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Leveraging Generative Artificial Intelligence to Enhance Carbon Performance in Supply Chains Through Green Product Innovation and End-of-Life Product Management: AI-Driven Carbon Performance

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ABSTRACT

This study illustrates how organizations reconcile their information processing capabilities with uncertainty within the supply chain (SC) through generative artificial intelligence (GAI) to achieve carbon performance (CP). A quantitative research methodology is applied, and 155 responses from manufacturing firms are analyzed through structural equation modeling (SEM) for hypothesis testing. The findings suggest that GAI for process automation and cognitive engagement has a positive influence on business intelligence (BI), whereas end-of-life (EOL) product management mediates the relationship between green product innovation (GPI) and CP. This study contributes to the SC context, focusing on GAI and BI in mitigating uncertainties within SCs to foster GPI and improve CP. This study highlights actionable frameworks for leveraging digital technologies in sustainable SCs by addressing technological challenges and integrating green innovation practices.

1 | Introduction

Carbon emissions harm both the economy and public health and are consistently rising (Mohmmed et al. 2019). Attaining carbon neutrality requires further developments in technology and energy alternatives (Raza and Dongsheng 2023). Advanced systems and digital technologies—including artificial intelligence (AI)—provide organizations with vast volumes of data to understand customer needs, optimize supply chain (SC) operations, and develop innovative green products (Kraus et al. 2019). Generative AI (GAI) and business intelligence (BI) have become indispensable for facilitating decision-making, addressing uncertainties, improving sustainability in SCs (Hsieh and Wu 2019), and end-of-life (EOL) product management (Mehrotra et al. 2024), which is a significant new frontier in the SC context (Awan, Gölgeci, et al. 2022). Despite this progress, significant gaps remain in understanding how to effectively integrate such technologies to address the challenges posed by SCs (Kurrahman et al. 2025) for improved circularity, particularly in the context of green product innovation (GPI). Recent literature suggests that green practices significantly enhance environmental performance (Awan, Braathen, et al. 2023). GPI involves managing both internal and external environmental dynamics—including relationships with suppliers and customers—to achieve sustainability goals (Grekova et al. 2014). Nevertheless, the pursuit of GPI presents unique challenges, including technological barriers and the need for advanced data-driven solutions

(Abdul-Rashid et al. 2017). For instance, EOL product management—which involves recovering materials for reuse, recycling, or remanufacturing—requires not only significant coordination and innovation across SCs (Guide et al. 2000) but also significant alignment among information and technology (Mehrotra et al. 2024), which GAI offers within the current study.

This study examines the relationship between the capabilities and uncertainties arising from the organizational information processing theory (OIPT) in the SC context, specifically focusing on capabilities such as GAI to enhance BI in addressing uncertainty through GPI and EOL product management through reverse SC management, ultimately leading to reduced carbon performance (CP). The current study categorizes GAI into three categories: GAI for cognitive insight (GAI-CI), GAI for process automation (GAI-PA), and GAI for cognitive engagement (GAI-CE; Davenport and Ronanki 2018; Y. Yu et al. 2024).

GAI-CI empowers BI in product designing strategies, data analyzing, and predicting future actions (Y. Yu et al. 2024), while GAI-PA empowers organizational BI for streamlining its manufacturing process, such as highlighting and detecting discrepancies through monitoring processes (Blackman 2018), ensuring uniformity by using AI (Y. Yu et al. 2024). Finally, GAI-CE refers to the influence of AI on the engagement, communication, and coordination processes of manufacturers' stakeholders (Y. Yu et al. 2024).

Kurrahman et al. (2025) suggest that future research should explore stakeholder endeavors that can enhance the seamless integration of advanced technologies—for instance, GAI and BI—for improved circularity in SCs through EOL product management. This study addresses the research question of how organizations manage to create a balance between information processing capabilities and organizational needs to mitigate SC uncertainties, considering the rapid rise in digitalization. GPI involves developing new or enhanced products, including advancements in technical components or materials (C. C. J. Cheng et al. 2014), striving to mitigate environmental impacts across a product's entire life cycle (Christensen 2011). It involves firms' internal and external dynamics of environmental management, including the organization itself, suppliers, and customers (Grekova et al. 2014), and is pertinent to SC management (Lai et al. 2015). Through reverse logistics, recovering materials for reintegration into the SC involves producing new or refurbished products through reuse, recycling, or remanufacturing (Abdul-Rashid et al. 2017). The reintegration process begins at the end of a product's life and is referred to as EOL product management (Abdul-Rashid et al. 2017), whereas some studies refer to it as product recovery management (Guide et al. 2000). Research has shown that integrating a sustainable SC and executing effective EOL product management techniques leads to enhanced environmental performance (Bowen et al. 2001). Organizations frequently modify their operations with the goal of enhancing their environmental performance, particularly in terms of carbon emissions (Ieng Chu et al. 2012). CP refers to the precise measurement of greenhouse gas emissions that contribute to climate change, as well as the strategies and methods employed to reduce these emissions from the environment (Hoffmann and Busch 2008). The incorporation of eco-innovation—for instance, GPI—into SC circularity through EOL product management is essential as it might reduce costs and provide enterprises with competitive advantages that assure sustainable company operations (Kurrahman et al. 2025). Organizations can enhance CP through implementing GPI, which includes enhancing product durability and recyclability, reducing the reliance on raw materials, using environmentally friendly materials, and eliminating dangerous ingredients or components (Kivimaa and Kautto 2010).

Studies also suggest that CP should be linked with SCs in the future (Velte et al. 2020). However, the pursuit of GPI presents a significant challenge, as technological challenges become increasingly significant as firms implement green innovation and sustainable practices both internally and in collaboration with other entities within the SC (Abdul-Rashid et al. 2017). These challenges are addressed by utilizing large-scale data focused on achieving sustainability objectives (Dubey et al. 2019). Several organizations are apprehensive about their ability to adapt to emerging technologies like GAI and want to see the outcomes of adoption by others before experimenting with it themselves (Gupta et al. 2021). The systematic analysis of data derived from different sources—such as production processes, SCs, and logistics networks—enables organizations to discern inefficiencies and identify opportunities for improvement (Ahmad and Mustafa 2022). BI predominantly concerns facilitating decision-making processes through data-driven methodologies, and there is a pressing need for a robust research model to provide strategic guidance to effectively integrate BI into the sustainability performance frameworks of manufacturing enterprises (J. Cheng et al. 2023).

