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Generative AI-Driven Supply Chain Digital Innovation: Enabling Integration, Resilience, and Sustainable Business Value Creation

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ABSTRACT

In today's volatile, uncertain, complex, and ambiguous (VUCA) business environment, organizations face mounting pressure to develop agile and resilient supply chains capable of withstanding increasingly frequent disruptions. At the same time, sustainability has evolved into a strategic necessity, requiring firms to balance competitiveness with economic, social, and environmental responsibility. Against this backdrop, Generative-Artificial Intelligence (GAI) has emerged as a transformative digital capability with the potential to drive innovation, strengthen integration, enhance resilience, and support sustainable value creation. Despite growing interest, empirical evidence examining the multi-dimensional effects of GAI within emerging economy supply chains remains limited. Responding to this gap, this study investigates how GAI-enabled digital innovation shapes supply chain integration and resilience in Malaysian manufacturing firms. The analysis is grounded in the resource-based view, positioning GAI as a valuable, rare, and hard-to-imitate resource that facilitates the development of integrated digital capabilities. Complementing this, dynamic capabilities theory frames GAI as an enabler that allows firms to sense, seize, and reconfigure operational processes in response to disruptions, thereby enhancing resilience and long-term sustainability. Data was collected through structured surveys and analyzed using Partial-Least Squares Structural-Equation-Modeling (PLS-SEM). The findings reveal both direct and mediated pathways through which GAI contributes to sustainable business value. Specifically, GAI advances digital innovation, which subsequently strengthens integration and resilience capabilities centrally to navigating disruptions and achieving sustainable outcomes. This study offers one of the earliest empirical examinations integrating GAI, digital innovation, supply chain integration, resilience, and sustainability, providing actionable insights for practitioners, policymakers, and technology providers operating within resource-constrained contexts.

1 | Introduction

Global businesses have encountered unprecedented challenges ever since the emergence of the COVID-19 pandemic in 2020 (Forliano et al. 2023; Ivanov 2021a). This includes disruptions in supply chains, demand fluctuations, and challenges in recovering production operations, and so on (Chen et al. 2025; Zamani et al. 2023). Consequently, these changing and uncertain characteristics of global marketplaces have demonstrated vulnerabilities in supply chains, and developing resilience has emerged as an essential concern for industries globally (Ozdemir et al. 2022). To overcome these challenges posed by disruptions, businesses

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are required to redesign their operations, processes, and supply chain activities to effectively manage them (Forliano et al. 2023). Supply chain resilience is acknowledged as a response to protect against disruptions and minimize vulnerabilities within the supply chain and recover from such disruptions while maintaining operational perpetuity at the required levels (Zamani et al. 2023; Ponomarov and Holcomb 2009). Developing resilience requires innovative, collaborative, and multifaceted strategies to create meaningful solutions (Dubey et al. 2024; Ivanov 2021b). For example, http://jd.com, through increased collaboration, sharing of information, and agility through its digital intelligence, enhanced its resilience, resulting in a 20.7% year-on-year sales growth in Q1 2020. This suggests that disruptions in the supply chain demand novel tools and innovative technologies to improve resilience (Chen et al. 2025). Generative AI has presented significant potential as a tool in contemporary supply chain management, which offers distinctive opportunities to address complexities in supply chain and fosters sustainable value creation (SBVC) (Li, Zhu, et al. 2024).

Generative AI (GAI) encompasses technologies that can produce new data and scenarios, offering significant potential to enhance supply chain operations through its predictive capabilities, data analysis, and simulating diverse scenarios (Wamba et al. 2024). Furthermore, GAI has the potential to analyze extensive personalized data and market dynamics, assisting firms in developing tailored and adaptable supply chain strategies (Jackson et al. 2024; Kar et al. 2023). By using generative capabilities to simulate demand fluctuations and optimize sourcing strategies, many organizations have begun employing GAI to examine the extensive distributed data assets, enabling businesses to make well-informed decisions more efficiently with greater accuracy (Kar et al. 2023). Amazon and Walmart have heavily invested in GAI to support demand forecasting, outsourcing, and automated vendor negotiations (Pearlson et al. 2024). Amazon also employs AI to optimize delivery efficiency. Manufacturing giants such as P&G, Toyota, and Volkswagen, as well as many SMEs, are leveraging GAI to drive product innovation, reduce waste, improve customer service, while also enhancing supply chain visibility and resilience (Norton 2024; Dubey et al. 2024; Wang and Zhang 2024). Even the shipping sector, with companies like Maersk, is moving toward integrating GAI into core operations (CNBC 2023).

Drawing from the real-world examples mentioned earlier, the integration of GAI into supply chain allows organizations to promote innovation and integration by offering intelligent adaptive and data-driven processes across supply chain functions (Ochieng et al. 2024). GAI systems can analyze complex supply chain scenarios, propose alternative solutions, and offer decision support that goes beyond the limitations of traditional analytical methods (Wang et al. 2023). These advanced capabilities empower organizations to undertake more ambitious digital innovation efforts, such as building autonomous SC networks, deploying intelligent procurement systems, and developing adaptive logistics platforms that can dynamically adjust to evolving market conditions (Singh, Hughes, et al. 2026; Jackson et al. 2024). For example, Siemens has introduced its Industrial Copilot, a generative AI-based solution that supports engineering, production, maintenance, and operational decision-making across manufacturing environments, enabling improved productivity, predictive maintenance, and process optimization (Siemens 2023). Similarly, manufacturers are increasingly utilizing AI-based systems for predictive maintenance, production scheduling, and supplier risk monitoring, enabling more proactive and data-driven supply chain management.

Likewise, GAI usage acts as key enablers of supply chain integration (SCI) by promoting seamless information exchange, harmonizing communication protocols, and establishing unified platforms for cross-functional collaboration among geographically dispersed partners (Li, Liu, et al. 2024). By integrating GAI, organizations can achieve exceptional levels of internal integration across the supply chain operations while also enhancing external integration with suppliers, distributors, and customers through intelligent data sharing and collaborative decision-making platforms (Singh, Hughes, et al. 2026). The GAI-driven SCI also improves forecasting accuracy, optimized stock management, and improved supplier relationships with more sophisticated risk assessment capabilities (Li, Liu, et al. 2024). Therefore, companies increasingly employ AI-assisted collaboration platforms to improve coordination among suppliers, logistics providers, and production facilities, allowing faster responses to disruptions and changing customer demands. In addition, the integration between entities improves supply chain capability to predict and respond to changes and accommodate disruptions proactively (Piprani et al. 2020; Schoenherr and Swink 2012), which ultimately leads to long-term sustainable value creation (Li, Zhu, et al. 2024; Wamba et al. 2025).

It is notable that despite the significant growth in artificial intelligence in the supply chain context (Mukhuty et al. 2025), scholarly attention has predominantly focused on traditional AI applications, while the strategic and transformational role of GAI remains relatively underexplored. Recent studies demonstrate that GAI can improve organizational performance, enhance innovation, support decision-making, and contribute to sustainability objectives (Li, Zhu, et al. 2024; Wang and Zhang 2024; Modgil et al. 2025). For example, firms are increasingly using GAI for demand forecasting, risk assessment, knowledge generation, supplier collaboration, and process automation, enabling faster and more informed decision-making across supply chains. Despite these advances, our understanding of how GAI creates broader business value within supply chain ecosystems remains limited. As summarized in Table A1, several important gaps remain in the current literature. First, prior studies largely investigate innovation, performance, and sustainability outcomes independently, providing limited understanding of how these outcomes are interconnected within supply chain contexts (Li, Zhu, et al. 2024; Wang and Zhang 2024; Modgil et al. 2025). Second, although SC resilience has emerged as a strategic priority in response to increasing disruptions, geopolitical uncertainty, and climate-related risks, insufficient empirical evidence exists regarding how GAI enhances resilience through SCDI and SCI (Dubey et al. 2024; Kar et al. 2023). Third, most empirical evidence is concentrated in developed economies, leaving limited insight into how these relationships operate in emerging economies characterized by institutional constraints, resource limitations, and varying levels of digital maturity (Jackson et al. 2024). Consequently, the mechanisms through which GAI translates into SBVC remain insufficiently understood.

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To address these gaps, this study draws upon the resource-based and dynamic capability view to develop and empirically test an integrated framework linking GAI adoption, SCDI, SCI, SC resilience and sustainable business value creation. Unlike previous studies that primarily examine innovation, sustainability, resilience, or performance outcomes separately, the proposed framework explains how GAI-driven capabilities jointly contribute to economic, environmental, and social value through enhanced supply chain resilience. More specifically, the framework positions GAI as a higher-order technological capability that stimulates digital innovation and strengthens supply chain integration, which subsequently enhances resilience and supports sustainable business value creation. In doing so, the study advances existing knowledge by examining the mediating roles of SCDI and SCI as critical pathways through which GAI capabilities strengthen SCR and ultimately contribute to SBVC (Dubey et al. 2024; Li, Zhu, et al. 2024; Wang and Zhang 2024; Kar et al. 2023; Jackson et al. 2024).

Research gaps are particularly evident in emerging economies, making Malaysia a highly relevant context for investigation. As a key ASEAN economy and one of the fastest-growing countries in the region, Malaysia is actively transitioning toward Industry 4.0 through national initiatives such as Industry4WRD, which promote the adoption of advanced digital technologies, including GAI. The manufacturing sector plays a central role in Malaysia's economic development, contributing approximately 23% to GDP and serving as a major driver of exports, thereby underpinning the country's upper-middle-income status (Statista 2023a; Zhang and Mia 2023). However, the rapid transition from an agro-based to a manufacturing-driven economy has also intensified environmental concerns, including increased waste generation and resource pressures. At the same time, Malaysian manufacturing firms face uneven levels of digital maturity, as well as resource and capability constraints that hinder the effective deployment of advanced technologies across supply chain partners (Nazir et al. 2025). These characteristics position Malaysia as a representative case of emerging economies where firms are actively embracing digital technologies, but where adoption remains fragmented and inconsistently operationalized across sectors. Consequently, examining this context offers valuable insights that can be generalized to other Southeast Asian countries and similar developing economies. Against this backdrop, it becomes crucial to investigate how GAI-driven supply chain digital innovation and SCI can enhance SCR while simultaneously supporting sustainability objectives.

In doing so, this study contributes to literature in three important ways. First, it advances the emerging Generative AI literature by developing an integrated framework that connects GAI adoption, supply chain digital innovation, supply chain integration, supply chain resilience, and sustainable business value creation. Second, it extends RBV and DCT by explaining how GAI functions as a strategic and dynamic capability that enables firms to build resilience and create sustainable value. Third, by focusing on Malaysian manufacturing firms, the study provides empirical evidence from an emerging economy context, where such research remains limited. The remainder of the paper is structured as follows: in Section 2 background of the study is outlined. Section 3 presents the research design, while Section 4 presents the study's findings. Section 5 presents a discussion that indicates implications for both theory and practice. Finally, in Section 6, the contribution of this research, limitations, and future research work is presented.

