aydiner et al., 2019), rapid manufacturing (Dubey et al., 2018), and meeting the ongoing changing demands of the clients by planning and creating constantly evolving products (Ghasemaghaei & Calic, 2019). The involvement of BDA-AI has pushed the revolution of supply chain digitalization (Tortorella et al., 2020). Hence, technologies like AI, machine learning, and big data have attracted much attention from research scholars (Ara & Mifa, 2024; Cavalcante et al., 2019; Lai et al., 2018; Lutfi et al., 2023).

In addition, many organizations have begun to employ sustainability technologies to maintain a competitive edge in the dynamic market environment (Aydiner et al., 2019; Dubey et al., 2020). Currently, Green Supply Chain Management (GSCM) is a popular technique adopted by

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organizations to promote sustainability (Khan, Chen, Lu et al., 2021; Oliveira et al., 2018). GSCM aids organizations in dealing with several environmental issues, including waste reduction, energy reduction, and air pollution. GSCM has also helped organizations operate efficiently and reduce daily operation costs (Rao & Holt, 2005). Previous research found a significant association between BDA-AI and the green supply chain process in the context of hospitals (Benzidia et al., 2021). However, this research aims to adopt the GSCM model by Khan et al. (2021), which includes Green Logistics (GL), Green Distribution (GD), Green Procurement (GP), and Green Manufacturing (GM). Hence, this study aims to discover the impact of BDA-AI and GSCM in the context of Taiwan's manufacturing industry.

Ambidexterity includes both exploitation and exploration. It is a concept that states that organizations can pursue both explorative (innovative) and exploitative (efficient) strategies within their supply chains. It is about balancing the need for innovation and efficiency in supply chain operations. Hence, in addition to big data and GSCM, organizations must also acquaint themselves with the notion of ambidexterity. Additionally, organizations need to find the right balance between employing both strategies. Overusing exploration strategies is risky, and the overuse of exploitation strategies can cause dependence on outdated practices (Levinthal & March, 1993). Previously, ambidexterity has been found to improve knowledge discovery (Borzillo et al., 2012), product manufacturing (Zhang et al., 2014), and performance (Junni et al., 2013). Supply Chain Ambidexterity (SCAX) employs both exploration and exploitation practices in combination throughout the manufacturing process (Khan, Chen, Lu et al., 2021; Kristal et al., 2010). Previously, BDA-AI technologies have significantly impacted manufacturing organizations' operations and supply chains (Aljumah et al., 2021; Lee & Mangalaraj, 2022). However, these findings are somewhat inadequate and do not mention the SCAX concept. Hence, this study seeks to investigate the correlation between BDA-AI and SCAX.

GSCM includes various tasks and can be evaluated in several ways due to its multi-dimensional nature. Previously, research recommended measuring GSCM with the help of four constructs, including external GSCM, internal GSCM, green design, and investment recovery (Zhu et al., 2005). Another study proposed GL, GP, logistics strategy, and supplier analysis as practices to measure GSCM (Kumar et al., 2015). Furthermore, management of green raw materials, promotion of green marketing activities, and reverse logistics were also found to measure GSCM (Younis, 2016). However, this research followed the methodology proposed by Khan et al. (2021) and used GM, GD, GL, and GP to measure GSCM because of its relevance to the manufacturing industries context. Previous research has found SCAX to significantly influence the GD, GL, GM, and GP of GSCM (Khan, Chen, Lu et al., 2021; Kumar & Putnam, 2008). However, these findings are somewhat inadequate, and some of the conclusions were inconsistent (Golicic & Smith, 2013). Consequently, this study intends to measure the relationship between SCAX and GSCM.

This investigation has the following research contributions. (1) It aims to discover the relationships of BDA-AI with GSCM and SCAX. (2) It measures the association between SCAX and GSCM. (3) It measures the indirect relationship of BDA-AI with GSCM, with SCAX

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as a mediating variable. In addition, this research provides several implications for fostering a responsible economy. It elucidates how leveraging BDA-AI enhances SCAX, reinforcing sustainable practices without detectable alterations.