BI is defined as "collecting and transforming structured data into meaningful information and insights that can be used by managers, executives, and other stakeholders to make informed business decisions" (J. Cheng et al. 2023), which invites the application of OIPT as a theoretical lens for the current study. OIPT is essential for facilitating well-informed strategic decision-making and enhancing implementation techniques in companies dealing with the complexities of modern information-driven settings (Y. Yu et al. 2024). The theory also states that the effectiveness of actions and decisions depends on how well an organization can process and comprehend information (Galbraith 1974). This study proposes that the efficacy of decisions related to GPI can be enhanced if the BI system is supported by GAI. GAI leverages a BI-enabled manufacturing system to promote GPI across stages—such as product design and packaging—facilitating reintegration into the SC after use (EOL product management in this study) and thereby improving CP.

Overall, the increasing trend of carbon emissions indicates that businesses must adopt more advanced technology and data-driven solutions to achieve sustainability (Raza and Dongsheng 2023). However, it is challenging for businesses to ensure that their information processing capabilities comply with SC needs (Galbraith 1974). GAI-supported BI has the potential to strengthen decision-making, GPI, and EOL product management (J. Cheng et al. 2023), although its integration into SC operations effectively remains underexplored (Kurrahman et al. 2025). Research indicates that these technologies could help mitigate the effects of CP (Enholm et al. 2022), although companies remain uncertain about adopting advanced technologies due to technological barriers, coordination problems, and a lack of robust frameworks. This necessitates an urgent examination of how GAI-enabled BI can facilitate GPI and EOL management through the OIPT framework to enhance SC circularity and reduce carbon emissions.

To address these issues, this study aims to explore how organizations balance information processing capabilities with organizational needs to mitigate SC uncertainties in the digital era. Specifically, it examines the role of GAI in enhancing BI through PA, CI, and CE. It further investigates how BI drives GPI, which in turn influences EOL product management and CP. Finally, the study assesses the mediating role of GPI in linking BI with both EOL product management and CP.

Following this background, the theoretical background section discusses OIPT in terms of how it supports the current study and how the constructs emerge from the theory, providing strong theoretical support for hypothesis development. The method section discusses the sample and data collection, measures, common method bias, and descriptive analysis. Subsequently, the results section discusses data reliability, validity, and hypothesis testing. The discussion section presents the important insights of the study, including its theoretical and practical contributions, study limitations, and future research recommendations, followed by the study's conclusion.

2 | Theoretical Background and Hypotheses Development

2.1 | Organizational Information Processing Theory

OIPT posits that one of the primary goals of organizational design is to effectively manage uncertainty (Gattiker and Goodhue 2004). The concept of uncertainty, as described by OIPT, refers to a lack of information about various aspects, including work, environment, and other relevant factors (Galbraith 1973). Organizations should enhance their information processing capabilities and efficiently manage and utilize information, particularly when conducting operations with significant levels of uncertainty (Galbraith 1973; Galbraith 1977; Srinivasan and Swink 2018). Firms that invest in improving their digital capabilities for processing information are more effectively equipped to use information for strategic decision-making and innovation. This digital information processing capability-building process is crucial for managing the complicated aspects of digital businesses (Kraus et al. 2019).

The capacity to predict and react promptly relies not only on the exchange of real-time information but also on the rapid pace at which the SC develops a collective understanding (W. Yu et al. 2022). The OIPT in the context of an SC refers to the systematic gathering, examination, and dissemination of information to facilitate decision-making and enhance overall performance (Huang et al. 2023).

The fundamental principle of OIPT is to guarantee that organizational information processing needs are congruent with organizational capabilities, with suitable synchronization between the two. BI involves the process of transforming raw data into information and then further analyzing it to obtain relevant insights (J. Cheng et al. 2023). Y. Yu et al. (2024) explore the role of GAI in optimizing information processing and its impact on organizational resilience and performance through the theoretical lens of OIPT. The current study asserts that BI functions as a process for processing information. When combined with GAI, it facilitates the alignment of organizational information processing capabilities, which are among the core principles of OIPT.

Another facet of the core principle of OIPT is the synchronization of the outcomes for which informational processing capabilities are required (Srinivasan and Swink 2018). Organizations require strong information processing capabilities to effectively manage and respond to SC disruptions (Huo et al. 2014; W. Yu et al. 2022), thereby enhancing their CP through EOL product management and GPI across the entire SC. It is interesting to investigate how organizations can achieve integration or alignment within and among their organizational information processing capabilities and the needs or outcomes, such as CP. Kurrahman et al. (2025) also suggest that future research should explore stakeholder endeavors that can enhance the seamless integration of advanced technologies—such as GAI and BI—as capabilities to improve SC circularity through EOL product management, thereby reducing uncertainty. SC strategies are essential to maximize SC circularity, which advanced technologies—such as GAI and BI—can facilitate by enhancing resource efficiency and minimizing waste, therefore benefiting both environmental and SC outcomes (Bag and Kumar Mangla 2025). It is essential to study because GAI and sustainable SCs are becoming increasingly important for achieving carbon neutrality. Increasing research on GAI compels companies to align their capabilities with strategic choices and essential circular economy strategies to mitigate the potential adverse effects of their products and accelerate societal transformation (Akhtar et al. 2024).

Suppliers must engage in information exchange to contribute to eco-design by focusing on reduction, recycling, and reuse in materials management throughout the entire lifespan of a product. This entails utilizing standardized materials and a modular design, which effectively minimizes the negative impact on the environment and enhances CP. Engaging in communication with suppliers throughout the product design phase enables the disassembly of components for recycling and reuse (Lai et al. 2015). Additionally, it enables enterprises to effectively involve suppliers in eco-design efforts and streamline take-back operations (Lai et al. 2015).

Organizational information processing capabilities—including BI backed by GAI, the urgency or need for enhancements such as CP through EOL product management, and GPI—are synchronized in the current study through an organizational information processing theoretical lens, according to its core principle.

2.2 | Generative Artificial Intelligence for Process Automation and Business Intelligence

OIPT asserts that possessing the capability to swiftly and precisely handle information beyond that of one's rivals is a noteworthy competitive edge in the contemporary, rapidly evolving business landscape (Dubey et al. 2021; Srinivasan and Swink 2018; Tiwari et al. 2024). OIPT also suggests that firms can enhance their information processing capabilities by implementing various strategies, including investing in cutting-edge information technology, optimizing communication routes, and refining decision-making procedures (Bensaou and Venkatraman 1995).