2 | Theoretical Background and Hypotheses Development

2.1 | Theoretical Background

The study grounds its theoretical foundation in an integration of the Resource-Based View (RBV) and Dynamic Capabilities to explore GAI as a strategic and dynamic resource that enables unique competencies necessary to build an integrated and resilient supply chain capable of sustainable business value creation (SBVC). RBV theory suggests that competitive advantage is achieved by cultivating internal resources that are valuable, rare, and difficult to imitate (Barney 1991). In the context of this study, GAI is perceived as a strategic resource by offering novel opportunities for innovation and delivering unique stakeholder value through reimagined approaches to supply chain design and coordination. Building on this foundation, it is arguable that the effective deployment of GAI requires firm-specific capabilities that are non-transferable and resistant to substitution. As GAI reshapes external environments across industries (Mukhuty et al. 2025), it generates both opportunities and disruptions, increasing operational speed and precision while challenging traditional roles and structures. Thereby aligning with RBV theory, cultivating GAI capabilities is likely to enhance value creation in a dynamic business environment. While being a resource, however, GAI is also a dynamic phenomenon in terms of models, costs, risks, and regulations. Thus, leading to changes in the firm's external stakeholder environment like competitive baselines, and requiring internal transformations to harness GAI potential in a manner that yields SBVC. Therefore, considering GAI only through the lens of resource-based view is not sufficient. It is important to evaluate the synergistic underpinning of RBV theory with Dynamic Capabilities Theory (Teece et al. 1997), as DCT stresses the firm's capability to reconfigure resources in response to market turbulence, and shifts in technological influences and business ecosystems (Teece 2007; Eisenhardt and Martin 2000). This theoretical synthesis offers a robust lens for understanding the evolving pathways of GAI adoption. Dynamic capabilities, as proposed by Teece (2007), are critical for staying competitive by adopting and reconfiguring in a fast changing environment and responding to market turbulence (Eisenhardt and Martin 2000). The GAI resource facilitates the development of dynamic capabilities to face business challenges (Kurrahman et al. 2026). Far from being a mere technological tool, GAI is recognized to have the potential to act as a catalytic resource for fundamental shifts in organizational value creation (Bitetti et al. 2026; Sánchez 2025), driving business model innovation (Modgil et al. 2025) and advancing sustainability goals (Alsaadi et al. 2026; Wang and Zhang 2024; Li, Liu, et al. 2024).

Supply Chain Digital Innovation leverages emerging technologies to transform conventional supply chain models (Tsolakis et al. 2023). Since supply chains are expected to deliver greater speed and customization while also managing disruptions from both natural and human-induced events (Chowdhury and Quaddus 2017), building supply chain resilience has become

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a critical organizational capability (Piprani et al. 2024). In this environment, supply chain resilience has become a critical organizational capability to manage risks, absorb shocks, and adapt swiftly (Ivanov 2024). Taken together, these perspectives underscore GAI's dual role as both an enabler of innovation and a source of disruption. From an RBV standpoint, GAI adoption fosters the creation of valuable, inimitable resources that drive digital supply chain innovation and resilience. However, realizing this potential depends on effective supply chain integration both internally across organizational functions (Basnet 2013) and externally among supply chain partners and customers (Kim and Chai 2016; Le et al. 2024). The convergence of these theoretical perspectives illustrates how GAI, as both a strategic resource and dynamic capability, can transform supply chain operations to deliver sustainable business value (Li, Zhu, et al. 2024) while balancing economic performance, environmental responsibility, and social impact (Laukkanen and Tura 2020).

The GAI has recently gained traction across diverse organizational settings. As summarized in Table A1, contemporary studies highlight its wide-ranging impact on innovation, operational performance, and sustainable initiatives. Far from being a mere technological tool, GAI acts as a catalyst for fundamental shifts in organizational value creation (Bitetti et al. 2026; Sánchez 2025), driving business model innovation (Modgil et al. 2025) and advancing sustainability goals (Wang and Zhang 2024; Li, Liu, et al. 2024). These insights are drawn from diverse methodologies, including PLS-SEM and the Gioia method, reflecting the multifaceted ways GAI generates value. Despite these advances, key research gaps persist, particularly in understanding GAI's role in enhancing supply chain resilience amid market volatility. For example, while Li, Liu, et al. (2024) address sustainability in supply chains, they do not fully explore how GAI mitigates disruption risks or enhances adaptive capacity in complex, global networks. Additionally, little is known about how GAI integrates with existing organizational capabilities to co-create sustainable value beyond environmental metrics, especially in relation to social impact and long-term economic viability. Most studies also adopt a firm-centric view, overlooking the ecosystem-level interactions critical for understanding value creation across supply chain partners. Table A1 consolidates recent empirical findings on GAI's organizational impact, while highlighting these critical gaps thus framing the agenda for this research.

2.2 | Hypotheses Development

2.2.1 | GAI Influence on SC Digital Innovation and SC Integration

GAI has emerged as a vital tool for businesses (Bitetti et al. 2026). It appears to be transforming how we interact with each other and with machines (Akhtar et al. 2024). At its core, it is based on generative adversarial networks (GANs), a machine learning technology that competes with two neural networks to produce novel, distinctive outputs (Dash et al. 2022). Thereby, GAI creates new and unique content at a high level of speed and sophistication, suggesting that it has the potential to completely transform a wide business sector. GAI uses machine learning and innovative deep learning technologies (Hirn et al. 2022) to process and analyze huge amounts of data intelligently. This facilitates creating new material or predicting future trends (Jovanovic and Campbell 2022). In comparison to traditional IT, GAI offers distinctive benefits, such as creating ideas or solutions that go beyond human comprehension while also facilitating innovation (Jackson et al. 2024; Li, Liu, et al. 2024). Here the innovation refers to the use of new technologies and tools to design and improve business processes and operations and respond to market (Chatterjee et al. 2023). Herein, aligning with the RBV theoretical perspective, GAI usage potentially enables sharing and coordination of information and activities across various partners in a heterogenous manner, which would be complex and challenging to imitate (Barney 1991). Digital innovations facilitated by GAI arguably enable new technology implementation potentially contributing toward improved supply chain integration necessary to dynamic challenges (Ivanov 2021b; Dubey et al. 2020; Zhao et al. 2023). Grounding this understanding in DCT emphasizing continuous reconfiguration to keep with changing environmental needs, it is arguable that through the implementation of GAI supply chains are not only likely to be prepared for innovations but would also be perpetually integrated entities across supply chain, leading to the development of the following hypotheses:

Hypothesis 1a. *Gen AI positively influences SC digital innovation.*

Hypothesis 1b. *Gen AI positively influences SC integration.*

2.2.2 | SC Digital Innovation and SC Resilience

The integration of structured and unstructured insights can transform the supply chain by creating new products and services and innovative business models. Christopher and Peck (2004), in their influential article, extolled the importance of agility, collaboration, and designing in risk mitigation for SC resilience (SCR). Through the adoption of digital innovations, companies can improve operational efficiencies and identify problems early using real-time supply chain monitoring and data analysis tools (Eller et al. 2020). This has also been shown to increase supply chain transparency, encouraging efficient resource allocation and boosting the chain's overall effectiveness (Carvalho and Ivanov 2024). Latest digital innovations like blockchain, AI, tracking and tracing capabilities have also contributed toward improving organizational resilience (Velyako and Musa 2024), enabling organizations to forecast, plan, and prepare ahead of unforeseen scenarios. Thus, as per RBV, digital innovation can reasonably be viewed as the firm-specific capability influencing stronger operational processes. Similarly, as per DCT, digital innovation would have the potential to enhance resilience by digitally pre-empting disruptions and environmental challenges and reconfiguring operations. Herein, investing in these digital innovation capabilities embodies high potential to build in early risk detection, agility, collaboration, and overcome vulnerabilities as advocated by early proponents like Christopher and Peck (2004) and Sheffi (2005). Simultaneously, digital innovation has the potential to build SC resilience by helping balance SC vulnerabilities with capabilities, advocated more recently by Piprani et al. (2025). Furthermore, these digital innovations can also enable firms to recover and either restore operations to their previous position or advance toward an even more optimal and resilient business position after the disruption (Chowdhury and

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Quaddus 2017; Ponomarov and Holcomb 2009). Therefore, the significant role of digital innovations in enhancing resilience in the supply chain leads to the development of the following hypothesis:

Hypothesis 2. *SC Digital Innovation positively influences the SC Resilience.*

2.2.3 | SC Integration and SC Resilience

Supply chain integration (SCI) refers to collaboration within and between supply chain entities to improve their combined performance in the development, marketing, and maintenance of a final product by employing management strategies (Burke et al. 2023). The studies have shown that integration among all tiers of supply chain leads to internal and external operations effectiveness (Basnet 2013), seamless information flow (Kim and Chai 2016), maximizes customer value creation (Ralston et al. 2015), and enhances operational excellence and supply resilience (Le et al. 2024). Furthermore, according to Piprani et al. (2025) and Jiang et al. (2024), when information from upstream and downstream is effectively integrated, it is more efficient and trustworthy and minimizes the likelihood of information distortion and delays in the delivery of information. Instead of working in silos, integration helps promote partnerships, trust, information sharing, cooperation, and collaboration, which is a fundamental shift from the traditional way of managing supply chain activities (Ponomarov and Holcomb 2009). Through RBV, SCI could be a valuable, challenging to replicate capability enhancing information coordination efforts, while based on DCT, SCI facilitates rapid and integrative reshaping of resources to adaptively respond to and recover from disruptions to supply chains. Therefore, the level of integration will have a direct effect on operational performance and provide an opportunity to make supply chain more productive and resilient. Thus, integration could enable building a resilient supply chain when different entities in a supply chain collaborate and plan for unforeseen events through crucial information sharing practices. Therefore, this leads to the development of the following hypothesis:

Hypothesis 3. *SC integration positively influences the SCR.*

2.2.4 | GAI Influence on SC Resilience and SBVC

GAI assists organizations in functions like demand forecasting, materials planning, transportation planning, and real-time tracking of supply chain metrics (Dubey et al. 2020). It is also redefining supply chain resilience by transforming how risks are identified and mitigated across multiple dimensions (Jackson et al. 2024) and emerged as a transformative force in SC resilience (Xia et al. 2026). Leveraging insights from historical disruptions and real-time operational data, GAI facilitates a shift from reactive to proactive supply chain risk management, developing a dynamic, resilient system to counter risks and challenges (Riad et al. 2024) eventually optimizing the processes and promoting the project's resilience and success (Ahmed et al. 2025). This adaptive capability of artificial intelligence empowers organizations to design contingency plans that address both established vulnerabilities and emerging ones, and previously undetected threats, ultimately helping develop resilient supply chains (Beta et al. 2025). Likewise, GAI, through leveraging its technologies, has shown potential to shift in how businesses create sustainable value and compete in the marketplace (Malhotra and Manzoor 2026; Maghroor et al. 2025). GAI grants businesses access to advanced tools for customer insight, product innovation, and operational efficiency while also creating sustainable value (Wang and Zhang 2025). This access empowers businesses to develop innovative, sustainable business models and deliver unique value propositions that were previously not available in conventional business settings (Rajaram and Tinguely 2024). Through the RBV lens, GAI can be viewed as a strategic resource, critical to analytical functions, decision-making and operational insights. Similarly, the DCT perspective underscores unique GAI capabilities to facilitate appropriate responses which are transformative and thereby heighten resilience and SBVC. Therefore, the following hypotheses are being proposed:

Hypothesis 4a. *GAI positively influences the SC Resilience.*

Hypothesis 4b. *GAI positively influences sustainable business value creation.*

2.2.5 | SC Resilience and SBVC

Supply chain resilience enables businesses to swiftly respond to market dynamics and associated environmental changes while minimizing the negative impacts and promoting sustainability (Ponomarov and Holcomb 2009). Underpinned by the RBV, SCR is classified as a crucial organizational capability to protect and maneuver the firm's resources during disruptions to supply chains. In addition, DCT helps underline the innovative capabilities of SCR to reallocate and reshape operations, ultimately leading to economic, environmental, and social value in the long term. Resilient firms have the potential for sustainable value creation due to their ability to absorb disruptions and react and resume their previous operations or even improve performance following a disruption (Li, Zhu, et al. 2024; Chowdhury and Quaddus 2017; Cui et al. 2022). Conversely, a resilient supply chain not only endures interruptions but also acts as a strategic facilitator of sustainable business value, promoting steady growth, operational efficiency, and environmental sustainability (Nazir et al. 2026). By proactively identifying and dealing with risks, resilient supply chains decrease waste, optimize resource utilization, and minimize disruptions, thereby preventing financial losses and environmental harm. Therefore, this leads to the development of the following hypothesis:

Hypothesis 5. *SC Resilience directly influence the sustainable value creation.*

2.2.6 | Mediating Role of Supply Chain Resilience

The growing level of uncertainty and complexity in global supply chains necessitates the implementation of advanced technologies and strategic integration to improve operational efficiency, resilience and sustainability (Chen et al. 2025; Zhao et al. 2023). Herein, adopting the RBV lens, digital innovation, integration, and GAI can be perceived as crucial resources for value creation, however these are more effective in generating value through the mechanism of SC resilience. Furthermore, DCT helps clarifies the role of SCR as the phenomenon helping translate the input of the aforementioned resources into sustained business

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value creation. A resilient supply chain fosters cooperation, risk-sharing, and collaborative decision-making through a seamless coordination of data, processes, and resources among supply chain partners, thereby promoting resilience and business value creation (Ponomarov and Holcomb 2009; Jiang et al. 2024; Burke et al. 2023). It also promotes agility, enabling businesses to mitigate risks and improve performance under uncertain conditions (Chen et al. 2025; Zhao et al. 2023). It achieves this by implementing digital innovations and GAI to improve operational efficiency, resilience, and sustainability. Furthermore, according to prior studies, Maghroor et al. (2024), Zamani et al. (2023), Dey et al. (2023), suggest that organizations can improve their supply chain resilience by integrating digital innovations that utilize AI-enabled technologies within their business operations. By enabling autonomous, intelligent, and adaptable operations, GAI can speed up the digital transformation of supply chain management (Boone et al. 2025). Nevertheless, the advent of generative AI has the potential to proactively identify risks, optimizing decision making, and improves operational excellency (Wang and Zhang 2024). It helps organizations to prepare for possible disruptions by analyzing past data, current market trends, and happenings in real-time through predictive analytics. Additionally, the implementation of GAI significantly improves visibility, evaluates supplier risks, and ensures alternative sourcing options (Jackson et al. 2024; Kar et al. 2023). This resilience allows firms to cope with disruptions and embrace continuity, thereby ensuring the creation of sustainable business value. By enhancing operational efficiency, lowering vulnerability, and developing long-term competitiveness in the supply chain, the resilience acts as a dynamic resource that reinforces the connection between these enablers and maintains consistency in business value creation. Therefore, this mediating role of supply chain resilience, through which supply chain digital innovation, supply chain integration, and generative AI usage contribute to sustainable business value, leads to the development of the following hypothesis:

Hypothesis 6a. *SC resilience mediates the relationship between SC Digital innovation and SBVC.*

Hypothesis 6b. *SC resilience mediates the relationship between SC integration and SBVC.*

Hypothesis 6c. *SC resilience mediates the relationship between GAI and SBVC.*

2.2.7 | Mediating Role of SC Digital Innovation

Supply chain digital innovation (SCDI) involves the incorporation of advanced digital technologies to improve efficiency, agility, and resilience of supply chains. Digital technological innovation can crucially assist businesses in identifying and locating risks, proposing alternative solutions, increasing supply chain responsiveness, decreasing operational risks, and boosting overall efficiency (Ivanov 2021b). Furthermore, SCDI can reasonably serve as a link between AI-driven capabilities and real supply chain improvements. Digital innovation, such as AI and GAI, can have a profound influence on supply chain performance improvement (Jackson et al. 2024; Chatterjee et al. 2023; Jovanovic and Campbell 2022). Herein, based on the RBV, it can be argued that GAI is a core resource for enhanced SC resilience. Thus, DCT helps us argue that SC digital innovation can act as an intricate mechanism to transform GAI capabilities leading to reconfiguration and adaptability in supply chains, ultimately enhancing resilience. Thus, by incorporating digital innovations, businesses can potentially improve supply chain resilience through the adoption of GAI technologies, which can help make informed decisions, foster increased collaboration, and achieve greater resilience (Chen et al. 2021). Digital innovation in the supply chain is vital for making sure that advancements steered by GAI in turn lead to strategies that enhance resilience. SCDI, through its enabling technologies, mediates the relationship between GAI and resilience. Thus, this leads to the development of the following hypothesis:

Hypothesis 7. *SC digital innovation mediates the relationship between GAI and SC resilience.*

2.2.8 | Mediating Role of SC Integration

Rahman et al. (2026) suggest that integration is the key mechanism through which digitalization translates into operational adaptability. Aligned with RBV, arguably GAI is a critical resource to facilitate SC resilience; however, underlined by DCT, this study recognizes that SC integration is imperative in harnessing and coordinating GAI led foresights along SC stakeholders to transform technological promise into reconfigured and resilient supply chains. GAI usage and SCI function as complementary enablers that, when effectively aligned, form robust mechanisms for enhancing organizational adaptability and performance (Li, Liu, et al. 2024; Li, Zhu, et al. 2024). Therefore, it is imperative that innovative technological implementations must be supported by suitable organizational structures to deliver performance improvements. Chesley and D'Avella (2020) urged that information processing capabilities contribute to resilience only when embedded within collaborative inter-organizational processes. These theoretical insights suggest that GAI's advanced predictive and prescriptive capabilities may be underexploited in the absence of integration mechanisms that enable cross-boundary information sharing, joint decision-making, and coordinated execution. Supply chain integration plays a key role in mediating the impact of GAI on supply chain resilience. While GAI enhances automation, prediction, and decision-making, its effectiveness depends on how well supply chain processes are integrated. Internal integration improves coordination and efficiency through GAI-driven operations (Li, Liu, et al. 2024; Maghroor et al. 2024). Supplier integration supports long-term collaboration and risk management via GAI analytics (Dwivedi et al. 2025). Customer integration enables firms to align GAI-powered demand forecasting with customer needs, boosting responsiveness and resilience (Cui et al. 2022; Wong et al. 2011). Overall, strong integration enhances consistency, coordination, and resilience across the supply chain (Sadia et al. 2024). Therefore, this leads to the development of following hypothesis:

Hypothesis 8. *SC Integration mediates the relationship between GAI and SC Resilience.*

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3 | Research Method

3.1 | Sample and Data Collection

This research investigates the adoption and impacts of Generative AI technologies across Malaysia's medium to large-scale manufacturing sector, focusing on the economically vibrant Klang Valley region, where a high concentration of manufacturing activities plays a crucial role in national economic contributions. The study employed a non-probability sampling technique, as the study focuses on a highly emergent phenomenon, the use of generative AI, for which no established sampling frame exists. Firms that effectively use generative AI in their operations remain relatively few and difficult to reach directly; thus, in such contexts, snowball sampling is considered a practical and accepted sampling technique, especially for technology application research. The study sampled firms affiliated with the Federation of Malaysian Manufacturers (FMM), targeting enterprises with over 100 full-time employees to ensure data reflected the medium to large-scale manufacturing firms. Data collection, conducted from October 2024 to December 2024 via online surveys, employed Google Forms, and the questionnaire link was disseminated through emails. The survey adhered to rigorous empirical research methodologies, with an emphasis on structural equation modeling (SEM) for data analysis. The required sample size was established using G*Power software, considering a medium effect size, an alpha significance level of 0.05, and a power of 0.95, resulting in a minimum necessary sample size of 119, though 173 responses were obtained.

3.2 | Instrument Development

The survey was developed following an extensive literature review to ensure the validity and reliability of the tools used. Pre-testing involved detailed evaluations by academic experts and industry practitioners who assessed the survey questions for their face and content validity. Drawn from the feedback, we fine-tuned the questions, retaining only those that precisely reflected contemporary practices and accurately measured the intended constructs. The pilot study of this refined questionnaire yielded results that were both reliable and valid, adhering to the rigorous standards of quantitative research methodologies, ensuring accurate construct measurement and thorough analysis of relationships. The measurement items as given in the Table A2 were carefully sourced from recognized studies: GAI usage from Li, Liu, et al. (2024) and Al-khatib et al. (2024), SCDI from Wang and Zhang (2024), Supply chain integration (consists of supplier, customer, and internal integration) from Kim and Chai (2016), Le et al. (2024), and Basnet 2013, Supply chain business value creation from Laukkanen and Tura (2020), Vrontis et al. (2022), Evans et al. (2017), and Acosta-Prado et al. (2022) and supply chain resilience from Zhao et al. (2023).

3.3 | Method and Non-Response Bias

Common method bias and non-response bias are significant methodological issues in research using self-administered questionnaires. CMB arises from the shared systematic error variance between variables when the same data collection method or source is employed, which can impact the validity of research findings if unaddressed (Podsakoff et al. 2012). To mitigate CMB, various procedural and statistical methods were utilized. Assurances of data confidentiality were given to encourage honest responses, and the questionnaire layout was designed to minimize bias by clearly separating measurements for each construct.

To assess CMB, we used Harman's single-factor test, where an eigenvalue unrotated exploratory factor analysis indicated the first extracted factor accounted for 35.19% of the total variance, significantly below the 50% threshold, suggesting minimal CMB influence on our results. While Harman's single-factor test had its constraints as reported in many OM/IS studies such as (Matarneh et al. 2024; Khan et al. 2023), we transitioned to a contemporary approach employing the PLS marker variable technique. We integrated four elements from the social desirability scale to serve as a marker variable. The analysis revealed negligible differences in R^2 values between models with and without the marker variable, indicating that the impacts in our data set were not exaggerated due to common method variance.