The research is structured as follows: Section 2 provides a comprehensive overview of the theoretical background and develops hypotheses for BDA-AI and GSCM, BDA-AI and SCAX, and SCAX and GSCM. Section 3 provides the methodology, focusing on the sampling method and data collection. Next, Section 4 provides the data analysis and shares the empirical results. Lastly, Section 5 concludes the research by providing detailed implications, future directions, and limitations.

THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

BDA-AI and GSCM

BDA-AI is employed to handle large amounts of data to conduct organizational research. Previously, BDA-AI was rarely applied to sustainability issues. BDA-AI can be linked to an increase in the environmental operation of companies (Benzidia et al., 2021). Additionally, researchers have acknowledged the importance of BDA-AI in GSCM (Dubey et al., 2017; Geng et al., 2017; Song et al., 2017). BDA-AI impacts the sustainability data through GSCM (Liu et al., 2020). Nonetheless, BDA-AI has not been completely utilized and employed to achieve the benefits of GSCM (Dubey et al., 2017). Moreover, the discrepancy in the employment of BDA-AI technologies eradicates the efficiency in data analysis and, therefore, faces barriers in measuring the sustainability of organizations (Raut et al., 2019). Currently, organizations lack awareness of the technologies that can be used in the efficient operations of GSCM (Liu et al., 2020; Wu et al., 2016). Previous research proposed that BDA-AI is efficient in handling environmental data and an integral part of GSCM (Wu & Pagell, 2011). In addition, it provides insights to practitioners for enhancing GSCM (Benzidia et al., 2021; Dubey et al., 2016). Centered on this discussion, this research postulates the following hypothesis.

> H1: Big Data analytics-artificial intelligence significantly impacts green supply chain management.

BDA-AI and SCAX

Organizations need to employ ambidexterity strategies and BDA-AI technologies to scan environmental issues (Raut et al., 2019) and vigilantly improve organizational performance. Furthermore, the current market trends data can help organizations identify and execute new opportunities, impacting their ambidexterity (Ojha et al., 2018). This research employs Wamba

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et al.'s (2020) dynamic capabilities view (DCV) to facilitate the balance between exploitation and exploration strategies. Organizations following ambidexterity techniques, SCAX in specific, can have more opportunities because of their ability to re-arrange a lean supply chain based on the current market demands (Khan, Chen, Suanpong et al., 2021). Previously, it was found that the commitment of decision-makers and practitioners has an essential role in the creation of data analysis capabilities of BDA-AI. Hence, corporate commitment to implement BDA-AI can enhance the environmental capabilities of organizations (Singh & El-Kassar, 2019). Consequently, a supplier's BDA-AI can be inferred to impact the circular economy and SCAX practices (Lee & Mangalaraj, 2022). Built on the above discussion, the following hypothesis is proposed.

H2: Big Data Analytics-artificial intelligence significantly impacts supply chain ambidexterity.

