Smart product platforming powered by AI and Generative AI: Personalization for the circular economy

Abstract

The interlocks between smart product platforming (SPP) powered by Artificial Intelligence (AI) and Generative AI, big data analytics, and machine learning are still in their infancy. Modern technology-driven SPP promotes personalized product design and manufacturing suited to support environmentally friendly products for the circular economy. In this study, we develop a framework pertaining to the interlinks between SPP, big data analytics, machine learning, and the circular economy. To test our framework, we apply structure equation modeling based on data collected from more than 200 automotive industry professionals operating in China. Our results demonstrate that SPP and big data analytics are the central determinants for manufacturing environmentally friendly products, ultimately promoting circular economy applications. SPP plays a pivotal role in innovative product design and in facilitating the relevant manufacturing procedures. Big data analytics significantly feed into SPP applications. Machine learning and flexibility in SPP perform moderating roles in strengthening environmentally friendly outcomes. The mediating role played by SPP between big data analytics and environmentally friendly products for the circular economy is partially encouraging. As SPP powered by AI and Generative AI is an emerging phenomenon, our study contributes to this new knowledge dimension. We conclude this paper by discussing the theoretical and practical implications of our study, its limitations, and directions for future research.

Keywords:
Smart product platforms and flexibility
Personalized product design and manufacturing
Environmentally friendly products and circular economy
Generative artificial intelligence and large language models
Big data analytics and machine learning

1. Introduction

Product platforming emphasizes the manufacturing of a family of products based on a common platform while adopting feature flexibility and optimizing the available resources to meet emerging customer demand (Jalali et al., 2022; Zhang., 2015). Smart product platforming (SPP) utilizes contemporary technology to control the related operations. SPP identifies the common interlocks between a firm's offerings, its ecosystem actors, and its personalized products and services (Hilbolling et al., 2021; Jalali et al., 2022). Artificial intelligence (AI), big data analytics, and machine learning are powerful tools for SPP. These technologies interlinked with Industry 4.0 are revolutionizing product processes and manufacturing arenas (Gong et al., 2021; Guo et al., 2021). The applications of generative artificial intelligence (GAI)—which are also called large language models (LLMs)—inherited with big data analytics (i.e., large volumes of unstructured and structured data) and machine learning (e.g., supervised and reinforcement learning) have simultaneously provided opportunities and created digital disruption (Akhtar et al., 2023; Gozalo-Brizuela and Garrido-Merchan, 2023: Wang et al., 2023). GAI tools like ChatGPT and DALL-E significantly increase productivity, enhance work quality, and refine ideas for product design innovation, providing the prospect of substituting hard work with smart work (Noy and Zhang, 2023; Zhu and Luo, 2022). This AI-driven substitution, combined with original human thinking, could be the key to personalized product design and related manufacturing, supporting environmentally friendly products for the circular economy, and thus reducing waste and consumption. Numerous complex tasks that require specific knowledge and technology underpin the successful execution of each part of the product design and manufacturing processes, which are effectively facilitated by two-way communication and a problem-solving approach involving GAI and human beings (Hettiarachchi et al., 2022; Wang et al., 2023). GAI, which also helps to create novel ideas and designs benefiting contemporary customers, produces significantly higher scores compared to human-generated ideas (Joosten et al., 2024). GAI is believed to have the potential to enhance "*gross domestic products by 7%*" and to replace *"300 million jobs of knowledge workers"*; as such, it simultaneously provides opportunities and challenges that need to be investigated (Feuerriegel et al., 2024, p.111).