Non-response bias was evaluated by comparing early and late respondents using *t*-tests for independent samples. This division of the sample into two groups and subsequent testing revealed no significant differences in the study variables among the groups ($t = -1.174$, $p = 0.258$), confirming that non-response bias did not materially affect our study. Through these comprehensive measures, the methodological rigor of our research was enhanced which ensured that the findings are robust and reliable, thus improving the overall quality and validity of our research conclusions.

3.4 | Data Analysis Tool

In this study, we utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) to explore the causal-predictive relationships within our research framework, following the guidelines by Hair et al. (2019) and Sarstedt et al. (2019). PLS-SEM is ideal for its proficiency in managing complex models comprising numerous latent and observed variables (Russo and Stol 2021), as well as its ability to handle smaller sample sizes and assess the predictive power of exogenous variables (Dijkstra and Henseler 2015). This variance-based approach is adept at simultaneously addressing both measurement and structural models, which was essential for the scope of our research.

For the practical application, we employed Smart PLS 4.0 software to analyze our research models. Key variables such as supply chain resilience, supply chain integration, and sustainable business value creation were defined as higher-order constructs. PLS-SEM is increasingly favored for its effectiveness in evaluating such complex constructs (Sarstedt et al. 2020). To ensure reliable statistical conclusions, bootstrapping with 5000 resamples was used to assess the significance of the path coefficients and factor loadings in our conceptual model.

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4 | Analysis and Findings

4.1 | Measurement Model Analysis

This research utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze its theoretical framework, which includes both measurement and structural models. Initially, the measurement model underwent a validity and reliability check, followed by an analysis of the structural model to explore the relationships between factors as shown in Figure 1. First, indicator reliability was assessed to evaluate the adequacy of the items' outer loadings and to identify items for possible removal in line with established PLS-SEM guidelines (Hair Jr et al. 2017). The decision to remove items did not rely solely on their loading threshold values. Instead, each potential item removal was evaluated in terms of its effect on construct reliability and validity, while also considering the conceptual coverage of the respective construct. As recommended by Hair et al. (2019), item loadings should exceed 0.60 on their respective latent constructs, with values above 0.70 considered ideal. As shown in Table 1, most items demonstrated loadings above 0.60, indicating satisfactory indicator reliability. Six items with loadings below the acceptable threshold were removed to improve the overall measurement quality (see Table 1). Since all constructs are reflective in nature, their indicators represent manifestations of the underlying constructs and are expected to share a common conceptual domain. Consequently, removing individual low-loading indicators is less likely to change the conceptual meaning of a reflective construct. After the removal of these six items, all constructs met the recommended reliability criteria. Following this, convergent validity was confirmed through the average variance extracted (AVE), with all constructs showing AVE values above 0.50, as shown in Table 1. This indicates that the indicators adequately captured more than 50% of the variance of the constructs.

The results show that each item strongly measures its intended construct. It is then followed by the Fornell–Larcker Criterion. The results presented in Table 2a show that all the squared AVE of the constructs (diagonal values) are greater than the corresponding correlational values. It is then followed by the Heterotrait-Monotrait ratio as suggested by Henseler et al. (2015), with all values below the 0.90 cut-off, as listed in Table 2b, ensuring robust discriminant validity across the constructs and supporting the model's structural integrity.

4.2 | Structural Model

The structural model was evaluated using path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2), as recommended in PLS-SEM literature (Hair et al. 2021). Prior to hypothesis testing, collinearity among predictor constructs was assessed using VIF values, which were found to be below the threshold of 3.3, indicating no multicollinearity issues. The significance of the path coefficients and indirect effects was assessed using a bootstrapping procedure with 5000 resamples. Bootstrapping is a non-parametric technique that does not assume normality and is considered more robust than traditional approaches such as the Sobel test for mediation analysis (Preacher et al. 2007; Hair and Alamer 2022).

After assessing the measurement model, we proceeded to evaluate the structural model's predictive capabilities using PLS-SEM. It is done through coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) as recommended by Hair et al. (2019). Prior to hypothesis testing, VIF values for collinearity were checked, which were found to be below the threshold of 3.3, indicating no multicollinearity issues. A non-parametric bootstrapping technique with 5000 resamples was employed to

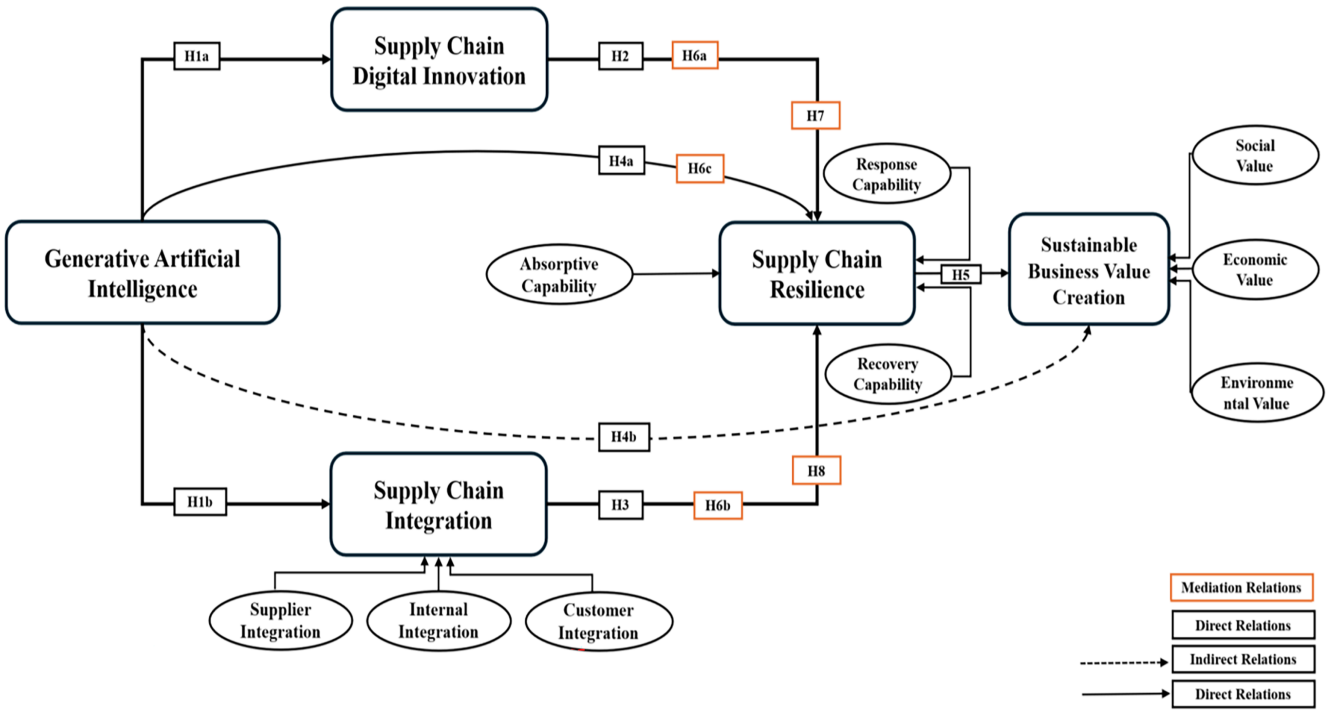

FIGURE 1 | Research framework.

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TABLE 1 | Reliability and validity results.

Constructs	Items	Loadings	CR	AVE
Generative AI Usage (GAIU)	GAIU1	0.728	0.848	0.527
	GAIU2	0.769		
	GAIU3	0.695		
	GAIU4	0.717		
	GAIU5	0.719		
Supply Chain Digital Innovation (SCDI)	SCDI1	0.698	0.809	0.515
	SCDI3	0.743		
	SCDI4	0.730		
	SCDI5	0.699		
Internal Integration (II)	II1	0.763	0.853	0.659
	II2	0.829		
	II3	0.841		
Supplier Integration (SI)	SI1	0.844	0.859	0.670
	SI2	0.805		
	SI3	0.807		
Customer Integration (CI)	CI1	0.785	0.723	0.567
	CI4	0.719		
Absorptive Capability (SAC)	SAC1	0.856	0.839	0.722
	SAC3	0.843		
Response Capability (SRC)	SRC1	0.787	0.786	0.551
	SRC2	0.717		
	SRC3	0.720		
Recovery Capability (REC)	REC1	0.663	0.817	0.601
	REC2	0.818		
	REC3	0.833		
Environmental Value (ENV)	ENV1	0.794	0.877	0.641
	ENV2	0.781		
	ENV3	0.825		
	ENV4	0.801		
Economical Value (ECN)	ECN1	0.752	0.828	0.567
	ECN2	0.772		
	ECN3	0.729		
	ECN4	0.702		
Social Value (SCL)	SCL2	0.704	0.701	0.527
	SCL3	0.749		

Note: GAIU6, GAIU7, SCDI2, SAC2, SCL1, SCL4, SI4, SI5, CI2, CI3, CI5, II4, II5 were dropped due to low loadings.
Abbreviations: AVE: average variance extracted; CR: composite reliability.

assess the significance of path coefficients and indirect effects. This is considered to be more robust than traditional approaches such as the Sobel test for mediation analysis (Preacher et al. 2007). In line with PLS SEM guidelines, the structural model was evaluated using path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). This evaluation focused on four primary metrics: the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2) derived from blindfolding, and SRMR for estimated model fit. The model displayed R^2 values of 0.422 for SCDI, 0.505 for SCI, 0.610 for SCR, and 0.386 for sustainable business value creation (see Table 3). According to benchmarks established by Hair et al. (2019), R^2 values of 0.25, 0.50, and 0.75 correspond to weak, moderate, and substantial predictive power, respectively. Therefore, the model demonstrates moderate predictive power for SCDI, SCI, and SBVC, and substantial predictive power for SCR.

Effect size analysis, using Cohen's f^2 statistic (Sawilowsky 2009), identified different degrees of impact among the hypothesized relationships. As shown in Table 4, H1a ($f^2 = 0.730$) and H1b ($f^2 = 0.809$) had a strong effect. Meanwhile H4a ($f^2 = 0.127$) and H5 ($f^2 = 0.132$) have moderate effect, while H2 ($f^2 = 0.080$), H3 ($f^2 = 0.103$) and H4b ($f^2 = 0.056$) have weak effect. Additionally, the Stone–Geisser Q^2 values for all dependent constructs were above zero, confirming the model's predictive relevance. This indicates that the model has adequate out-of-sample predictive capability and can reliably reconstruct observed values, thereby supporting its external predictive validity. From a practical standpoint, the positive Q^2 values suggest that the model can meaningfully predict key outcomes such as supply chain resilience and sustainable business value creation, offering actionable insights for managers in anticipating performance and improving decision-making. In addition, the standardized root mean square residual (SRMR) was examined as an approximate model fit measure. The obtained value of 0.073 is below the recommended threshold of 0.08, indicating an acceptable model fit. Collectively, these results confirm the model's predictive accuracy across various constructs and validate its structural integrity.