SCAX and GSCM

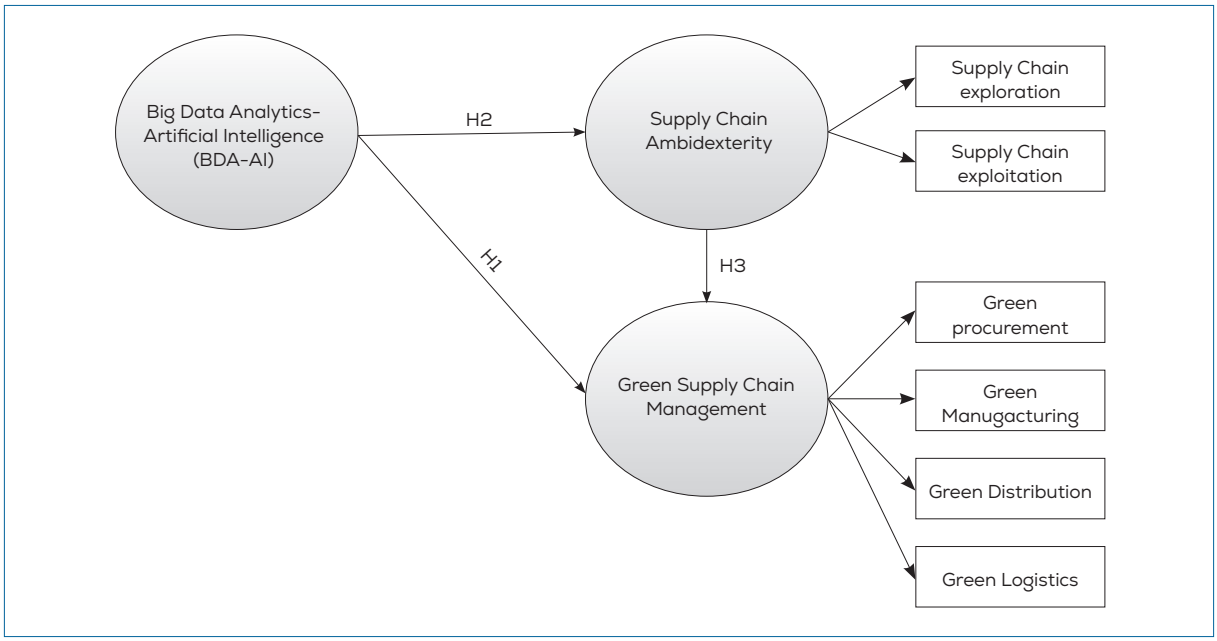
In the concept of ambidexterity, enhancing the firm's current strategies is called exploitation, whereas exploring new opportunities is called exploration (Partanen et al., 2020). Previously, firms were required to select either one of the strategies at a time (March, 1991), but currently, researchers agree to use both exploration and exploitation concurrently (Kortmann, 2015). Previous research has employed supply chains in the ambidexterity context. Hence, in SCAX, supply chain exploration (SEP) denotes the techniques of identifying novel prospects for supply chain operations, and supply chain exploitation (SET) denotes the maintenance and enhancement of the organization's current supply chain strategies (Kristal & Roth, 2010). According to research, organizations employing SCAX techniques can modify and tailor their supply chain operations to meet customer demands and increase firm performance (Lee & Rha, 2016). GSCM is designed to cover the flow of materials, capital, and information. It also ensures collaboration between the supply chain partners and employs the triple bottom line (TBL) to ensure financial, societal, and sustainability goals (Alves & Nascimento, 2014; Bui et al., 2020). Organizations use GSCM to attain sustainability goals (Oliveira et al., 2018; Vieira et al., 2021) and enhance organizational performance (Rao & Holt, 2005). SCAX can be enabled with the help of organizational performance evaluation, and hence, it can be deemed an essential factor in influencing GSCM (Birkinshaw & Gibson, 2004). Previous research found that SCAX positively influences the GSCM of organizations (Khan, Chen, Lu et al., 2021). However, the previous research provides somewhat limited information regarding the implementation of GSCM and SCAX strategies in Taiwan's manufacturing industries and this context is yet to be explored by research scholars. Hence, this study postulates the following hypothesis.

H3: Supply chain ambidexterity significantly impacts green supply chain management.

The theoretical framework is shown in Figure 1

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Figure 1. Theoretical Framework



METHODOLOGY

The research used a convenience sampling methodology and collected data from 220 employees of the Taiwanese manufacturing industry via a questionnaire. The questionnaire used a seven-point Likert scale system to identify respondents' attitudes, with 1 signifying a strong disagreement and 7 demonstrating a strong agreement. A pilot study was conducted, and data were collected from 90 employees to test the reliability of the questionnaire items. This study adopted and modified the items to measure GSCM and SCAX from research by Khan et al. (2021). In addition, the items to measure BDA-AI were modified from Benzidia et al.'s (2021) research.