Despite the research conducted to understand the interlinks between traditional AI/big data analytics and performance outcomes (e.g., Akhtar et al., 2023), addictive technology and the circular economy (Hettiarachchi et al., 2022), and product platforming and customer needs (Jalali et al., 2022; Zhang., 2015), how SPP powered by AI and GAI—and fueled by big data analytics and machine learning—is linked to environmentally friendly products for the circular economy remains unclear. The research emerging in this domain could revolutionize the design and manufacturing industry. Although the industrial implications of GAI have hitherto remained unaddressed, its ability to generate complex texts, answer specific questions, and write code suited to build and design human-friendly interfaces has surprised many professionals (Wang et al., 2023). The concept of generating AI-based design is evolving (Zhu and Luo, 2022). In 2022, ChatGPT (Chat Generative Pre-trained Transformer) booted this domain when it recorded more than 100 million active users in just a few months after its release (Wu et al., 2023). Although GAI models present many advantages—such as saving time, enhancing innovation, and improving quality—they should be used with care, as the accuracy of any specific knowledge and information involved may be questionable. It is also important to carefully address how the questions are asked, as the models may not be trained to obtain specific technical information. Additionally, the reliability of the online resources used by GAI models and the related ethical issues are important (Wang et al., 2023; Bartlett and Camba, 2024).

Simpson et al. (2014) posited that industry decision-makers are more involved in designing a platform, defining the characteristics of a successful one, and assessing how it measures up against its competitors. Therefore, a significant number of firms are investing considerable time and resources into the creation of product platforms and the associated product ranges. Saporiti et al. (2023) identified 18 key challenges and proposed a set of countermeasures suited to solve the problems of smart platforms. However, little empirical evidence has hitherto been provided in relation to SPP impacts on firm performance (Bai et al., 2020), the circular economy and environmental aspects notwithstanding (Awan et al., 2021; Batista et al., 2023; Wang et al., 2023). As the circular economy makes steady progress in sustainability domains (Agrawal et al., 2019; Hettiarachchi et al., 2022), a limited number of recent studies conducted in relation to the circular economy have examined SPP interlinks. For instance, Lim et al. (2020) recognized the importance of reusable and transparent digital-physical systems capable of situational recognition and self-correction to enhance engineering product lifecycles. The latest studies have found that GAI is emerging and has the potential to be used as a tool for the design process, rather than as one for final designs (Bartlett and Camba, 2024). The design principles should include responsibility, mental models, trust and reliability, generative variability, and co-creation. This helps to explore the ideas and then optimize them (Weisz et al., 2024). As it involves aspects of originality, copyrights, and ethical issues, GAI should be used carefully and responsibly (Bartlett and Camba, 2024). The algorithms used in GAI could enable the optimization of processes, compared to traditional design ones. However, the integration of human factors is vital to make GAI more effective and innovative (Demirel et al., 2024). GAI, which generally provides cost-effective production and manufacturing processes, also facilitates design (Soldatos, 2024). Although these emerging studies are providing the fundamentals needed to understand the captivating benefits of GAI, the connections and specifics between GAI, SPP, and the circular economy for environment sustainability are still evolving.

In the literature, advanced technologies and the circular economy for environmental sustainability are still disconnected (Nascimento et al., 2019). Most such literature has been focused on advanced technologies, the circular economy, and environmental sustainability, either independently or in combination. Kristoffersen et al. (2021) examined the lump sum of business analytics technology for circular economy implementations. Liu et al. (2023) studied the role played by integrated manufacturing systems in the adoption of circular manufacturing. In their review of the literature on circular supply chains, Gunasekara et al. (2023) found that there is currently a lack of a nuanced view of the role played by product design in manufacturing in the circular economy context in relation to environmental imperatives. In response to the recent calls made for further research to be conducted on digitalization in a sustainability context and to complement the underexamined role of product design in the circular economy (Gunasekara et al., 2023), along with emerging relevant directions on GAI and AI (Bartlett and Camba, 2024; Rashid et al., 2024; Soldatos, 2024; Weisz et al., 2024), we provide a nuanced view of SPP powered by AI and GAI—and fueled by big data analytics and machine learning techniques—examining the direct and indirect effects of these advanced technologies for environmentally friendly personalized product design and manufacturing for the circular economy. Our study is among the first to consider such interlinks in the digital-enabled circular economy context through personalized product design and manufacturing.