The strong effect of Gen AI on SCDI is expected, as SCDI is closely linked to technology. With the use of Gen AI, firms can more effectively utilize data, automate processes, and enhance the speed of decision-making, thereby improving digital innovation in the supply chain. Likewise, the use of Gen AI improves real-time visibility, facilitates automation in information sharing among supply chain partners, and provides predictive and data-driven solutions in making decisions, thus improving integration across supply chain partners. Meanwhile, the weak effect of SCDI on SCR suggests that while digital initiatives support resilience, their impact is not immediate. SCR requires additional factors in terms of risk management infrastructure, organizational capabilities, and other supporting or enabling factors, which may strengthen this relationship over time. Likewise, the weak effect of GenAI on SBVC indicates that GenAI may not directly and meaningfully contribute to business value. Rather, its impact typically occurs through operational and strategic measures such as improved processes, coordination, and integration, which require time and strategic alignment to translate into meaningful outcomes.

4.3 | Hypotheses Testing

The results from the structural equation modeling, as detailed in Table 5 and Figure 2, identified several significant relationships between key constructs. The findings highlighted a significant positive relationship between paths GAIU → SCDI ($\beta = 0.650$; $p < 0.01$), GAIU → SCI ($\beta = 0.710$; $p < 0.01$), GAIU → SCR ($\beta = 0.341$; $p < 0.01$) and GAIU → SBVC ($\beta = 0.263$; $p < 0.01$), thus supporting H1a, H1b, H4a, and H4b. Similarly, a positive and significant relationship was observed between

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TABLE 2a | Fornell–Larcker criterion.

	CI	ECN	ENV	GAIU	II	REC	SAC	SCDI	SCL	SI	SRC
CI	0.753										
ECN	−0.097	0.739									
ENV	−0.007	0.610	0.800								
GAIU	−0.056	0.495	0.492	0.726							
II	−0.056	0.449	0.398	0.519	0.812						
REC	−0.028	0.452	0.487	0.599	0.518	0.775					
SAC	−0.047	0.409	0.409	0.619	0.399	0.447	0.850				
SCDI	−0.043	0.414	0.423	0.649	0.549	0.554	0.500	0.718			
SCL	−0.044	0.164	0.069	0.118	0.089	0.215	−0.027	0.125	0.726		
SI	−0.171	0.453	0.438	0.677	0.498	0.498	0.571	0.549	0.126	0.819	
SRC	−0.166	0.308	0.305	0.317	0.273	0.359	0.277	0.433	−0.054	0.382	0.742

TABLE 2b | HTMT results.

	CI	ECN	ENV	GAIU	II	REC	SAC	SCDI	SCL	SI	SRC
CI											
ECN	0.263										
ENV	0.161	0.793									
GAIU	0.142	0.663	0.614								
II	0.136	0.616	0.507	0.684							
REC	0.180	0.648	0.650	0.818	0.738						
SAC	0.129	0.616	0.580	0.884	0.589	0.696					
SCDI	0.212	0.590	0.569	0.887	0.773	0.813	0.767				
SCL	0.794	0.594	0.417	0.423	0.326	0.827	0.129	0.493			
SI	0.396	0.619	0.557	0.880	0.666	0.697	0.839	0.763	0.691		
SRC	0.416	0.473	0.447	0.466	0.410	0.559	0.465	0.678	0.522	0.561	

TABLE 3 | R^2.

Endogenous variable	*R*-square
SC Digital Innovation (SCDI)	0.422
SC Integration (SCI)	0.505
SC Resilience (SCR)	0.610
Sustainable Business Value Creation (SBVC)	0.386

TABLE 4 | f^2.

Path relationship	*f*-square
Generative AI Usage → SC Digital Innovation	0.730
Generative AI Usage → SC Integration	0.809
Generative AI Usage → SC Resilience	0.127
Generative AI Usage → Value Creation	0.056
SC Digital Innovation → SC Resilience	0.080
SC Integration → SC Resilience	0.103
SC Resilience →Value Creation	0.132

the SCDI and SCR ($\beta = 0.244$; $p < 0.01$), SCI and SCR ($\beta = 0.300$; $p < 0.01$), SCR and SBVC ($\beta = 0.406$; $p < 0.01$), thus supporting H2, H3, and H5.

Following the procedural guidelines by Preacher et al. (2007), we performed an analysis of indirect effects, using 95% confidence intervals and employing bootstrapping for the sampling distribution of these effects, a recommended technique by Hair et al. (2019) for analyzing complex mediating relationships. The findings demonstrated that SCI ($\beta = 0.213$, $p < 0.001$) and SCDI ($\beta = 0.158$, $p < 0.001$) both mediate the relationship GAIU and SCR. Additionally SCR mediate the relationship between GAIU and SBVC ($\beta = 0.138$, $p < 0.001$). Furthermore, SCR mediates the path SCDI → SBVC ($\beta = 0.099$, $p < 0.05$) and SCI → SBVC ($\beta = 0.122$, $p < 0.05$). Thus, support H6a, H6b, H6c, H7 and H8. The indirect effect results are presented in Table 6.

Although the sequential mediation effects of SCDI and SCI were not explicitly hypothesized at the outset, post hoc analysis as shown in Table 7 reveals that the sequential paths (GenAI → SCI → SCR → SBVC) and (GenAI → SCDI → SCR → SBVC) are both positive and significant. This indicates the important role of SCDI and SCI in translating the benefits of the use of GenAI into enhanced supply chain resilience, which ultimately contributes

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TABLE 5 | Direct effect results.

Path relationship	*β*-value	*T* statistics	*p*	*F*-square
H1a: Generative AI Usage → SC Digital Innovation	0.650	14.742	0.000	0.730
H1b: Generative AI Usage → SC Integration	0.710	16.793	0.000	0.809
H2: SC Digital Innovation → SC Resilience	0.244	3.232	0.001	0.080
H3: SC Integration → SC Resilience	0.300	3.208	0.001	0.103
H4a: Generative AI Usage → SC Resilience	0.341	4.215	0.000	0.127
H4b: Generative AI Usage → Value Creation	0.263	3.105	0.002	0.056
H5: SC Resilience →Value Creation	0.406	4.218	0.000	0.132

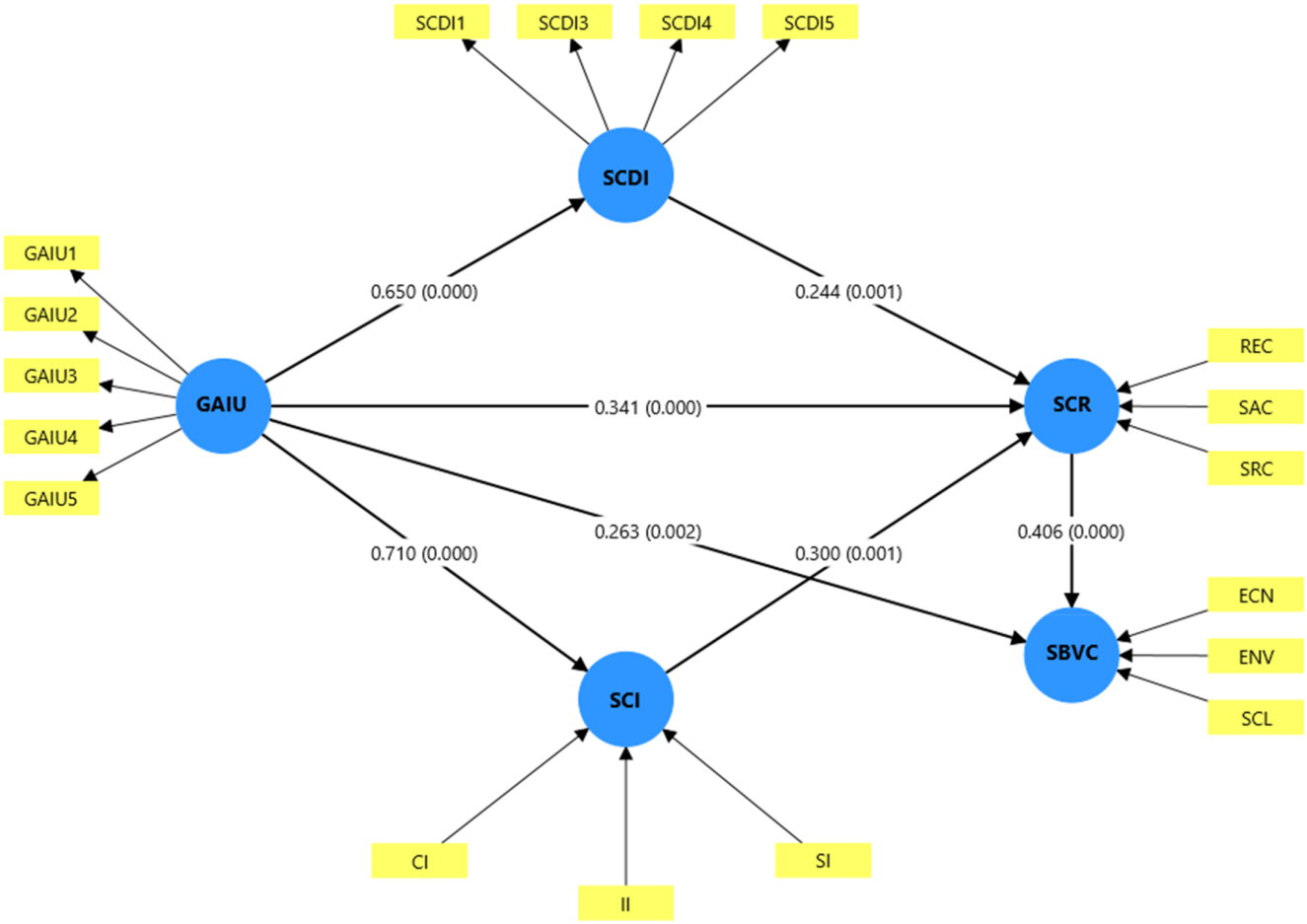

FIGURE 2 | PLS SEM path model. GAIU—generative AI usage; SBVC—sustainable business value creation; SCDI—supply chain digital innovation; SCI—supply chain integration; SCR—supply chain resilience.

to business value creation. These sequential mediation effects demonstrate the hierarchical nature of capability development in supply chains, whereby the use of GenAI leads to SBVC through SCDI/SCI and SCR.

4.4 | Importance Performance Map Analysis

The research utilized Importance-Performance Map Analysis (IPMA) alongside PLS-SEM, as described by Sarstedt et al. (2024) to enhance theoretical and managerial understanding. IPMA represents structural relationships on a two-dimensional grid, plotting importance on the *X*-axis and performance (variable index values) on the *Y*-axis. This approach is instrumental in discerning which exogenous variables significantly impact the variations in target constructs, thus identifying key predictors of the phenomenon under study (Hair Jr et al. 2017). The use of this methodology is particularly beneficial for recognizing underperforming yet important variables, highlighting areas with the most substantial potential for improvement (Hauff et al. 2024). Such analysis is crucial for decision-makers, providing vital insights for prioritizing areas that need focus and guiding resource allocation, strategic planning, and process optimization (Streukens et al. 2017).

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TABLE 6 | Indirect effect results.