Data analysis

This study used Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the data and the hypothetical relationships. PLS-SEM is popular due to its ability to analyze diverse data samples and complicated research models (Ficapal-Cusí et al., 2023; Hair, Sarstedt et al., 2016). The evaluation was executed in two stages. First, the reliability and validity of the model were measured, followed by the path analysis of the proposed hypotheses. SMARTPLS statistical software was used to conduct the data analysis (Ringle et al., 2015).

Convergent and discriminant validity

Convergent validity assesses how well two measures capture the same concept. When alternative measures lack strong convergent validity, it might create uncertainty in providing clear interpretations of research findings. This research employed Cronbach's alpha to ensure internal reliability. The reliability of the internal model was ensured based on the Cronbach alpha values. Furthermore, Average Variance Extracted (AVE) and Composite Reliability (CR) measured the convergent validity. As indicated in Table 1, the values of Cronbach alpha were higher than 0.7 (Taber, 2018), the AVEs were greater than 0.5 (Fornell & Larcker, 1981), and the values for CR were greater than 0.7 (Hulland, 1999), representing a good convergent validity.

In research with latent variables and multiple indicators, evaluating discriminant validity is crucial. The role of discriminant validity is to ensure that the constructs representing causal relationships are genuinely separate from each other. This study used cross-loadings and Fornell-Larker criteria to measure the discriminant validity. As shown in Table 2, every indicator shows an acceptable discriminant validity (highlighted in yellow in Table 2) because its value is greater than the loading values of the remaining indicators in the latent structure (Hair, Hult et al., 2016).

Table 1. Convergent Validity

Constructs	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
BDA-AI	0.955	0.961	0.712
GD	0.987	0.989	0.919
GL	0.916	0.947	0.857
GM	0.921	0.950	0.864
GP	0.954	0.965	0.845
SEP	0.884	0.920	0.743
SET	0.879	0.918	0.737

Note: BDA-AI = Big Data Analytics - Artificial Intelligence, GD = Green Distribution, GL = Green Logistics, GM = Green Manufacturing, GP = Green Procurement, SEP = Supply Chain Exploration, SET = Supply Chain Exploitation

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Table 2. Cross Loadings

Constructs	BDA-AI	GD	GL	GM	GP	SEP	SET
BDAI1	0.844	0.229	0.444	0.466	0.613	0.299	0.395
BDAI2	0.875	0.202	0.443	0.498	0.669	0.370	0.393
BDAI3	0.864	0.208	0.451	0.452	0.686	0.343	0.380
BDAI4	0.887	0.162	0.448	0.455	0.682	0.327	0.368
BDAI5	0.875	0.200	0.481	0.464	0.707	0.397	0.413
BDAI6	0.861	0.201	0.535	0.523	0.640	0.347	0.386
BDAI7	0.778	0.167	0.418	0.402	0.533	0.356	0.390
BDAI8	0.773	0.198	0.336	0.409	0.478	0.296	0.253
BDAI9	0.834	0.262	0.449	0.534	0.557	0.382	0.345
BDAI10	0.839	0.199	0.458	0.497	0.587	0.480	0.407
GD1	0.225	0.959	0.443	0.520	0.332	0.290	0.301
GD2	0.236	0.977	0.472	0.533	0.349	0.311	0.311
GD3	0.216	0.967	0.457	0.519	0.332	0.309	0.299
GD4	0.240	0.972	0.494	0.525	0.355	0.319	0.319
GD5	0.229	0.961	0.479	0.517	0.346	0.302	0.319
GD6	0.241	0.969	0.460	0.532	0.353	0.314	0.317
GD7	0.215	0.913	0.421	0.495	0.352	0.211	0.258
GD8	0.241	0.947	0.478	0.536	0.362	0.285	0.308
GL1	0.511	0.468	0.941	0.757	0.729	0.475	0.431
GL2	0.513	0.462	0.955	0.757	0.736	0.469	0.434
GL3	0.449	0.410	0.879	0.701	0.665	0.480	0.441
GM1	0.566	0.406	0.804	0.906	0.815	0.478	0.518
GM2	0.506	0.541	0.738	0.951	0.720	0.473	0.466
GM3	0.487	0.571	0.684	0.932	0.680	0.437	0.462
GP1	0.619	0.406	0.784	0.817	0.911	0.377	0.429
GP2	0.665	0.331	0.701	0.759	0.931	0.363	0.353
GP3	0.676	0.324	0.673	0.686	0.915	0.340	0.350
GP4	0.717	0.289	0.691	0.705	0.930	0.311	0.330
GP5	0.697	0.307	0.672	0.668	0.909	0.372	0.369
SEP1	0.369	0.296	0.420	0.435	0.318	0.815	0.694
SEP2	0.324	0.247	0.466	0.429	0.327	0.900	0.666
SEP3	0.388	0.267	0.525	0.437	0.363	0.891	0.678
SEP4	0.397	0.245	0.351	0.415	0.316	0.840	0.665
SET1	0.386	0.259	0.355	0.436	0.320	0.637	0.870
SET2	0.381	0.303	0.384	0.474	0.345	0.678	0.912
SET3	0.360	0.216	0.361	0.394	0.281	0.700	0.886
SET4	0.402	0.315	0.522	0.478	0.436	0.676	0.756