BI can evolve in both technological and managerial dimensions, and socio-environmental data are seldom integrated with financial data, leading to a balanced performance (Menaouer et al. 2022). The incorporation of sophisticated technologies—such as GAI and data analytics—into BI systems has revolutionized how organizations acquire and analyze information. These technologies facilitate autonomy (Balje 2023), optimize operations, and enhance the resilience of organizations in the face of uncertainty (Chalmers et al. 2021). Although firms face significant obstacles in perceiving and using business information, the effective use of data analytics can facilitate balanced, responsible, and sustainable development (Jayakrishnan et al. 2018). Further studies are required at the organizational level to further evaluate the impact of BI on corporate sustainability performance (Qushem et al. 2017).

BI in firms can enhance business process performance by boosting efficiency metrics (Coombs et al. 2020). Automation with GAI entails substituting human labor with a machine. Through the implementation of PA, firms can alleviate employees from repetitive and monotonous tasks, allowing them to focus on more intellectually demanding activities that contribute greater value to the organization (Makarius et al. 2020).

Digital threats including data-oriented technological gaps and an absence of future preparedness pose a threat to the long-term survival of sustainability performance antecedents (Arumugam et al. 2022). Report generation time, data accuracy, and decision-making speed are considered key performance indicators that are used to evaluate the efficacy of BI. Forecasting sales, analyzing finances, and monitoring operational efficiency are all possible with the help of BI. Furthermore, BI can also be utilized to discover creative commercial prospects aligned with sustainability objectives, such as producing green products or services, reducing waste and energy usage, and exploring renewable energy options (Menaouer et al. 2022). BI is essential for enhancing sustainability achievement as it equips firms with the necessary data and insights to make well-informed decisions, track their progress, and effectively communicate their performance to stakeholders (J. Cheng et al. 2023).

All of these BI activities related to data analysis and information sharing can be undertaken through GAI; for example, with a large language model-backed GAI, as performed by Google (Cosentino et al. 2024). GAI can take control of these activities to collect real-time data from various sources, including suppliers, vendors, production, and even customers, to process it and provide more accurate, timely, and precise strategic options for decision-making. GAI is employed in production, planning, and regulation to automate multiple processes, exposing deviant processes in manufacturing, enhancing the efficiency of wastewater treatment methods, and facilitating supplier selection (J. Cheng et al. 2023).

SC has led to increased data creation and consumption, enabling organizations to easily acquire market data for real-time analysis using GAI and advanced analytics, which is crucial for the speed, accuracy, and optimization of autonomous-based systems (Smyth et al. 2024). GAI is capable of efficiently analyzing tremendous amounts of data while producing novel insights and concepts. Producing novel insights from analyzing vast amounts of data is the fundamental concept of OIPT (Galbraith 1973; Galbraith 1974). Analyzing data is the capability of processing available information to produce information that the organization requires to deal with uncertainty. This characteristic renders it an indispensable tool for organizations operating in highly unpredictable circumstances (Dubey et al. 2024). By harnessing the power of GAI, firms can enhance their competitive advantage by accurately forecasting future trends, identifying new opportunities, and developing innovative solutions. Furthermore, this technology has the potential to help organizations streamline their processes, minimize expenses, and enhance customer satisfaction (Dubey et al. 2024).

GAI is being adopted to enhance BI, aiming to improve organizational CP through GPI and EOL product management by synchronizing information processing capabilities and utilizing data from SCs. Based on the discussion above, the study hypothesizes the following:

H1. *GAI-PA has a positive relationship with BI.*

2.3 | Generative Artificial Intelligence for Cognitive Insight and Business Intelligence

BI can significantly enhance organizational performance by identifying new opportunities, uncovering potential hazards, providing deeper industry insights, and improving decision-making processes (Niu et al. 2021; Zhao et al. 2021). At present, BI predominantly depends on centralized and internal corporate data. Big data enables BI to offer firms valuable insights for improved customer understanding and marketing strategies, personalized communications, and real-time identification of obstacles and opportunities (Niu et al. 2021). GAI can boost BI by generating CI. Similar to BI, GAI also relies on data (Lee et al. 2019), although multidimensional data (Enholm et al. 2022). Prescriptive analytics—utilizing GAI-driven suggestions—strongly connects with the objective of boosting resilience within the SC by providing practical insights that facilitate the creation and execution of preventive and reactive actions (Belhadi et al. 2024). As discussed above, BI provides crucial insights for enhanced customer understanding, enhanced marketing strategies, personalized communication, and real-time identification of obstacles and opportunities. Insights derived by GAI-CI can assist or enhance a firm's BI through generative insights based on real-time multidimensional data. In line with OIPT, the capability of GAI-CI to produce novel insights by analyzing vast data is crucial for producing the required information to mitigate the uncertainty of carbon emissions. Google recently utilized GAI to analyze its data, whereby this advanced technology not only examined the data but also identified issues and provided suggestions for future actions (Cosentino et al. 2024). GAI-CI can uncover concealed information from data to provide CI, thus enhancing BI. Based on these arguments, this study proposes the following hypothesis.

H2. *GAI-CI has a positive relationship with BI.*

2.4 | Generative Artificial Intelligence for Cognitive Engagement and Business Intelligence

GAI-CE refers to the influence of AI on the engagement, communication, and coordination processes of manufacturers' stakeholders (Y. Yu et al. 2024). GAI-CI possesses the capacity to extract hidden information from data to offer CI, whereas GAI-CE has the capability to communicate or disseminate these insights to stakeholders for execution (Y. Yu et al. 2024), and organizational AI must inherit this feature of disseminating information to stakeholders to reduce uncertainty (Belhadi et al. 2024). OIPT also discusses how organizations can reduce uncertainty depending upon their ability to process available information (Galbraith 1973; Galbraith 1974). GAI has the capacity to have a beneficial influence on every significant facet of the SC, encompassing activities such as enhancing consumer understanding, selecting suitable suppliers, streamlining internal operations, refining organizational SC design, planning, and improving SC visibility (Smyth et al. 2024). Simultaneously, AI is unable to create successful and productive businesses without engaging with human capabilities (Daugherty and Wilson 2018). Manufacturers have utilized AI to actively involve stakeholders, including consumers, suppliers, and employees. AI is a prerequisite for efficiently interacting with consumers and improving customer satisfaction (Prentice et al. 2020). The widespread adoption of AI by manufacturers facilitates the management of their relationships with suppliers and enhances their level of engagement (Saenz et al. 2020). By contrast, BI depends predominantly on centralized and internal corporate data, whereas BI will be enhanced when assisted by GAI-CE. Hence, the current study proposes the following:

H3. *GAI-CE* has *a positive relationship with BI.*

2.5 | Business Intelligence and Green Product Innovation

GPI is a crucial element in improving sustainability within the SC framework. It includes designing environmentally friendly products, methods for efficient transportation and delivery, and innovative services that strive to reduce energy usage, emissions, and promote sustainable practices (He et al. 2019). Manufacturers frequently participate in collaborative GPI throughout the SC to optimize resource allocation, enhance core competencies, and attain sustainable growth (He et al. 2020; Wu and Li 2020).