Given the persistence of inconclusive findings pertaining to interlinks, contradictory thoughts, and challenges, there is a need for more research to be conducted on the use of GAI for personalized product design and manufacturing, big data analytics, machine learning, and environmentally friendly products for the circular economy, particularly in regard to SPP. First, we contribute by developing a theoretical framework that borrows concepts from product platforming (Jalali et al., 2022; Zhang., 2015), GAI/AI (Akhtar et al., 2023; Wang et al., 2023;

Soldatos, 2024), and by examining their impacts on the manufacturing of environmentally friendly products for the circular economy (Akhtar et al., 2018; Hettiarachchi et al., 2022; Wang et al., 2023). As SPP powered by AI and GAI for creative product design and related manufacturing was a crucial theme of our study, we scrutinized the interplay between SPP and environmentally friendly products for the circular economy. Second, although big data analytics, machine learning, and flexibility in SPP play fundamental roles in supporting GAI and generating useful and practical content for industrial applications, few empirical studies have hitherto been conducted on the links between GAI applications for personalized product design and manufacturing, big data analytics, machine learning, and environmentally friendly products for the circular economy. We thus developed new relative measures and constructs suited to be utilized by future studies. We advanced such measures and constructs using comprehensive statistical procedures and with the involvement of practitioners from the automotive industry. Finally, we analyzed the implications of our framework for business practitioners.

This paper is organized as follows. Section 2 provides a background understanding of SPP, product families, GAI, and the circular economy. The relationships between the underlying constructs to develop the hypotheses and relevant theoretical framework are also presented. In Section 3, the methodological procedures—including measurements, respondent characteristics, data collection, and analyses—are provided. Section 4 reveals the key results against our set of hypotheses. In the final section, the discussion and conclusion—including a summarization of the key findings, theoretical and practical implications, research limitations, and directions for future research—are provided.

2. Literature Review

2.1. Smart product platforming and product families

Smart product platforming is interlinked with the development and implementation of technological components or subsystems that are shared across multiple products, production lines, and product features. To optimize the utilization of the system, smart platforms are utilized for the manufacturing of multiple products (Meyer et al., 2018; Van et al., 2018). The types of platforms are characterized by their functional abilities in relation to production, along with the customization options available for each category of products (Van et al., 2018). The emergence of Industry 4.0—one of the pillars of which is aimed at integrating cyber-physical connectivity to boost smart manufacturing platforms—suggests state-of-the-art technologies such as big data analytics and machine learning as a green technology (Vinuesa et al., 2020) with digital-to-physical transfer capabilities in enhancing materials efficiency, reducing life cycle impacts, and enabling greater engineering functionality in product platforms and relative supply chains (Fatorachian and Kazemi, 2020). Scholars have provided a rich literature on the technological feasibility, highlighting the merits of Industry 4.0 technology in delivering real-time communication and collaboration with ecosystem actors both within and outside production systems, which open up opportunities for the smooth flow of the materials and components pertaining to the diverse products within a family. The current literature, thus, encourages the examination of the opportunities and challenges presented by the technological characteristics of Industry 4.0 on SPP within product families (Raj et al., 2020). Smart product platforming connects devices and systems, enabling real-time data exchange between the different products manufactured within a family. Zhang et al. (2020) proposed an evaluation method suited to the design and manufacturing of affordable customized products with shorter lead times through the integration of information drawn from sales, products, and production configuration. Weng et al. (2020) posited that artificial intelligence (AI) and the robotic capabilities afforded by Industry 4.0 will enable companies to analyze the large volumes of data generated by product family components, enhancing the optimization of production processes. For instance, smart sensors installed in manufacturing equipment can provide insights into the production process, improving efficiency, quality, and affordability across a product family. By creating digital replicas of physical products or processes, a smart product platform can facilitate efficient development and testing.

2.2. Generative artificial intelligence, the circular economy, and interlinks

GAI is a domain of AI that utilizes generative models capable of learning patterns or drawing insights from large volumes of input data (called training data) and then generating new data based on such learning. In other words, it draws upon any available data (e.g., big data) and the ability to mimic human intelligence and uses trained models and algorithms to generate outputs (e.g., text-based answers, images or their reciprocals, audio clips, and videos). GAI can also provide data for training and can use machine learning to improve model performance. GAI provides trained solutions interlinked with machine learning. Big data (e.g., large texts) are fed to machine learning models to produce outcomes that depend on what users ask. Consequently, GAI applications bring innovation, creativity, and efficiency to selective tasks, including image generation from text or vice-versa (e.g., creative arts and 3D product designs), text generation from text (e.g., answers to manufacturing-related questions), audio outputs from text (e.g., music and voice), video from texts (e.g., movies and video clips), codes from text (e.g., R/VBA for analysis and the development of AI-driven PowerPoint slides) (Gozalo-Brizuela and Garrido-Merchan, 2023; Sætra., 2023; Wu et al., 2023).