Note: BDA-AI = Big Data Analytics - Artificial Intelligence, GD = Green Distribution, GL = Green Logistics, GM = Green Manufacturing, GP = Green Procurement, SEP = Supply Chain Exploration, SET = Supply Chain Exploitation

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Furthermore, the Fornell-Larker criterion uses the square root of the AVEs in a diagonal structure; below the diagonal structure are the correlation coefficients, which are lower than the diagonal values, indicating good discriminant validity, as explained in Table 3.

Table 3. Fornell-Larcker Criterion

Constructs	BDA-AI	GD	GL	GM	GP	SEP	SET
BDA-AI	0.844						
GD	0.240	0.959					
GL	0.532	0.483	0.925				
GM	0.559	0.545	0.798	0.930			
GP	0.733	0.362	0.768	0.794	0.919		
SEP	0.429	0.306	0.512	0.498	0.384	0.862	
SET	0.445	0.318	0.470	0.518	0.400	0.784	0.858

Note: BDA-AI = Big Data Analytics - Artificial Intelligence, GD = Green Distribution, GL = Green Logistics, GM = Green Manufacturing, GP = Green Procurement, SEP = Supply Chain Exploration, SET = Supply Chain Exploitation

Empirical results

This study conducted the path analysis with the help of SMARTPLS statistical software. If the p-value of a proposed relationship is less than 0.05 and the t-value is greater than 2, it is accepted.

Corresponding to the research conclusions given in Table 4 and Figure 2 of the research, BDA-AI was discovered to be significantly associated with GSCM (β = 0.473, T-value = 4.406), thus accepting hypothesis 1. Moreover, BDA-AI also significantly impacted SCAX (β = 0.457, T-value = 3.757), accepting hypothesis 2. Finally, SCAX was found to be significantly associated with GSCM (β = 0.296, T-value = 2.859), consequently accepting hypothesis 3.