BI plays a crucial role in fostering GPI throughout SC, intending to improve CP. Digital technologies such as GAI optimize BI, facilitating the dissemination of information and allocation of resources while improving the transparency of information to enhance the green innovation capacity of firms (Chen et al. 2023; Dou and Gao 2023; Song et al. 2024). GPI can be enhanced by extracting and analyzing data gathered from external stakeholders (Fernández et al. 2021; Xu et al. 2023). BI-supported GAI ensures the rapid acquisition of information, while also prioritizing environmental friendliness and minimizing the environmental effects of products. BI facilitates the gathering and examination of customer behavior and preferences concerning green products (Zameer et al. 2022), whereby this data and information are crucial in developing innovative green products that meet market requirements. Utilizing BI to analyze market trends allows organizations to identify gaps and possibilities for introducing innovative green products that align with client demands (Laroche et al. 2001). BI plays a crucial role in identifying new market potential for GPI, enabling development into previously unexplored eco-friendly segments (Eidizadeh et al. 2017).

The central point of OIPT is the alignment of information processing needs and capabilities (Premkumar et al. 2005). In this context, BI constitutes the information processing capabilities that meet the firm's GPI-related information needs. This alignment illustrates OIPT in practice, showing how information processing needs and capabilities can be aligned. Based on these arguments, the current study proposes the following hypothesis.

H4. *BI has a positive relationship with GPI.*

2.6 | Green Product Innovation and End-of-Life Product Management

Integrating EOL product management into the SC and CP can be achieved by considering product design, material procurement, manufacturing processes, product distribution, and EOL product management (Adhitya et al. 2011). GPI is a crucial aspect in shaping how companies handle the disposal and recycling of their products at the end of their life cycle. It entails the creation or improvement of goods and processes to reduce environmental consequences (Kong et al. 2016). GPI encompasses several domains, including pollution mitigation, waste recycling, and environmentally conscious product designs (Chen 2008). Moreover, the implementation of environmentally conscious product designs involves incorporating environmental and social factors throughout the entire product lifecycle, including its management after the end of its useful life, referred to as EOL product management (Heng et al. 2021). Implementing a well-designed system for EOL products management—including product recovery and warranty returns—can enhance customer loyalty and feedback, whereas a poorly managed system can result in substantial increases in operating expenses (Abdul-Rashid et al. 2017). EOL product management involves the reintegration of used products into the SC through reverse logistics material recovery (Abdul-Rashid et al. 2017), which is only possible if the organization utilizes its information processing capabilities transparently and discloses all environmental threads and instructions for handling products (Lai et al. 2015). All of this information—including threads and handling instructions—is taken into account during the product design phase, which is a crucial component of GPI (Dangelico 2016). Producers alone possess this ability through GPI to create strategies for product designing and producing goods that maximize lifespan and—if necessary—determine the most effective means for recycling and disposing of them (Toffel 2003). OIPT emphasizes aligning information processing capabilities with organizational information needs. In our context, these needs are GPI and EOL product management, and their alignment generates synchronization and synergy. Based on these arguments, this study proposes the following hypothesis.

H5. *GPI has a positive relationship with EOL product management.*

2.7 | End-of-Life Product Management and Carbon Performance

According to the International Energy Agency (2009), the manufacturing industry is responsible for 38% of global carbon emissions. Reducing carbon emissions is crucial due to its adverse effects on the environment, such as global warming, changes in weather patterns, the occurrence of acid rain, and air pollution, all of which can influence human health and disrupt the natural balance of the ecosystem. Manufacturing strategies that prioritize the management of carbon emissions, pollutants, and waste often lead to improved environmental performance (Abdul-Rashid et al. 2017; Duflou et al. 2012; Sarkis 2001). For example, in the context of CP, empirical evidence has shown that using EOL management practices leads to enhanced CP across the SC, as applied through transaction cost theory (Vachon and Klassen 2006). Van Loon and Van Wassenhove (2018) examined the environmental consequences of remanufacturing—which involves reusing components to extend their lives—and found that it has a beneficial influence on the environment. Environmental impacts refer to the consequences of EOL product management (Nag et al. 2022). The organization's information processing on the manufacturer, product attributes, and product return for reuse, recycling, and refurbishing is crucial (Kianpour et al. 2017), specifically within its SC circle, because EOL product management is realized through the establishment of a reverse SC (Bockholt et al. 2020). OIPT within the setting of an SC pertains to the systematic collection, analysis, and distribution of information to enhance decision-making (Huang et al. 2023), such as when a product was sold and when the reverse SC or logistics needs to be initiated. Based on these arguments, this study hypothesizes the following:

H6. *EOL product management has a positive relationship with CP.*

2.8 | Green Product Innovation and Carbon Performance

In light of the demands from environmental degradation and energy inefficiency, firms must innovate to mitigate significant environmental hazards (Peters and Buijs 2022). According to information processing theory, GPI must be considered an essential need to boost CP, which is uncertain in the context of the current study (De Medeiros et al. 2022). During product development, firms must enhance the environmental performance of their goods through the adoption of GPI (Chen and Jin 2023). Energy consumption in the production and operation of firms releases carbon emissions, while the intensity of emissions increases at each stage of the SC (Waltersmann et al. 2021). Through product innovation, substituting non-sustainable products with environmentally friendly products mitigates environmental harm over the product life cycle, hence enhancing CP (Mingyue and Yingming 2022). Improving CP throughout the product life cycle is achievable by effectively utilizing processed information through information processing capabilities during all stages, including product design, packaging, dispatch, storage, and—crucially—EOL product management. In line with OIPT, organizations must use their information processing capability to fulfill the need for GPI to mitigate the uncertainty of carbon emissions (Galbraith 1973; Galbraith 1974). Based on these arguments, this study proposes the following hypothesis:

H7. *GPI has a positive relationship with CP.*

2.9 | Green Product Innovation Mediation Among Business Intelligence and End-of-Life Product Management