Traditional AI performs allocated tasks interlinked with a predefined set of rules and relative datasets; the key being that it does not generate any new ideas or content. On the other hand, as an emerging subfield of (traditional) Al, GAI creates new ideas and content interlocked with learning from data. In other words, (traditional) AI uses data to make predictions while GAI generates new ideas and data or content (Forbes, 2023). GAI is linked to computational techniques that can generate ostensibly new and profound content; e.g., scripts, visuals, and audio from training datasets (Feuerriegel et al., 2024). According to Cooper and McCausland (2024), AI is a predictive technology that reduces the cost of predictions due to its higher efficiency in terms of time and accuracy, whereas GAI assists in the exploration of creative solutions and can be very useful in combination with human creativity. GAI is linked with LLMs that have exceptional capabilities to handle complex tasks and provide solutions based on user requirements (Joosten et al, 2024). This distinction between AI and GAI is aimed at aiding the examination of their integrations in our constructs and relative applications.

Over the last couple of years, LLMs have been the subject of increasing attention. ChatGPT, one of the most popular examples of an LLM, is an automatic artificial intelligence-generated content (AIGC) model. The public version of ChatGPT, which was released toward the end of 2022, recorded 100 million active users in just a few months. Such LLMs (ChatGPT; Make-A-Video) use powerful advancements in technology, efficiency in computational power, and deep networks with various trained parameters. ChatGPT can even reject tasks that are not appropriated, and it can remember previous ones (Wu et al., 2023).

To perform the tasks they are assigned, AIGC models/LLMs draw useful information and insights from information and large datasets and generate outputs (Gozalo-Brizuela and Garrido-Merchan, 2023; Sætra., 2023; Wu et al., 2023). This recently developed (and still emerging) domain represents a new dimension of organizational information processing theory (OIPT), which emphasizes how organizations access information/data and process them for effective operational or supply chain activities (see Cegielski et al., 2012, for more information on OIPT) that can impact their operational and managerial level work (Korzynski, et al., 2023). Developments related to big data and AI enhance data and information processing capabilities, strengthening OIPT and its implications. Ultimately, OIPT-associated advancements strengthen performance and sustainable manufacturing to achieve environmental goals (Rashid et al., 2024). Additionally, GAI substantially increases productivity (Feuerriegel et al., 2024). These aspects fueled by big data and analytics empower organizations to process more complex data (e.g., unstructured data) for their operational and manufacturing activities. In our study, we found that SPP powered by AI and GAI leads to the production of more environmentally friendly and personalized products for the circular economy. In this regard, organizations use any actionable insights drawn from big data and analytics to enhance their data and information processing capabilities, eventually promoting OIPT applications. Our finding thus directly contributes to OIPT and its constituents.

The circular economy is a multifaceted societal concept pertaining to rebuilding and reframing the economy in relation to sustainable growth by promoting environmental stewardship (Valenzuela and Böhm, 2017). In the traditional one-way process pertaining to the ‘take, make, dispose’ manufacturing method, material resources are disposed of in landfills or incinerators, meaning that their economic value is not fully exploited. As opposed to a linear system, the circular economy is a production and consumption manufacturing method suited to enable organizations to improve their resource utilization, efficiency, and productivity via a circular system (Awan et al., 2021). Advanced innovations play a critical role in reducing any environmental impacts by transforming the existing materials into desirable environmentally-friendly designed products for net zero goals (Abdul-Hamid et al., 2022). This can be achieved by planning the utilization of resources with the integration of a digital-enabled circular economy at the early stages of product design, extending the lives of the products for which the materials are sourced and remanufacturing new products from secondary raw materials through the loop. However, challenges remain in regard to the following question: "*how can designers or design teams come up with truly sustainable or circular innovations if the current manufacturing methods only lead them to optimize what is already there?*" (Den Hollander et al., 2017:518). We aim to contribute to this domain by adopting a new lens of advanced innovations by drawing on how big data analytics—with their higher predictive accuracy in regard to environmentally friendly products supported by GAI-driven design and manufacturing—could unlock circular economy potentials, along with other interlinks with machine learning applications.