Table 4. Empirical Results

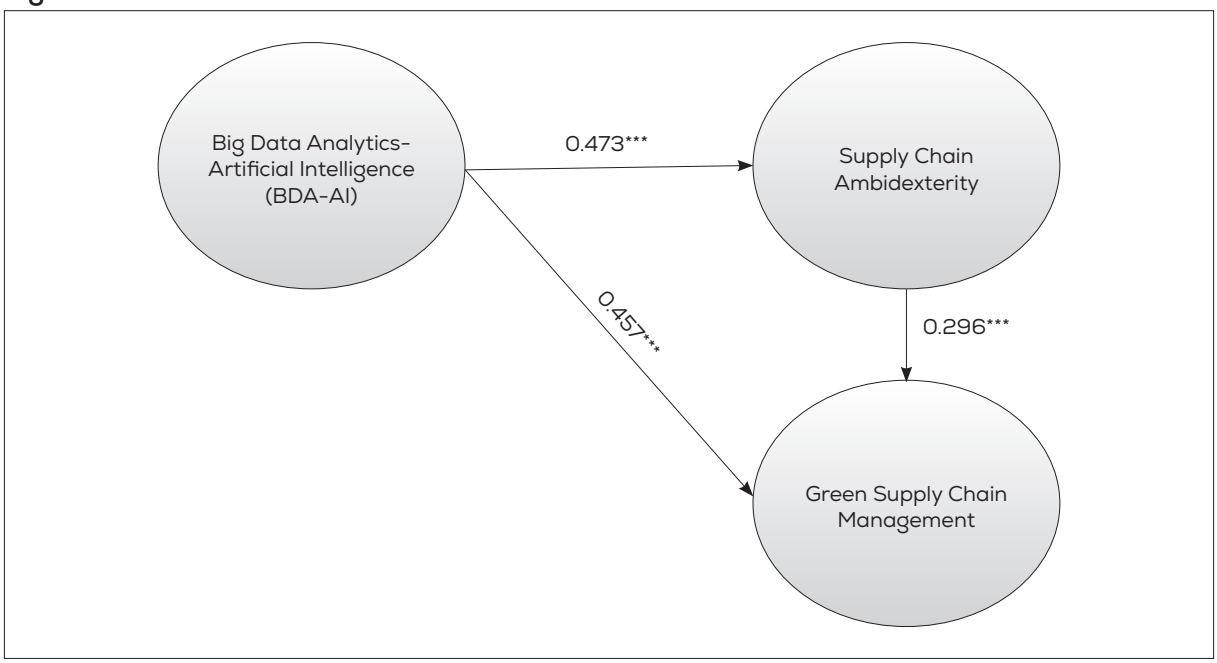
Hypotheses	Path Coefficients (M)	T values	P values
H1: BDA-AI -> GSCM	0.457	3.757	0.000
H2: BDA-AI -> SCAX	0.473	4.406	0.000
H3: SCAX -> GSCM	0.296	2.859	0.004

Note: BDA-AI = Big Data Analytics - Artificial Intelligence, SCAX = Supply Chain Ambidexterity, GSCM = Green Supply Chain Management.

Moreover, to study the indirect relationship BDA-AI -> SCAX -> GSCM, this study employed the values generated by the SMARTPLS software and activity theory by Kofod-Petersen and Cassens (2005). It was found that BDA-AI indirectly impacted GSCM (β = 0.136, T-value = 2.789) via SCAX as a mediator.

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Figure 2. Research Results



Note: * p < 0.05, ** p < 0.01, *** p < 0.001

DISCUSSIONS

Comparison with other studies

Corresponding to the outcomes of this study, BDA-AI significantly impacted SCAX. This research corroborates earlier research by Wamba et al. (2020), which provides a somewhat similar result. Wamba et al.'s (2020) paper addresses these gaps by adopting the dynamic capability view (DCV), considering the provisional impact of environmental dynamism. Utilizing 281 surveys, their research revealed that BDA positively influenced SCAX and performance metrics. Wamba et al.'s (2020) findings contributed to a theory-grounded comprehension of organizational-level BDA management and its consequences on supply chain characteristics.

Furthermore, the results of this study show that BDA-AI was significantly associated with GSCM. The findings are fairly comparable to prior research by Benzidia et al. (2021). Benzidia et al.'s (2021) study expanded the BDA-AI concept by introducing digital learning as a moderating variable within the context of the GSCM. The research framework was devised and tested using data from French hospitals. Benzidia et al.'s (2021) results revealed a significant impact of BDA-AI technologies on ecological process incorporation and GSCM. The study also emphasized the noteworthy influence of both environmental process integration and GSCM on ecological performance.

Additionally, the results show that SCAX was significantly related to GSCM. The findings are comparable to an earlier study by Khan et al. (2021). Khan et al.'s (2021) paper aimed to investigate the role of SCAX in supporting GSCM within the context of top-level management in diverse manufacturing companies based in Pakistan. Data from top-level managers from the manufacturing industries were analyzed. Khan et al.'s (2021) study results indicated a positive influence of SCAX on GSCM. However, the study revealed that networking capabilities did not have a moderating impact on the relationship between SCAX and GSCM. Khan et al.'s (2021) research focused on the unique context of manufacturing industries in Pakistan to comprehend SCAX practices and their associations with various facets of GSCM.