OIPT asserts that organizations can enhance their information processing capabilities or reduce the uncertainty (Galbraith 1973; Galbraith 1977). EOL product management, the removal of hazardous elements from products, and enhanced information dissemination also correlate with the capacity to minimize trade-offs between uncertainty and opportunities associated with innovation and integration management (Preuss 2005). Technological integration such as BI and GAI provides an opportunity for organizations to integrate their SC across departments and partners, including customers (Rizzi et al. 2013). SC strategies are essential to maximize SC circularity, and advanced technologies such as AI-backed BI can facilitate this by enhancing resource efficiency and minimizing waste, thereby benefiting both environmental and SC outcomes (Bag and Kumar Mangla 2025). Such integration allows organizations to analyze data and information collected from multiple sources to design green innovative products, considering all stages of the product life cycle, including EOL product management. Reverse SC networks are occasionally less efficient than forward SC networks (Bernon et al. 2011). Organization information processing theory plays a vital role through technological integration among partners. Throughout the forward SC network, the organization gathers data and information from suppliers, consumers, and other stakeholders to introduce GPI through its information processing capabilities. Organizations will distribute all pertinent information on how to handle, transport, and store these innovative green products to the forward SC networks, whereas throughout the reverse SC network, organizations depend upon customers and other SC partners to act according to the instructions regarding EOL product management disseminated along with the products during the forward SC process. Organizations with more integration control external factors that affect reverse logistics or EOL product management more effectively (Mollenkopf et al. 2007). Based on the above discussion, the following hypothesis is proposed:

H8. *GPI mediates the relationship between BI and EOL product management.*

2.10 | Green Product Innovation Mediation Among Business Intelligence and Carbon Performance

BI can boost economic and environmental performance. The firm's information processing capabilities enable BI tools to evaluate extensive data sets, allowing firms to identify inefficiencies and opportunities for improvement in their strategies for addressing the uncertainty of carbon emissions (Goede 2021). The theoretical lens of OIPT provides support for the capability of BI for information processing to deal with uncertainty, such as carbon emissions. To balance the equation between capability and uncertainty, a need is required, as per OIPT (Galbraith 1973; Galbraith 1974), which is GPI in the context of this study. Research also demonstrates that GPI plays a crucial role in mitigating environmental consequences, such as CP (Li and Hamblin 2016). By using sustainable materials and methods, companies can reduce their carbon emissions and waste creation, therefore promoting cleaner manufacturing practices (Zhang et al. 2021). Aligning product design with CP is essential for enhancing CP (Dangelico and Pujari 2010). After identifying inefficiencies and opportunities for improving CP, BI plays a vital role in decision-making (Goede 2021), as well as designing, producing, packing, storing, and transporting these environmentally friendly products (Kam-Sing Wong 2012). This creates a balance between the information processing capabilities and the need to process this information. The BI system facilitated by GAI plays a vital role for GPI, which further enhances the firm's CP. BI is the information processing capability of an organization, and CP is the reason or uncertainty for which the information is required to be processed, whereas GPI creates a balance between capability and uncertainty. This is also reflected in conceptual framework, Figure 1. Based on these arguments, this study proposes the following hypothesis.

H9. *GPI mediates the relationship between BI and CP.*

3 | Methodology

3.1 | Sample and Data Collection

This study employs a quantitative survey methodology, gathering data from manufacturing firms in Pakistan to address the study's topic. Numerous aspects contribute to the selection of an appropriate study setting and the use of a quantitative methodology to evaluate our hypothesis. Under the Paris Agreement, Pakistan is required to report on the combined challenges of boosting economic growth and enhancing CP (Raza and Dongsheng 2023). The World Health Organization (2019) reported that 2.4 million individuals die each year in Pakistan, adversely affecting both the economy and public health. Carbon emissions in Pakistan are persistently increasing, consistent with the findings of Mohmmed et al. (2019) for the top 10 emitting nations. Achieving carbon neutrality necessitates further efforts in technology and energy substitution (Raza and Dongsheng 2023).

To gather data, the study follows a combination of convenience and snowball sampling techniques. Issues related to bias, non-representation, and over-representation were avoided by collecting data from four major cities and four different industries, with firms ranging from five to 30 years of age. The authors contacted manufacturing firms to solicit their participation in the study. We required participants to possess a comprehensive understanding of SC management and intended to target the top management personnel, such as the chairman, CEO, general manager, or senior managers responsible for operational and technological management within the company. Once the consent was provided, we approached their managers, introduced ourselves, and explained the aim of the study. We also provided assurance regarding the confidentiality of their identity. We then requested that they refer other respondents from the industry who fulfill the eligibility criteria. A total of 540 questionnaires were distributed, 187 of which were returned, and 155 were deemed valid, resulting in a response rate of 28.7%. This meets the minimum criterion of a response rate of 20%, as suggested by Malhotra and Grover (1998). While 155 respondents is a decent sample size, 153 is suggested for a minimum path coefficient of less than or equal to 0.2, a significance level of less than or equal to 0.05, and a minimum statistical power of 80% (Kock and Hadaya 2018).

3.2 | Measures

The scale's measurement elements were all drawn from established scales in the literature. We rated responses on a seven-point Likert scale, ranging from "*strongly disagree*" to "*strongly agree*" (see Appendix A1 for detailed information).

GAI was measured using 11 items, comprising four, four, and three items for GAI-PA, GAI-CE, and GAI-CI, respectively. This

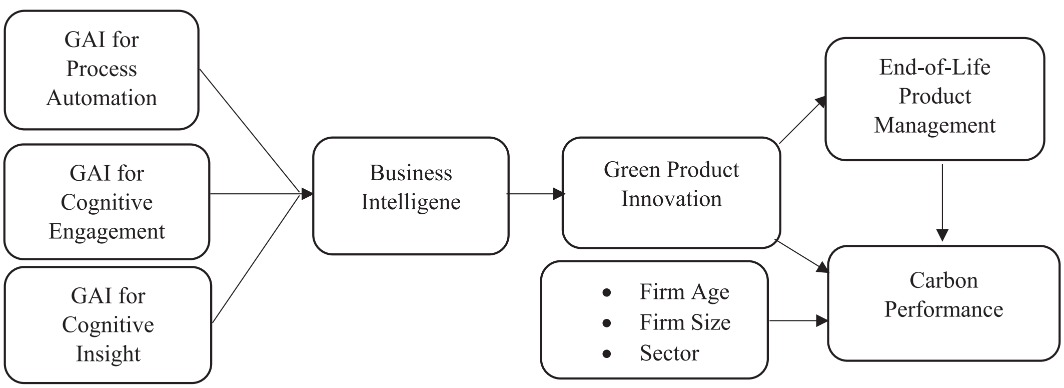

FIGURE 1 | Conceptual framework.

scale has previously been used in existing literature (Davenport and Ronanki 2018; Bag et al. 2021; Benzidia et al. 2021; Y. Yu et al. 2024).

BI was measured using five items by Paulino (2022) and has also been used by J. Cheng et al. (2023), which confirms the reliability and validity of the scale. Items on the scales discuss issues related to customers, competition, opportunities, efficiency, and data-driven decisions. GPI was measured through four items by El-Kassar and Singh (2019) that discuss non-toxic or environmentally friendly material usage that is easy to recycle, reuse, and decompose, eco-labeling, and finally EOL product management.