Big data-driven decisions are getting increasing attention because, due to dynamic market trends and the depletion of natural resources, businesses are being forced to use and manage such resources more sustainably. Furthermore, businesses are held responsible in regard to adopting eco-efficient practices and engaging in eco-efficient activities that have a high economic value and take social considerations into account while still dealing with operational activities. The resource-based view of sustainable competitive advantage, which provides the means for this approach, deals with how firms create value for their customers. Furthermore, it also posits that firms can achieve sustainable competitive advantages by developing and exploiting strategic resources that are valuable, rare, inimitable, and non-substitutable. In our research, the applications of GAI and big data analytics are strategic resources for SPP, contributing to the new dimensions of OIPT that can be used to develop environmentally friendly automobiles. SPP-based systems, which can carry out knowledge-intensive work faster than human beings, add a strong cognitive level to a firm's processes and operations. With SPP, GAI can be used to create new automobile designs that are more efficient and environmentally friendly. Big data analytics provide avenues suited to enforce new firm capacities by collecting and analyzing real-world data to support SPP. Furthermore, the literature identifies big data analytics as a critical factor for the adaptability and responsiveness of dynamic ecosystems inherited in SPP. Big data analytics performed through machine learning techniques are used to identify patterns in consumer behaviors and other stakeholder data that may be used to develop new environmentally friendly automobiles. SPP devises long-term goals that turn into improved firm performance through value creation, innovation, and competitiveness. Big data analytics and machine learning feed insights to the GAI mode that supports SPP, which then ultimately generates more value and productivity (Akhtar et al., 2023; Hilbolling et al., 2021; Jalali et al., 2022; Noy and Zhang, 2023).

Therefore, SPP powered by AI and GAI is valuable because it can help firms devise new products that are more environmentally friendly. It is a rare resource because not all firms have the technical capabilities needed to use these technologies (Akhtar et al., 2023; Dubey et al., 2019). It is also difficult for competitors to copy due to its unique usage in processes or operations. Moreover, it is non-substitutable as no other resources can provide the same benefits. Smart IT-based initiatives and projects establish high-performance benchmarks suited to enhance manufacturing capabilities in the era of screen and digitization through innovation-driven production techniques (Li, 2018; Liu et al., 2020). Additionally, Industry 4.0 technologies can be crucial in reducing any negative effects and assisting decision-makers in making decisions and taking the measures best suited to deal with any difficult and uncertain situations (Zamani et al., 2022). For instance, machine learning algorithms are used to analyze large volumes of data and to identify patterns that are useful to improve the design and performance of environmentally friendly products. Machine learning applications can be utilized to improve the accuracy of GAI models to support SPP. Under the OIPT umbrella, we argued that the use of SPP can help firms develop forms of personalized product design and manufacturing suited to lead to environmentally friendly products for the circular economy.

To summarize, although it provides important insights into efficiency and optimization outcomes, the current literature on SPP suffers from the limitations discussed above. The mechanisms that trigger SPP for the circular economy remain unclear. Our research was aimed at empirically investigating how advanced technologies—such as big data analytics and machine learning applications—can be applied alongside SPP powered by AI and GAI to advance extended product platforming in addressing the challenges of the circular economy. The adoption of advanced Industry 4.0 applications helps in enabling better-informed decision-making concerning the development of products suited to meet customer needs. Furthermore, data-driven applications within the circular economy context involve analyzing consumer consumption patterns for recycling. Such activities—which involve tracking consumer behaviors—help to predict resource usage in production planning. The accuracy of such predictions is enhanced by leveraging past historical data, further optimizing product lifecycles and resource allocations for sustainability within SPP and supporting the circular economy concept. Our research was aimed at advancing the current literature by postulating that Industry

4.0 technologies such as AI, GAI, big data analytics, and machine learning represent digital developments necessary for SPP within product families. These technologies connect manufacturing to data analytics and flexible automation, ultimately enhancing efficiency, agility, and customization, thus unlocking circular economy opportunities for companies developing diverse and environmentally friendly products.