Finally, this paper found SCAX to mediate the association between BDA-AI and GSCM significantly. This result is somewhat comparable to an earlier study by Pertheban and Arokiasamy (2019). Pertheban and Arokiasamy's (2019) paper aimed to provide a theoretical rationale for the interplay between elements of supply chain resilience, SCAX, and corporate performance. Pertheban and Arokiasamy's (2019) paper posited that SCAX significantly mediated the association between supply chain resilience and corporate performance.

Theoretical implications of the research

This study combines the concepts of BDA-AI (Gallo et al., 2023), SCAX (Lyu et al., 2022), and GSCM (Bag et al., 2022). Using BDA-AI and SCAX strategies efficiently can ensure groundbreaking decision-making for GSCM. This research indicates that applying novel technologies like BDA-AI will improve organizational operations and performance (Benzidia et al., 2021; Bharadiya, 2023; Gallo et al., 2023). This research also agrees with establishing and maintaining a sophisticated technological structure to support collaboration among different stakeholders (Benzidia et al., 2021).

SCAX necessitates managing two conflicting approaches: exploration and exploitation. Dynamic capabilities (DC) facilitate this balance by constantly monitoring the environment for new prospects and risks while effectively utilizing current resources. Hence, this research employs and provides insights into DCV in relation to establishing connections between ambidexterity, sustainability, and the DC of a firm (Munir et al., 2023; Wamba et al., 2020). SCAX manifests through the opposing characteristics of exploration and exploitation within a company, while DC and sustainability represent different yet coexisting elements in ambidextrous organizations (Lyu et al., 2022). This study provided theoretical guidelines for cultivating dynamic capabilities in the supply chain. Furthermore, this study also emphasized that DCs are not inherent but can be enhanced through effective organizational processes. The research advocates for improving visibility, agility, and adaptability within the supply chain as key strategies for developing dynamic capabilities over the long term (Munir et al., 2023).

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The theoretical implications of the study are also crucial for advancing a responsible economy. It focuses on sustainability, ethical behavior, and societal well-being within economic paradigms. By demonstrating the positive influence of BDA-AI and SCAX on GSCM, the study highlights how cutting-edge technologies can promote environmental sustainability through operational optimization, waste reduction, and carbon footprint mitigation. Moreover, the amalgamation of BDA-AI and GSCM practices nurtures transparency, responsibility, and ethical conduct, fostering a culture of corporate social accountability. This, in effect, enhances societal welfare by tackling societal dilemmas, enhancing living standards, and promoting equitable progress. Consequently, the research underscores the transformative capacity of BDA-AI and SCAX in shaping a responsible economy prioritizing sustainability, ethical behavior, and societal well-being.

Practical implications of the research

The conclusions of this study have significant practical implications for practitioners, managers, and policymakers engaged in the realms of BDA-AI and GSCM. For practitioners in the business domain, the findings highlight the tangible benefits of incorporating BDA-AI technologies into supply chain processes. Organizations can enhance their sustainability initiatives by leveraging these advanced technologies, ensuring a competitive edge in dynamic markets (Mugoni et al., 2023). Managers stand to gain comprehension of the pivotal function of SCAX as a mediating construct, guiding them in crafting strategies that synergize technological advancements with sustainable supply chain practices (Lyu et al., 2022). Policymakers, in turn, are informed about the transformative potential of fostering an environment conducive to incorporating BDA-AI in supply chain operations, contributing to broader sustainability objectives (Gallo et al., 2023; Lee & Mangalaraj, 2022). Practitioners, managers, and policymakers can collectively foster more resilient, adaptive, and environmentally conscious supply chain ecosystems by aligning technological investments with supply chain ambidexterity.