EOL product management was measured using five items by Abdul-Rashid et al. (2017). These items discuss prolonging product services, waste treatment after product recovery, warranty returns, product recalls, and recycling support. Finally, the CP measurement was initially explored through five items by Montabon et al. (2007), also used by Lai et al. (2015). However, due to reliability issues, the authors removed the last item of the CP during analysis and ultimately measured it with four items.

3.3 | Control Variable

Prior studies on green innovation and CP show that firm size (Adu et al. 2023; Ganda 2022; Martínez-Ros and Kunapatarawong 2019), firm age (Adu et al. 2023), and sector (Nuber and Velte 2021) can affect a firm's CP. Accordingly, our study implements endogeneity controls by controlling for firm size, firm age, and sector. It is also represented in Figures A1 and A2.

3.4 | Common Method Bias

We endeavored to reduce common technique bias. For instance, data was collected in two waves, and respondent anonymity was guaranteed. We also randomized the questionnaire items. The Harman single-factor test showed that a single component explained only 40.25% of the variation, which was not sufficiently substantial to affect the findings. This technique matches the literature (Yang et al. 2017).

3.5 | Descriptive Analysis

A descriptive analysis of the data was conducted using IBM SPSS Statistics, including the respondents' positions, industries, company ages, staff counts, cities, and genders. Data were collected from manufacturing firms in major industrial cities in Pakistan. Details regarding the descriptive analysis of the study are also provided in Table 1.

4 | Results

4.1 | Reliability and Validity

The reliability of the scales was evaluated based on Cronbach's alpha and composite reliability. Cronbach's alpha for the entire construct is greater than 0.7 (0.787–0.897), and composite reliability was greater than 0.8 (0.843–0.924), as detailed in Table 2. These measurements ensure the reliability of the constructs (Fornell and Larcker 1981).

TABLE 1 | Descriptive analysis.

City	Frequency	Percentage (%)	Sector	Frequency	Percentage (%)
Karachi	53	34.2	Textile	33	21.3
Lahore	45	29	Chemical	36	23.2
Islamabad	31	20	Electrical	24	15.5
Faisalabad	26	16.8	Beverage	62	40
Total	155	100	Total	155	100
Firm age			**Firm size**		
5 years or less	21	13.5	100–199	33	21.3
6–10 years	28	18.1	200–299	33	21.3
11–15 years	20	12.9	300–399	27	17.4
16–20 years	30	19.4	1000–2000	32	20.6
21–30 years	27	17.4	Above 2000	30	19.4
31 or above	29	18.7	Total	155	100
Total	155	100	**Position**		
Gender			CEO	17	11
Male	142	91.6	Director	21	13.5
Female	13	8.4	Senior Manager	117	75.5
Total	155	100	Total	155	100

TABLE 2 | Reliability and convergent validity.

Construct	Indicator	Outer loadings	Indicator reliability	rho_A	Cronbach's alpha	Composite reliability	(AVE)
GAI-CE	GAI-CE1	0.828	0.686	0.803	0.788	0.858	0.603
	GAI-CE2	0.741	0.549				
	GAI-CE3	0.789	0.623				
	GAI-CE4	0.745	0.555				
GAI-CI	GAI-CI1	0.875	0.766	0.861	0.848	0.893	0.737
	GAI-CI2	0.789	0.623				
	GAI-CI3	0.907	0.823				
GAI-PA	GAI-PA1	0.853	0.728	0.870	0.856	0.902	0.698
	GAI-PA2	0.830	0.689				
	GAI-PA3	0.800	0.640				
	GAI-PA4	0.857	0.734				
BI	BI1	0.712	0.507	0.773	0.767	0.843	0.520
	BI2	0.644	0.415				
	BI3	0.820	0.672				
	BI4	0.707	0.500				
	BI5	0.711	0.506				
CP	CP1	0.912	0.832	0.855	0.833	0.899	0.748
	CP2	0.871	0.757				
	CP3	0.809	0.654				
EOL	EOL1	0.826	0.682	0.900	0.897	0.924	0.708
	EOL2	0.817	0.667				
	EOL3	0.836	0.699				
	EOL4	0.833	0.694				
	EOL5	0.893	0.797				
GPI	GPRD1	0.891	0.794	0.872	0.853	0.900	0.693
	GPRD2	0.864	0.746				
	GPRD3	0.818	0.669				
	GPRD4	0.751	0.564				

All measuring items were derived from existing literature, confirming the content validity of the scale (Flynn et al. 2010). Furthermore, Table 2 reflects outer loadings and indicators' reliability value for all constructs, which is greater than 0.6, while composite reliability is greater than 0.7, and AVE is greater than 0.5 for constructs, demonstrating that the scale has strong aggregate validity (Flynn et al. 2010; Fornell and Larcker 1981). Table 3 indicates a strong discriminant validity as the square root of AVE of each construct that is reflected in bold is greater than its underlying constructs (Flynn et al. 2010; Fornell and Larcker 1981).

4.2 | Hypothesis Testing

Partial least squares structural equation modeling (PLS-SEM) was used for data analysis. Initially, the measurement model was evaluated for reliability and validity, followed by hypothesis testing by structural model analysis. SmartPLS software was used to execute the PLS-SEM processes. The rationale for using PLS-SEM lies in its lack of assumptions about data normality. It has been employed in several studies across diverse domains, including the behavioral sciences, organizational studies, management information systems, and corporate strategy (Wong 2013).

TABLE 3 | Discriminant validity.

	BI	CP	EOL	GAI-CE	GAI-CI	GAI-PA	GPI	Firm age	Firm size	Sector
BI	**0.721**									
CP	0.183	**0.865**								
EOL	0.556	0.618	**0.842**							
GAI-CE	0.646	0.384	0.724	**0.776**						
GAI-CI	0.213	0.699	0.686	0.513	**0.858**					
GAI-PA	0.716	0.449	0.654	0.704	0.45	**0.835**				
GPI	0.462	0.375	0.579	0.71	0.505	0.606	**0.833**			
Firm age	−0.042	−0.041	−0.015	0.042	−0.028	−0.085	0.012	**1.000**		
Firm size	0.070	−0.087	−0.004	0.009	0.040	0.023	0.008	0.095	**1.000**	
Sector	0.052	−0.060	0.021	0.063	0.068	0.021	0.023	0.122	0.930	**1.000**

TABLE 4 | Hypothesis testing.