Hypotheses: path relationship	β-value	T statistics	p	Confidence interval [LCL, UCL]
H6a: SC Digital Innovation → SC Resilience → Value Creation	0.099	2.571	0.010	[0.031, 0.182]
H6b: SC Integration → SC Resilience → Value Creation	0.122	2.256	0.024	[0.039, 0.247]
H6c: Generative AI Usage → SC Resilience → Value Creation	0.138	3.136	0.002	[0.060, 0.234]
H7: Generative AI Usage → SC Digital Innovation → SC Resilience	0.158	3.110	0.002	[0.057, 0.259]
H8: Generative AI Usage → SC Integration → SC Resilience	0.213	3.052	0.002	[0.089, 0.359]

TABLE 7 | Post hoc analysis.

Path relationship	β-value	T value	p	Confidence interval [LCL, UCL]
Generative AI Usage → SC Digital Innovation → SC Resilience → Value Creation	0.064	2.431	0.015	[0.020, 0.124]
Generative AI Usage → SC Integration → SC Resilience → Value Creation	0.086	2.171	0.030	[0.025, 0.175]

The IPMA analysis provides essential insights into the interactions among four constructs (GAIU, SCDI, SCI, and SCR) and their influence on SBVC, offering clear strategic directions for decision-makers. This analysis assesses both the total effects and performance levels, delivering a comprehensive understanding of each construct's importance and role.

Table 8 presented the total effect and performance of each endogenous construct, while Figure 3 shows the visual map. GAIU emerges as the most significant construct, boasting the highest total effect of 0.552, followed by SCR with a notable total effect of 0.406. SCI presents a moderate influence with a total effect of 0.122, while SCDI has the least impact, recording a total effect of 0.099. The performance scores, however, reveal notable disparities. Among the constructs, SCI and GAIU record the highest performance scores, at 61.237 and 61.007, respectively, indicating a relatively strong level of development. SCR exhibits a moderate performance level, with a score of 55.783, suggesting there is still room for improvement. In contrast, SCDI records the lowest performance score at 48.389 and also demonstrates the lowest impact, indicating that digital innovation remains comparatively underdeveloped despite firms having more established SCI capabilities. With GAIU's substantial total effect of 0.552 and a high-performance score, current strategies appear effective and are recommended for continuation, with potential for significant improvements due to its critical role in driving sustainable business value creation. It is crucial to document and standardize successful practices around GAIU to sustain its influence on SBVC. SCR presents a significant opportunity for strategic enhancement, having the second-highest total effect of 0.406 but a comparatively lower performance score of 55.783. This disparity indicates that SCR is a prime candidate for development initiatives. Organizations should investigate barriers to SCR's performance and implement targeted enhancement programs. Improving SCR's performance through added resources, process improvements, or specialized training could greatly benefit SBVC.

TABLE 8 | Effect and performance.

Constructs	Total effect	Performance
Generative AI Usage (GAIU)	0.552	61.007
SC Digital Innovation (SCDI)	0.099	48.389
SC Integration (SCI)	0.122	61.237
SC Resilience (SCR)	0.406	55.783

5 | Discussion

This research study examines how the use of GAI can facilitate supply chain resilience, aiming to enhance sustainable business value creation, with an emphasis on the mediating effects of SC digital innovation and SC integration. This research model offers a comprehensive framework illustrating the interaction of these constructs and their cumulative impacts from technology adoption to sustainable outcomes. The findings provide empirical evidence that GAI is not merely a technological tool but a strategic capability that enables firms to innovate, integrate, and adapt more effectively in dynamic business environments. Drawing upon the resource-based and dynamic capability view, the results reveal a capability-building pathway in which GAI strengthens digital innovation and integration capabilities, enhances resilience, and ultimately contributes to sustainable value creation in contemporary supply chains.

The study found a positive influence of GAI on both SCDI and SCI. This finding is consistent with previous studies suggesting that GAI enhances organizational learning, knowledge sharing, innovation capabilities, and collaborative decision-making processes (Li, Zhu, et al. 2024; Wang and Zhang 2024; Modgil et al. 2025). However, this study extends prior research by demonstrating that GAI does not merely improve individual organizational outcomes but serves as a foundational capability that enables

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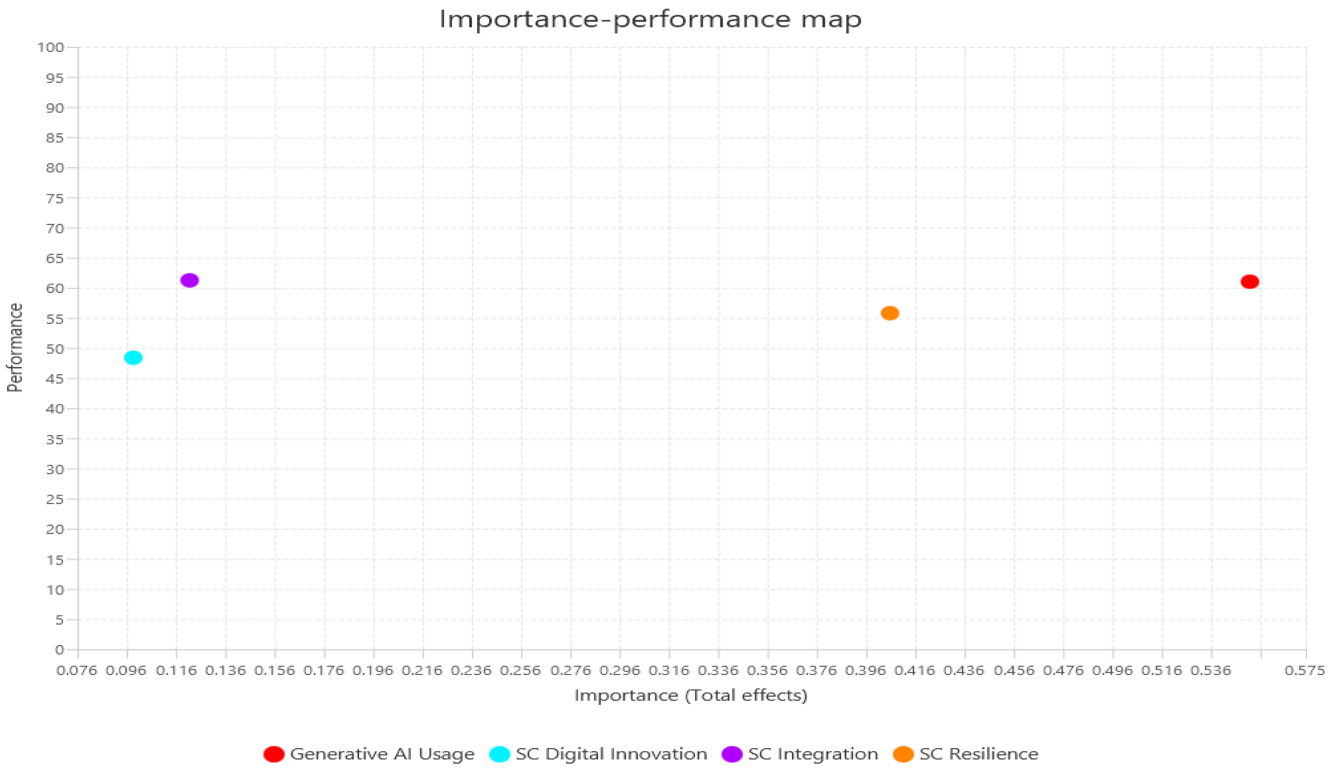

FIGURE 3 | IMPA Map.

firms to simultaneously strengthen innovation and integration across supply chain networks. In addition, this study further enhances the resource-based view (RBV) by framing GAI as a fundamental enabler rather than just a firm-level resource. This also supports the RBV's claim that unique firm resources, when integrated with complementary assets, directly enhance sustained superior performance (Chen et al. 2017; Barney and Clark 2007). Therefore, it suggests the importance of integrating GAI with dynamic capabilities, such as SC digital innovation and SC integration, to foster resilience and sustainable value. These findings are particularly important because they suggest a shift from traditional information exchange toward intelligent, data-driven collaboration and real-time decision-making, thereby preparing firms to respond more effectively to uncertainty and disruption.

The findings of the study also support that SCDI and SCI positively influence SC resilience, highlighting the importance of complementary organizational capabilities in building resilient supply chains. Consistent with Christopher and Peck (2004), Sheffi (2005), and more recent studies (Zhao et al. 2023; Wang and Zhang 2024; Jiang et al. 2024), digital innovation enables early risk detection, enhanced visibility, and agile responses to disruptions. Similarly, supply chain integration strengthens resilience by improving information quality, coordination, trust, and collaboration among supply chain partners. While previous studies have examined the direct relationship between innovation, integration, and resilience, the present findings provide empirical support for a more integrated perspective in which innovation and integration work together to strengthen adaptive and recovery capabilities.

The study also found positive effects of GAI on SCR and SBVC. This finding supports previous research suggesting that AI-enabled technologies improve organizational responsiveness, forecasting accuracy, and recovery capabilities during disruptions (Kar et al. 2023; Maghroor et al. 2024). However, unlike earlier studies that primarily focused on operational or performance outcomes, this study demonstrates that GAI creates value through resilience-building mechanisms that contribute to broader sustainability objectives. In this regard, GAI should be viewed not merely as a technological tool but as a resilience-enhancing capability that enables firms to maintain operational continuity while creating long-term value.

This study also demonstrates an important finding which is the relationship between SCR and SBVC, showing that resilient firms have a greater capacity for sustainable value creation, attributable to their ability to absorb disruptions and effectively respond, allowing them to restore previous operations or enhance performance post-disruption (Al-khatib et al. 2024). Furthermore, the study's findings demonstrate that resilience can be crucial to sustainable value creation. This builds on prior studies indicating the interrelation between resilience and supply chain sustainability (Priyadarshini et al. 2025). Thus, arguably, resilient supply chains can help Malaysian manufacturers who participated in this study and similar manufacturing firms in the supply chain minimize operational inefficiencies, avoid costly disruptions, and comply with environmental and social governance (ESG) objectives. From an economic perspective, resilient supply chains reduce disruption-related costs, improve operational efficiency, and strengthen long-term competitiveness. From an environmental perspective, improved visibility, forecasting, and coordination help reduce waste, optimize resource utilization, and support more sustainable production and logistics activities. From a social perspective, resilient and integrated supply chains enhance stakeholder collaboration, support responsible decision-making,

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improve supplier relationships, and contribute to more stable and secure working environments. Therefore, the findings reinforce the view that sustainable business value creation extends beyond financial performance and encompasses economic, environmental, and social value simultaneously (Laukkanen and Tura 2020; Vrontis et al. 2022; Evans et al. 2017).

Another important finding of this study is that SC resilience acts as a second-stage mediator in the relationship among SCDI, SCI, and SBVC. The findings indicate that GAI does not automatically translate into resilience and sustainable value creation. Rather, its impact materializes through a sequence of complementary organizational capabilities. Specifically, SCDI and SCI act as capability-building mechanisms that enable organizations to convert GAI-generated insights into operational actions and collaborative processes. This finding helps explain why technology investments alone may not generate sustainable benefits unless accompanied by sufficient innovation and integration capabilities. Consequently, SCR presents as a crucial element that transforms the advantages of technological and process-level advancements not only in obtaining sustainable results (Ding et al. 2025; Dwivedi et al. 2023) but also positively influences SC digital innovation and integration (Chen et al. 2025; Zhao et al. 2023).