Practitioners are further recommended to employ BDA-AI technologies to proactively search, engage, and implement GSCM activities based on the company's sustainability goals. Furthermore, BDA-AI measurement techniques should be efficiently employed to get a complete picture of sustainability issues and gain a better understanding of how to tackle environmental concerns (Benzidia et al., 2021). This research demonstrates the importance of planning SCAX strategies to effectively monitor current market opportunities and maintain existing GSCM practices to stay competitive in the dynamic environment.

The study's practical implications regarding a responsible economy are extensive. They indicate that businesses can employ BDA-AI to improve supply chain sustainability, fostering transparency and ethical conduct. BDA-AI integration with GSCM practices encourages corporate social responsibility and stakeholder involvement. Collaboration among businesses, policymakers, and stakeholders is vital for innovative policy development and regulatory frameworks promoting sustainability. Embracing these approaches enables organizations to

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contribute to a responsible economy, prioritizing environmental responsibility and social welfare for a sustainable future.

The Responsible Economy, as envisaged within this study, necessitates a conscientious fusion of economic pursuits with ecological sustainability and societal well-being (Lima & Júnior, 2014). As businesses increasingly align their operations with the principles of a Responsible Economy, understanding and harnessing the synergies between advanced technologies and supply chain structures become imperative (Alves & Nascimento, 2014). Ultimately, our research contributes valuable insights to the discourse on fostering responsible economic practices. Embracing the tenets of a Responsible Economy is not merely an ethical imperative but a strategic choice that aligns economic growth with societal and environmental well-being, ensuring a harmonious trajectory for future endeavors.

Policy-makers implications of the research

The study's outcomes carry substantial implications for policymakers and governmental bodies shaping economic and environmental regulations. Initially, policymakers can use the study's findings to advocate for adoption of BDA-AI technology in supply chains, fostering enhanced efficiency, innovation, and environmental sustainability. Subsequently, policymakers can integrate SCAX principles into policy frameworks, encouraging businesses to embrace adaptable strategies promoting both innovation and efficiency. Moreover, policymakers can craft incentives and regulations incentivizing GSCM, such as tax breaks for green practices and BDA-AI investments. Additionally, collaboration with industry stakeholders can facilitate the development of standards for BDA-AI and GSCM, fostering research initiatives and knowledge-sharing platforms to drive responsible economic transitions.

Limitations and future research directions

This investigation focuses on the effect of BDA-AI and GSCM. However, this research avoids measuring the factors influencing BDA-AI in the GSCM context. Hence, to gain more insights, future researchers are recommended to identify and model the antecedents impacting BDA-AI in the GSCM context. This study treated SCA as a single construct and failed to measure the distinct effects of SET and SEP. Hence, future researchers are recommended to treat SEP and SET as two constructs to measure the differential effects and gain further understanding regarding the associations of SCAX.

Furthermore, this study only focused on the Taiwanese manufacturing industry sector. Since Taiwan is considered a developing economy, the findings cannot be generalized to a developed economy. Hence, future researchers can conduct this study in a developed economy and compare the results of both studies. Moreover, this study used cross-sectional data to conduct the analysis. Hence, the study failed to provide insights regarding changes in data over time. Consequently, future researchers are encouraged to collect longitudinal data to observe changes over time.

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CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare.

AUTHORS' CONTRIBUTION

Shanshan Wang: Conceptualization; Writing – original draft; Writing – proofreading, and editing.

Chenge Jia: Conceptualization; Writing – original draft; Writing – proofreading, and editing.

Asif Khan: Conceptualization; Formal analysis; Methodology; Writing – original draft; Writing – proofreading, and editing.

Naila Habib Khan: Conceptualization; Writing – original draft; Writing – proofreading, and editing.

Chia-Hung Hsieh: Conceptualization; Writing – original draft; Writing – proofreading, and editing.

Chung-Wen Hung: Conceptualization; Writing – original draft; Writing – proofreading, and editing.

Shih-Chih Chen: Conceptualization; Writing – original draft; Writing – proofreading, and editing.