Hypothesis	Relationship	Original sample (β)	Sample mean (M)	Standard deviation (STDEV)	t statistics (|O/STDEV|)	p values	Result
H1	GAI-PA → BI	0.760	0.758	0.05	15.259	0.000	Accepted
H2	GAI-CI → BI	−0.252	−0.223	0.087	2.877	0.004	Rejected
H3	GAI-CE → BI	0.240	0.227	0.090	2.654	0.008	Accepted
H4	BI → GPI	0.462	0.457	0.087	5.312	0.000	Accepted
H5	GPI → EOL	0.579	0.579	0.063	9.178	0.000	Accepted
H6	EOL → CP	0.599	0.598	0.073	8.159	0.000	Accepted
H7	GPI → CP	0.029	0.035	0.088	0.331	0.741	Rejected
H8	BI → GPI → EOL	0.267	0.268	0.072	3.702	0.000	Accepted
H9	BI → GPI → CP	0.013	0.015	0.041	0.329	0.742	Rejected

The reflecting model of this research is another justification for using PLS-SEM. The model in which latent variables reflect their items is termed a reflective model, and a correlation exists among these items. Accordingly, PLS-SEM is considered appropriate for such a reflective model (Wong 2013).

Table 4 summarizes the results. GAI-PA and GAI-CE are positively related to BI with β values of 0.760 and 0.240, respectively, and p values smaller than 0.05. Therefore, H1 and H3 are accepted. By contrast, after applying SEM, the results indicate that GAI-CI is negatively associated with BI, and thus H2 is rejected. BI has a significant positive effect on GPI, with a β value of 0.462 and a p value smaller than 0.05, which supports the acceptance of H4. H5 is also accepted due to the effect of GPI on EOL, with a positive β value of 0.579 and a p value smaller than 0.05. EOL also has a significant positive effect on CP with a β value of 0.599 and a p value smaller than 0.05, which indicates the acceptance of H6. However, the proposed significant positive effect of GPI on CP does not align with expectations, as it has a β value of 0.029 and a p value greater than 0.05. Given that neither of these values meets the acceptable criteria, H7 is not accepted.

The causal methodology proposed by Baron and Kenny (1986) has been critiqued by Preacher and Hayes (2004). Multiple stages are required, and each step must demonstrate a substantial influence of one variable on another; otherwise, the mediation hypothesis lacks evidence (Preacher and Hayes 2008; Hayes 2009). The bootstrapping approach for mediation—endorsed by Hair et al. (2016)—is deemed most appropriate for SmartPLS software since it requires no assumptions about the sampling distribution and size (Preacher and Hayes 2008).

The results show that GPI significantly mediates the relationship between BI and EOL product management, with a β value of 0.267, and the p value is also smaller than 0.05. Therefore, H8 is accepted. The findings show that GPI does not mediate the relationship between BI and CP, with a β value of 0.013 and a p value greater than 0.05. Since neither value is within the acceptance criteria, H9 is not accepted.

5 | Discussion

The study was initiated from the perspective that green innovative products are the outcome of the convergence of technology, supported by advanced BI backed by GAI. Technology-intensive organizations are the context in which these advanced technologies are applied. In a technology-intensive environment, organizations strongly rely on advanced systems and digital technologies—including AI—to enhance their operations and integrate various SCs within their sectors (Yáñez-Valdés and Guerrero 2024). SCs are the context of the current study, where GPI is a mediatory construct between BI, EOL product management, and CP. GAI supports BI, and together these advanced digital technologies form a strong organizational capability for processing collected information. GPI, EOL product management, and CP relate to the uncertainty within the SC for which the advanced digital technologies process the collected information.

BI has a positive effect on GPI, which represents the effectiveness of GAI. GPI influences EOL product management and mediates the relationship between BI and EOL product management, whereas GPI does not mediate the relationship between BI and CP. A comparison of the results is not possible, as such relationships have not been previously tested. It is essential to emphasize the significance of EOL product management, which directly contributes to enhanced CP and mediates the relationship between GPI and CP. Although the mediation of EOL product management was not proposed, once we had the data, we came to know that GPI can enhance CP through EOL product management. EOL product management not only requires forward SC integration but also reverse SC integration (Abdul-Rashid et al. 2017). It indicates that CP can be enhanced through proper step-by-step SC integration—both forward and reverse—rather than focusing on a specific domain.

5.1 | Theoretical Contributions

This study advances the literature on sustainability by contributing to the growing discourse on SCs and their intersection with CP. Specifically, it addresses significant gaps in understanding the role of GAI and BI in mitigating uncertainties within SC to foster green GPI and improve CP. The theoretical contributions of this study are multifaceted. First, this study extends the application of OIPT by demonstrating its relevance to SC contexts. By categorizing GAI into three distinct capabilities—that is, GAI-CI, GAI-PA, and GAI-CE—it offers a nuanced understanding of how these technologies support BI systems. The study categorizes GAI capabilities and explains their specific applications in SCs. For instance, GAI-CI supports strategic product design and predictive analytics, GAI-PA streamlines manufacturing and monitoring processes, and GAI-CE enhances stakeholder communication and coordination. These insights offer a deeper theoretical understanding of the technological pathways through which GAI contributes to sustainability and innovation in the SC context.

Second, by focusing on technology-intensive SCs, this study enriches the understanding of how advanced digital technologies—including GAI—enable SCs to innovate and operate sustainably. It highlights the role of GAI and BI in overcoming technological and operational challenges, particularly those related to GPI and EOL product management. This work positions SCs as a critical interface for integrating green innovation practices, offering a fresh perspective on the capabilities required for sustainable SCs.

Third, this study contributes a theoretical framework linking GAI, BI, and organizational capabilities to GPI outcomes. It emphasizes the importance of EOL product management and reverse SC processes in achieving sustainability goals. This framework provides a structured approach to understanding how organizations can leverage data-driven solutions to address environmental challenges while enhancing CP.

Fourth, the study addresses the pressing need for actionable frameworks in the domain of sustainable SCs by linking the adoption of GAI and BI with environmental performance metrics such as CP. It provides theoretical underpinnings for how digital technologies can drive sustainable practices across the entire SC, paving the way for future empirical research on SCs and environmental innovation.

5.2 | Practical Implications

The findings reveal significant insights for managers aiming to enhance both BI and sustainability outcomes. First, the positive influence of GAI-PA and GAI-CE underscores their critical role in improving BI. Accordingly, managers should prioritize integrating GAI technologies into their operations to streamline processes, reduce human error, and foster deeper analytical insights. Investing in employee training to maximize the cognitive benefits of GAI is equally important, ensuring that the workforce is equipped to interact effectively with advanced AI systems.