2.3. Hypotheses development

2.3.1. Big data analytics and environmentally friendly products for the circular economy

The analysis of large structured and unstructured datasets (called big data analytics) ultimately provides several environmental benefits—such as material efficiency and reduced energy consumption—that support the circular economy's goals (Akhtar et al., 2018; Nascimento et al., 2019). The trends and patterns gleaned through big data analytics are used to improve production and operational activities. Big data analytics provide relevant insights for firms that operate in dynamic and fast-paced industrial environments in which timely and informed decision-making is crucial (Wamba et al., 2017; Yin et al., 2022).

As a result of conscious evolution, human beings have started to think about the preservation of their surroundings and, in a wider context, the planet. In this era, such consciousness enables human beings to think about environmental preservation, resource conservation, climate change, air quality, waste and pollution reduction, fossil fuel depletion, and a sustainable economy (Akhtar et al., 2018; Zhang and Hou, 2022). These practices are integrated into environmentally friendly initiatives, which are the subject of the 12th United Nations Sustainable Development Goal. This goal addresses sustainable consumption and production patterns that are in line with environmentally friendly product development. Offering 'green' or 'sustainable' automobile options is a requirement of our times. Such automobiles, which are designed to have minimal negative impacts on the environment through their reduced carbon footprints, specifically address concerns related to air pollution, greenhouse gas emissions, and the depletion of natural resources.

Applications of big data analytics (ABDAs) are technical resources suited to enhance firms' manufacturing capabilities through innovation-driven production techniques and designs (Li, 2018; Bag et al., 2021). ABDAs supply precise and timely supply network insights suited to assist in the incremental improvement and transformation of operational models

(Roden et al., 2017). The advantage of ABDAs is their capacity to deliver in-depth insights for superior decision-making and the ability to adjust strategies appropriately (Bag et al., 2021). On the other hand, automobile manufacturing firms are acting ‘eco-responsibly’ by offering environmentally friendly products designed and manufactured with a minimal negative impact on the environment. International expectations and policies, local government policies, automotive industry rules and regulations, independent entities’ pressure, and customer awareness are forcing automobile firms to produce environmentally friendly products. This pressure started to manifest itself over the last decade, as the 2014 Intergovernmental Panel on Climate Change (IPCC) proposed specific environmentally friendly practices to be adopted by the automotive and other industries—e.g., improving energy efficiency in new processes and technologies, promoting efficient materials and products, and recycling (IPCC, 2015). ABDAs are currently aiding in the manufacturing of environmentally friendly cars by enabling the implementation of design optimization (Lepenioti et al., 2020), simulation and modeling (Mišić and Perakis, 2020), supply chain optimization, and effective material selection and delivery (Jahani et al., 2023).

To summarize, firms usually gather information from historical performance, customer feedback drawn from an online presence on social media/apps/websites, sensor readings taken during the manufacturing stages, the actual usage/operation of product designs, simulations of various aspects of the manufacturing process and the final product, materials characteristics, and the environmental impact of a product. Such information—in the form of insights drawn from big data—can provide a path to the design and manufacture of automobiles with minimum environmental impacts throughout their entire lifecycles, including their operational and eventual disposal stages. Therefore, the integration of ABDAs into the development and operation of automobiles can contribute to a more holistic and conscious approach to environmentally friendly production. Through the power of big data analytics, automobile manufacturers can make better-informed decisions, optimize processes, and drive innovation with the ultimate goal of reducing their products’ environmental footprints. Ultimately, the sensible and timely use of big data analytics in the manufacturing of environmentally friendly automobiles can help to attain a competitive advantage. Hence, we formulated the following hypothesis.