Similarly, this study also confirms the SCDI's mediating role between GAI and SCR. Based on the findings of this study, this suggests that firms must first develop digital innovation capabilities before the full resilience benefits of GAI can be realized. The findings suggest that a strategy of digital innovation adoption promotes advanced technologies and collaboration within an organization through information sharing, leading to building resilience. Digital innovation in the supply chain is vital to ensure that advancements driven by GAI in turn lead to strategies that enhance resilience. Likewise, the mediation effect of SCI indicates that the benefits of GAI become significantly stronger when information, resources, and decisions are effectively coordinated across supply chain partners. SCI promotes integration and removes silos, leading to information sharing and effective collaboration between GAI and SCR (Jiang et al. 2024; Ahmed et al. 2025). Which are in line with the previous studies that information processing capabilities contribute to resilience only when embedded within collaborative inter-organizational (Piprani et al. 2025; Chesley and D'Avella 2020). Therefore, through SCI, the information from GAI can be rapidly disseminated throughout the supply chain enabling proactive and quicker decision making to manage or avoid disruptions (Richey Jr et al. 2023). Hence, strong integration enhances consistency, coordination, and resilience across the supply chain (Tarigan et al. 2021; Sadia et al. 2024). These results demonstrate that innovation and integration are not merely complementary factors but essential mechanisms through which GAI enhances resilience and sustainable business value creation.

6 | Research Contribution and Conclusion

6.1 | Theoretical Contribution and Implications

This study applies the resource-based view theory and dynamic capabilities theory to investigate the different mediational pathways of GAI adoption leading to sustainable business value creation. Theoretically, this study contributes to supply chain literature by evidencing the influence of GAI as a dynamic meta-capability. This study shows that, as opposed to being simply another element in the toolbox, GAI poses as a central reconfiguration mechanism, reshaping and strengthening digital innovation, integration, and resilience capabilities. Herein, this study contributes by highlighting that supply chain integration is more beneficial when it aligns closely with GAI-augmented decision support, rather than drawing solely upon traditional coordination practices.

Furthermore, this research contributes to digital innovation literature by demonstrating the critical and central role that SCDI can play by harnessing GAI capabilities in relation to transforming supply chains with better designs and performance. Through its generative capabilities to produce simulations, experimentation, and organizational redesigns, GAI shows the potential to facilitate SCDI by AI-driven resilience and sustainable value creation. Thus, this study contributes by extending RBV and dynamic capabilities theory by positioning GAI as a critical enabler as opposed to simply a firm-level resource. Moreover, in line with RBV theory, findings demonstrate that firm-level capabilities like GAI, when integrated with other resources and skills like supply chain digital innovation and supply chain integration, provide an enhanced synergistic impact on resilient and sustainable value creation.

Moreover, theoretically this study contributes by illustrating the value of integrating RBV theory with dynamic capabilities theory, whereby GAI emulates the dynamic ability to maneuver, making sense of large and complex data, with a view to generating actionable insights and outputs, even in volatile and uncertain circumstances. This not only cements GAI as an invaluable resource possession, but also extends the dynamic capability theory, espousing the role of novel capabilities like GAI in helping organizations maneuver and work through technological changes, market transformations and unexpected disruptions in supply chains, in a way that retains sustainable competitive advantage and builds resilience. Thus, this study extends the RBV and DCT in supply chain theory and digital innovation by highlighting that GAI is not an isolated or self-contained resource; rather, it is a meta-capability bolstering reconfiguration mechanisms moving from innovation, integration, resilience, to sustainable value creation. Crucially, in this process, this study contributes by signaling a shift from digital transformation as a process improvement mechanism, toward digital transformation as a continuous loop of capability evolution.

6.2 | Practical Contribution and Implications

This study makes a practical contribution by significantly endorsing the benefits of incorporating GAI usage within manufacturing firms and their supply chains. This study highlights the important role of GAI in strengthening supply chain resilience and creating sustainable value. Specifically, GAI can support better decision-making, predictive analytics, and real-time data processing. It also enables organizations to improve inventory management, resource allocation, and collaboration across the supply chain. Similarly, the findings also demonstrate the critical role of

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GAI adoption in combination with digital innovation and supply chain integration, to help make supply chains resilient by encouraging agility and responsiveness, so that firms can address, recover, and transform sustainably during and after unforeseen challenges and crises. Building resilience was directly related to demonstrating competitive advantage and thereby sustainable value creation. Thus, this study contributes to immediately emphasizing the need for various firms and stakeholders along the supply chain to invest in learning, experimenting with, and investing in appropriate GAI use and development. Based on this study, it is arguable that human resource strategies will need to focus on attracting and retaining employees who are competent in applying and redesigning GAI technology to fit the needs of the firm and supply chains. The findings suggest that firms should focus on building trust in GAI, developing a supportive organizational culture, and adopting sector-specific strategies to fully utilize its potential. These insights provide practical guidance for both managers and policymakers to proactively manage supply chain risks and improve resilience. Moreover, GAI adoption to facilitate resilience and sustainable value creation, as examined in this study, inherently contributes to the field of ESG. Prior research highlights AI capabilities to effect green transformation and environmental performance of firms (Khan et al. 2024). This study demonstrates that GAI positively aligns with digital innovation and supply chain integration in achieving the above. Thus, by strengthening resilience in a proactive, as opposed to reactive manner, there will arguably be higher resource optimization and waste reduction, facilitating environmental gains. GAI informed digital innovation and sustainability can also benefit social and governance prerogatives (Wang and Zhang 2024) through speedy and more transparent reporting based on superior tracking, monitoring, and decision-making.

For managers, the results suggest that Gen AI should be implemented as part of a broader capability-development strategy aimed at strengthening digital innovation, integration, and resilience rather than as a stand-alone technological investment. Managers should prioritize employee training, cross-functional collaboration, data governance, and AI-enabled decision support systems to improve organizational responsiveness and sustainability performance. For policymakers, the findings highlight the importance of supporting industrial digital transformation through AI adoption programs, workforce upskilling initiatives, digital infrastructure development, and incentives for technology investments, particularly among manufacturing firms operating in emerging economies. For technology providers, the results underscore the need to develop interoperable, scalable, and industry-specific AI solutions that improve information sharing, collaboration, visibility, and resilience across supply chain networks. Such efforts can help organizations create greater economic, environmental, and social value through more resilient and sustainable supply chains.

However, GAI is a rapidly developing and improving arena; therefore, it is critical to ensure that decision makers and employees are aware of and have opportunities to continuously upskill and improve their GAI capabilities (Mukhuty et al. 2025). The continued exponential advancement of GAI technology makes it imperative for organizations to ensure continuous investment in developing GAI competence and knowledge sharing, including defining GAI related skills, like prompt engineering, data analysis, and ethical GAI use, needed for procurement, logistics, and production. Mukhuty et al. (2025) offer a phased implementation framework of training strategies cumulatively moving through the phases of Getting Urgent, Exploration, Formulation, Iteration, and Embedding (GEIFIE model) transitioning employees from GAI novices to confident, competent users. Furthermore, this study contributes by advocating upskilling and knowledge sharing through vendor partnerships with GAI technology providers, to accelerate access to necessary knowledge and training content. Such tech-driven vendor partnerships simultaneously offer cost-effectiveness, competitive advantage and skills acquisition (Findikoglu et al. 2021). Firms would also benefit from case-based training involving simulations to analyze supply chain operations, to understand GAI capabilities, to identify risks in advance through simulation of disruptive scenarios, develop contingencies, and optimize decision-making along the supply chain. While investing in GAI adoption and training will incur investment costs upfront, the return on investment is likely to significantly supersede the initial costs. This is particularly so, as this study suggests that enhancing GAI related supply chain resilience will help enhance operational efficiencies through the breaking down of silos and better and timely information sharing between the supply chain stakeholders. This is likely to speed up the flow of information, decision-making and responsiveness across logistics, procurement and production functions. Furthermore, this built-up resilience will also help to mitigate expensive disruptions while delivering on environmental and social governance objectives.

This study focuses on the manufacturing sector in Malaysia, which is a key contributor to the Malaysian economy, its exports and gross domestic product (Ngu et al. 2020; Zhang and Mia 2023; Zhang and Yang 2022). This emerging economy, which is reputed to be one of the fastest growing economies in the ASEAN region (Newaz et al. 2025), has approximately 2.8 million employees in the manufacturing sector (Statista 2023b). This article draws upon a robust sample size of 173 responses, making the results particularly relevant to various Malaysian manufacturing firms evaluating the business case for adoption of Industry 4.0 and particularly GAI technology. These outcomes can also be beneficial for similar manufacturing firms within emerging economies. Thereby, this study also contributes to the contextual understanding of supply chains and digital transformation in emerging economies. This study shows that within emerging economies, GenAI is not only being harnessed to build efficiencies; rather, GenAI is presenting as a critical catalyst to develop innovative forms of resilience, sustainability and competitiveness in dynamic, volatile and ambiguous SC environments. This potentially shifts the paradigm from solely focusing on conventional cost- and growth-driven models dominant in prior research (Wang et al. 2024) to embracing resilience-oriented digital innovation models in emerging economies.

6.3 | Ethical and Governance Considerations

While Generative AI offers significant opportunities for innovation, resilience, and sustainable value creation, its implementation also introduces important ethical and governance challenges. As mentioned in Table 9, which summarizes the key ethical and governance considerations associated with GAI adoption

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TABLE 9 | Ethical and governance considerations for GAI adoption.

Challenge area	Potential risk	Recommended managerial action
Data Privacy	Unauthorized access or misuse of sensitive supply chain data	Establish robust data governance policies and access controls
Cybersecurity	Increased exposure to cyberattacks through interconnected AI systems	Implement cybersecurity monitoring and regular risk assessments
Accountability	Unclear responsibility for AI-supported decisions	Define governance structures and assign clear ownership for AI use
Workforce readiness	Limited employee capability to effectively use GAI	Invest in continuous training, upskilling, and AI literacy programs
Ethical AI use	Inappropriate, misleading, or harmful AI outputs	Develop ethical AI guidelines and establish usage protocols
Vendor and technology governance	Dependence on external technology providers	Build strategic vendor partnerships and conduct regular compliance reviews

in supply chain environments and provides practical recommendations for organizations.

6.4 | Limitations and Future Research Directions

This study, however, has limitations, whereby it concentrates on a single emerging economy and a single sector (manufacturing) with its specific cultural orientations and infrastructural base. Organizational and national cultural dimensions can arguably have differential impacts on supply chains (Tran et al. 2025) and machine learning adoption (Eitle and Buxmann 2020). There is a lacuna in the understanding of cultural connotations on GAI integration in supply chains. Therefore, future research would benefit from comparative studies on multi-country samples examining the influence of GAI on supply chain integration, digitalization, and resilience in different national and organizational cultures.