Furthermore, these findings suggest that organizations seeking to achieve competitive advantage should adopt a dual focus, leveraging GAI to enhance decision-making capabilities while simultaneously prioritizing innovation in eco-friendly products. Allocating resources to research and development in GPI can amplify the impact of BI systems on sustainability metrics.

Finally, managers must ensure that the deployment of GAI and green innovation strategies aligns with overarching corporate goals, fostering a culture that values both technological advancement and environmental stewardship. Integrating these initiatives into long-term strategic planning will enable firms to remain resilient and sustainable in a rapidly evolving business environment.

5.3 | Limitations and Future Research

While this study reflects the SC context of the manufacturing sector, future studies could focus on the service sector, especially examining GPI in connection with CP. Future research is strongly recommended to focus on the role of GAI in enhancing CP through EOL product management. While AI is well-discussed in the literature in conjunction with green knowledge management that promotes knowledge related to the environment, organizations need a leadership style that focuses on the management of environmental knowledge through digital technologies such as AI. The evolving digital era requires leaders to focus on technological integration and knowledge management, enabling environmental knowledge to be managed effectively and efficiently through evolving digital technologies. Furthermore, studies should explore the relationship between information processing capabilities and dynamic capabilities, specifically how information processing capabilities contribute to the development of dynamic capabilities. Examining the emergence of information processing capabilities into dynamic capabilities could also be a future research agenda.

6 | Conclusion

This study addresses a persistent problem with carbon emissions, with the World Health Organization (2019) reporting that 2.4 million individuals die annually in Pakistan as a result, negatively affecting both the economy and public health. Attaining carbon neutrality requires increasing advancements in technology and energy replacement. From the standpoint of OIPT, current research examines how organizations achieve equilibrium between information processing capabilities utilizing GAI and SC uncertainties (CP) in light of the swift advancement of digitalization. This study's findings indicate that EOL product management significantly enhances CP, specifically serving as a mediator in enhancing organizational CP through GPI, which is bolstered by BI and GAI. Accordingly, this study offers theoretical foundations for how digital technologies promote sustainable practices throughout the SC, encouraging future empirical study on SCs and environmental innovation.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Appendix

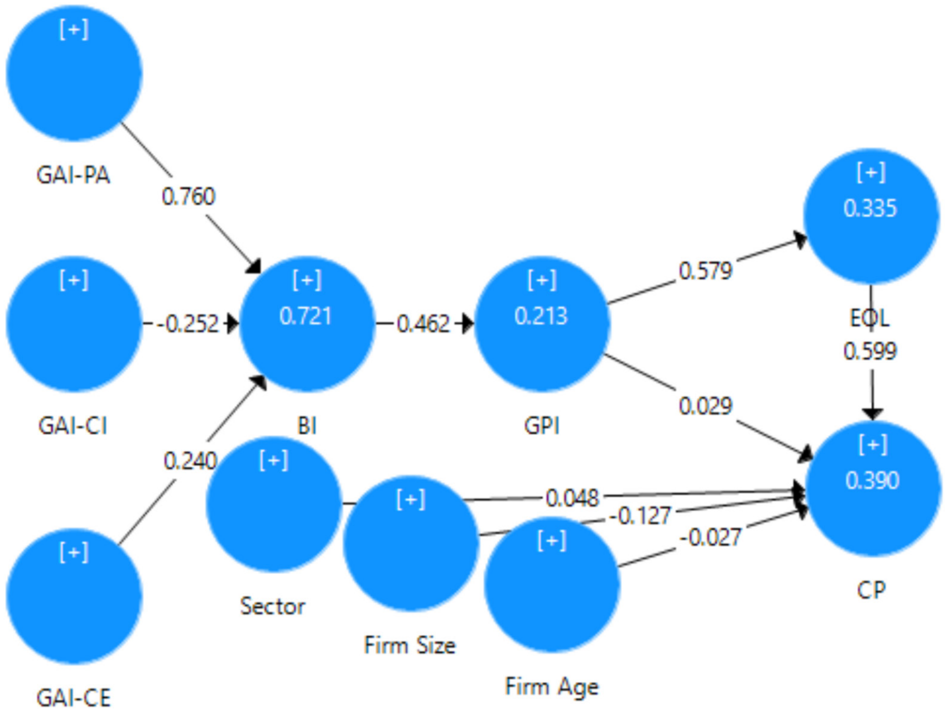

FIGURE A1 | PLS algorithm.

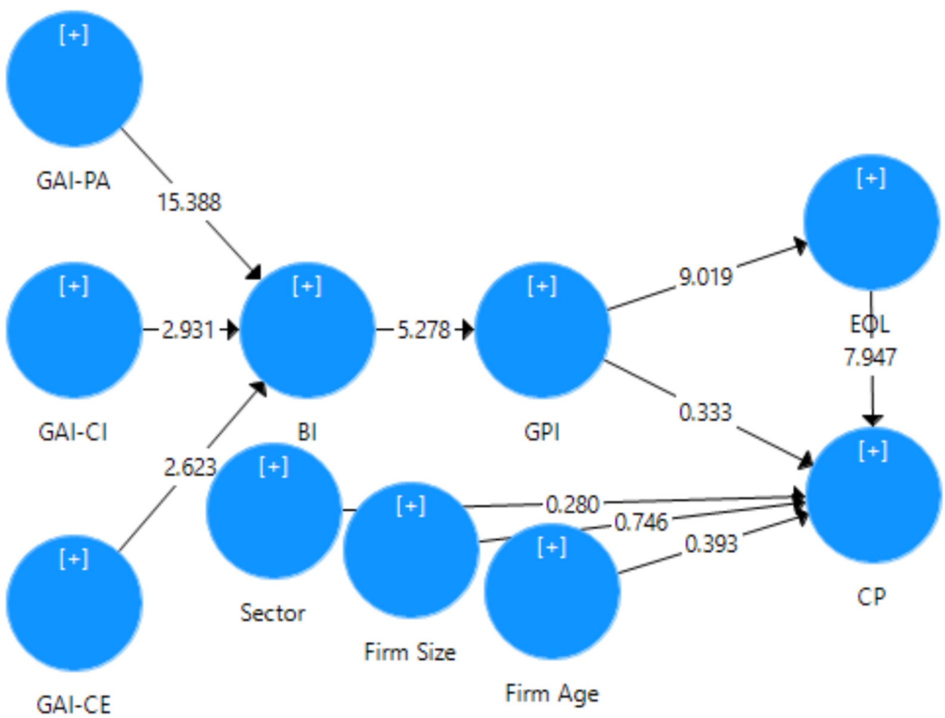

FIGURE A2 | Bootstrapping.