Moreover, since the study employed a non-probability snowball sampling technique, it may result in homogeneity bias, as referrals originate from similar professional networks or may be concentrated within specific manufacturing sectors or job functions. There is also a possibility of self-selection bias, where participants who are more inclined toward the use of generative AI may be more willing to participate and refer peers, potentially inflating its perceived role in resilience and business value creation. Thus, future research could adopt mixed sampling strategies by combining snowball sampling with quota sampling to ensure adequate representation across sectors, regions, firm sizes, and job functions. Moreover, developed and emerging economies have differential degrees of infrastructural investments and digital and infrastructural readiness. Hence, the field would benefit from cross-national/regional comparisons examining differences in GAI adoption and implementation between global and local regions with different digital infrastructures and readiness. The field would benefit from an understanding of whether infrastructurally constrained regions would need a different GAI integration trajectory and the nature of that trajectory to strengthen GAI-enabled SC resilience and sustainability in these regions.

Furthermore, the study employs a cross-sectional research design, which limits the ability to examine how the relationships among GAI, supply chain digital innovation, supply chain integration, supply chain resilience, and sustainable business value creation evolve over time. Future studies could adopt longitudinal approaches to capture the dynamic nature of capability development and value creation. Another limitation of this study focuses exclusively on the single sector of manufacturing. To build on and extend the findings of this study, future research could investigate different sectors like retail, finance and healthcare, with a view to uncovering the potential of GAI in establishing resilience and value creation within these industries. In this vein, a deeper understanding of human-AI collaboration can be critical to designing appropriate algorithms (Tutul et al. 2024) for maximum efficiency and value creation. Therefore, research on human-GAI collaboration within supply chain contexts would be valuable to unveil how human employees interact with GAI, the challenges encountered and how to optimize these interactions for enhanced efficiencies and performance.

As this study did not account for the impact of governance and regulatory prerogatives on GAI adoption and integration in supply chains and their impact on SC resilience and sustainability. Regulatory frameworks pertaining to GAI are not yet universally developed; however, this has begun to take shape differentially in different countries and continents, along global supply chains. For example, as of 2025, the European Union (EU) has the risk-based EU AI act requiring mandatory compliance (Leyden 2025), China has introduced standards related to GAI labeling, content and model regulation (Liu et al. 2024; Luo 2025), while other countries like the United States, India, and Malaysia are still maturing their GAI regulatory frameworks. Future research is needed on how the different GAI regulatory and governance frameworks will interact along global supply chains and influence SCDI, collaboration, resilience, and sustainable value creation.

In addition, future research could also extend the proposed framework by examining contextual and organizational factors that may influence the strength of the identified relationships. In particular, variables such as organizational culture, digital maturity, and environmental uncertainty may moderate the effects of

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GAI on supply chain digital innovation, supply chain integration, supply chain resilience, and sustainable business value creation. Exploring these moderating effects would provide deeper insights into the conditions under which GAI-enabled capabilities generate the greatest value and would further enhance the generalizability of the proposed framework across different organizational and environmental settings.

Author Contributions

Arsalan Zahid Piprani: conceptualization, methodology, software, data curation, investigation, formal analysis, writing – original draft, validation, visualization. **Sajid Nazir:** conceptualization, funding acquisition, project administration, writing – review and editing, resources, visualization. **Mahmood Ali:** conceptualization, writing – review and editing, writing – original draft. **Sumona Mukhuty:** writing – review and editing. **Jyri Vilko:** project administration, supervision.

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Appendix A

TABLE A1 | GAI studies in organizational settings.

Category	Authors	Context and background	Methodology	Findings
GAI for Performance	Liu and Wang (2024)	Investigated how tangible, intangible, and human GAI resources influence entrepreneurial performance in China, mediated by internal integration and external collaboration	Purposive sampling of 491 student-founders in China; analyzed using PLS-SEM	GAI resources enhance internal/external collaboration, boosting entrepreneurial success
	Abumalloh et al. (2024)	Explored the experiences of citizen data scientists in retail, analyzing the benefits, challenges, opportunities, and threats of using GAI	Survey of 268 retail firms; novel model validated with PLS-SEM	GAI enables real-time decisions and advanced analytics, improving retail responsiveness
	Singh et al. (2024)	Evaluated how GAI affected future organizational performance through exploratory and exploitative innovation, moderated by ethical concerns and environmental dynamics (DOI, RBV)	Survey of 326 firms across industries; analysis via PLS-SEM	GAI fosters exploratory and exploitative innovation; ethics hinder, environment boosts it
GAI for Innovation	Kanbach et al. (2024)	Presented six propositions on GAI's business impact, illustrated through cases in software, healthcare, and finance	Qualitative content analysis of 513 data points from literature, reports, media, and interviews	GAI supports new and improved business models, with practical implementation insights
	Modgil et al. (2025)	Investigated how non-tech firms adopted GAI to enhance business value, risk management, information sharing and competitive advantage	98 semi-structured interviews with non-tech professionals; Gioia method applied to develop a framework	GAI enhances risk management, forecasting, and BI, though ethics and adoption challenges exist
	Mariani and Dwivedi (2024)	Outlined future research directions in innovation management related to GAI, highlighting key gaps	Combines literature review with Delphi method involving innovation experts	Ten GAI-innovation themes proposed, including creativity, IP, regulation, and ethics
	Khan et al. (2025)	The study aimed to examine the factors influencing GenAI acceptability and its impact on both explorative and exploitative innovation	Analyzed data from an online survey of 302 manufacturing organizations using Smart-PLS	GenAI can support both exploratory and exploitative innovation, with environmental dynamism playing a moderating role
	Sedkaoui and Benaichouba (2024)	Examined factors influencing GenAI acceptability and its effects on both exploratory and exploitative innovation	The study conducted a comprehensive literature review of recent GenAI research published between 2022 and 2024	Generative AI is significantly changing business models, processes, and value propositions across industries, though the impact varies in intensity
GAI for Sustainability	Wang and Zhang (2025)	Proposed the GAI&ABC model to guide sustainable business model innovation in manufacturing	Survey of 402 Chinese manufacturing startups; ABC model and PLS-SEM used to examine mediators and moderators	A new framework links GAI, learning, and context to enable sustainable business innovation
	Li et al. (2024)	Applied a practice-based view to study how GAI utilization enhanced supply chain sustainability, considering capability differences	Survey of 213 Chinese manufacturing firms; analyzed using AMOS 21.0 to assess GAI–SSCP link	Organizational processes mediate GAI's effect on sustainable supply chain outcomes
	Wang and Zhang (2024)	Investigated GAI's contribution to ESG performance in Chinese tourism SMEs	Survey of 429 international SMEs; PLS-SEM used to study GAI's role in ESG through digital supply chains	GAI improves ESG by boosting innovation and collaboration in digital SME supply chains
	Hevi et al. (2025)	Examined the role of evolutionary sense-making and pro-environmental behaviors in influencing the relationship between GAI adoption and sustainable innovation in Ghana	Stratified sampling was used to select 391 owners/managers of extractive-based artisanal firms in Ghana. Regression analysis was employed to test the hypothesized relationships	The findings reveal that Gen-AI adoption positively predicts sustainable innovation

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TABLE A2 | Measurement Scale.

1. Generative AI Usage (Li, Liu, et al. 2024; Al-khatib et al. 2024)	
GAIU1	Our firm's top management encourages Generative AI technology adoption and its use by all the firm's departments
GAIU2	Our firm's supply chains use Generative AI technology to help plan and organize demand and supply
GAIU3	The extent to which generative AI is used in supplier selection
GAIU4	The extent to which generative AI is used in purchase order processing
GAIU5	The extent to which generative AI is used in distribution, warehousing and logistics
GAIU6	The extent to which generative AI is used in invoice and payment processing
GAIU7	The extent to which generative AI is used in customer management
2. Supply Chain Digital Innovation (Wang and Zhang 2024)	
SCD1	We integrate generative artificial intelligence to enhance the effectiveness of our supply chain processes
SCD2	Our digital supply chain solutions incorporate advanced features that significantly improve process efficiency
SCD3	Our digital supply chain solutions are developed based on insights into emerging market trends
SCD4	We update our digital supply chain solutions to meet evolving market demands
SCD5	Our digital supply chain solutions leverage generative artificial intelligence to offer our clients novel products (services)
3. Supply Chain Resilience (Zhao et al. 2023)	
A. Absorptive capability	
SAC1	We can have redundant resources in place prior to the onset of disruptions
SAC2	We can achieve a high level of data visibility
SAC3	We were able to maintain a high level of situational awareness and crisis prediction
B. Response capability	
SRC1	We are able to make the right risk management decisions at the time of disruptions
SRC2	We are able to provide a quick response to supply chain disruptions
SRC3	We are always able to maintain supply chain connectivity and collaboration at the time of disruptions
C. Recovery capability	
SRC1	We are able to speedily and efficiently return to normal operations after being disrupted
SRC2	We were able to restructure resources and develop new supply chain continuity business plans after being disrupted
SRC3	We are able to extract useful knowledge from disruptions and achieve better supply chain operations after being disrupted
4. Sustainable Value Creation (Laukkanen and Tura 2020; Acosta-Prado et al. 2022; Vrontis et al. 2022; Evans et al. 2017)	
A. Environmental Value	
ENV 1	We are able to make reduction in raw material use
ENV 2	We are able to make reduction in electricity consumption
ENV 3	We are able to reduce water waste in the company's processes
ENV 4	We are able to reduce waste in the company's processes
B. Economical Value	
ECN1	Our firm can achieve economic value by adopting various technologies
ECN2	Our firm can achieve economic value through profit maximization
ECN3	In my organization, economic value increases with the enhanced utilization of advanced tools and technologies
ECN4	Our firm has been able to reduce product development costs through the use of appropriate technologies
C. Social Value	
SCL1	Our firm could gain social benefits by performing work that benefits society
SCL2	Our firm believes that social value originates from corporate social responsibility programs
SCL3	Improving the social value is an important aspect of our organization
SCL4	Our firm believes in fostering shared values among employees
5. Supply Chain Integration (Basnet 2013; Kim and Chai 2016; Le et al. 2024)	
A. Supplier Integration	
SI1	We enjoy a high level of strategic alliance with our principal suppliers
SI2	We let our main suppliers know about our manufacturing schedules
SI3	Our primary suppliers are informed about our inventory levels
SI4	With important suppliers, we have tightly linked information systems
SI5	We communicate with essential suppliers at the highest corporate level on crucial topics
B. Internal Integration	
II1	We use cross functional teams to solve problems
II2	Internal management communicates frequently about goals and priorities
II3	Formal meetings are routinely scheduled among various departments
II4	Share information regarding own department with other departments
II5	Understand the pressures and concerns of each other
C. Customer Integration	
CI1	Our customers give us feedback on quality and delivery performance
CI2	Customers frequently share demand information with our firm
CI3	Our inventory levels are shared with our customers
CI4	Our production plans are shared with our customers
CI5	Customers are actively involved in our new product development process

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