H1. Applications of big data analytics aid in promoting environmentally friendly products for the circular economy.

2.3.2. *Big data analytics and smart product platforming powered by AI and GAI*

Big data acts as fuel for AI and GAI because it provides all the inputs required to learn and get useful and actionable insights, which ultimately power SPP. Digital initiatives establish clear objectives and performance benchmarks suited to enhance industrial capabilities (Liu et al., 2020; Geyer, 2023). Munir et al. (2022) posited that ABDAs enable firms to make timely decisions that provide a wide range of benefits toward sustainability in the market. Also, AI is better capable of performing tasks that typically require a human presence. ABDAs and GAI make large datasets and data streams valuable, relevant, and actionable for task precision and efficiency. SPP powered by AI and GAI can play a pivotal role in supporting data-driven decision-makers in taking actions appropriate to tackling challenging situations (Akhtar et al., 2023; Hilbolling et al., 2021; Jalali et al., 2022; Wang et al., 2023). Budhwar et al. (2023) found that the quality of GAI output relies on that of the input it receives (e.g., big data quality), considering both the training data it has been exposed to and the prompts provided by users to describe the task they want accomplished. This training yields the capacity to deal with big datasets to identify patterns and models and to make predictions or classifications about certain phenomena. GAI understands and reads any big data patterns, analyzes them, and creates a new or unique version of a product or output.

The sheer volume and complexity of the available large datasets have made it challenging for manufacturers to extract useful data and generate actionable insights. This is where GAI is useful because it represents a transformative solution suited to deal with data overload in machine manufacturing (Geyer, 2023). AI, GAI, and big data work shoulder to shoulder to enhance product quality and its related developments, ultimately supporting SPP (Gong et al., 2021; Guo et al., 2024; Soldatos, 2024). Geyer (2023) stated that, in relation to the adoption and use of AI technologies to manage large datasets, GAI algorithms can learn from historical data and can provide useful information for operations. Thus, big data analytics powered by AI and GAI fuel SPP. Big data helps AI to operate effectively for new product design and development (Bartlett and Camba, 2024; Cooper and McCausland, 2024). According to the literature, there is a connection between these two underlying concepts. Big data processing provides the foundation for SPP systems that eventually add human intelligence (i.e., learning, comprehending, and suggesting innovative designs hidden in the data) to derive smart manufacturing processes and personalized automobile design inherited in SPP. We therefore made the following hypothesis.

H2. The applications of big data analytics encourage smart product platforming powered by artificial intelligence and generative artificial intelligence.

2.3.3. Smart product platforming powered by artificial intelligence and generative artificial intelligence and the circular economy.

Smart production platforming is the result of intense competition and the intent to fulfill the needs of sensitive customers (Hilbolling et al., 2021; Jalali et al., 2022; Lee, 2015). Lee (2015) proposed that, in the component stage, sensory data are transformed into information, enabling the cyber-twins of components to capture time records and self-predict. In the next stage, machine data are combined with component information to monitor and generate machine cyber-twins, enhancing self-comparison. Finally, in the third stage (production system), aggregated knowledge ensures self-configurability, self-maintainability, and optimized production planning for seamless and efficient factory operation. These stages increase the efficiency and effectiveness of the product optimization process, supercharge development cycles, and create a more sustainable ecosystem, supporting environmentally friendly products for the circular economy (Hettiarachchi et al., 2022; Wang et al., 2023). It is changing the way vehicles are designed, manufactured, and maintained, leading to cost reduction, improved efficiency, and sustainability (Yu et al., 2022).

Jalali et al. (2022) suggested that smart platform-based development becomes increasingly attractive when there is a greater disparity in the quality preferences among market segments, and heightened sensitive customer demand for the specific features of a market segment. AI inherited in SPP is being used in the automotive industry for various kinds of decision-making, such as access control through facial recognition and the analysis of road conditions. From the perspective of our study, AI/GAI is a viable option to be used in designing automobile parts or to be integrated into a product family. Previous research has stated that product family design is an effective strategy to provide variety at a reduced cost (Simpson et al. 2014). Product family design commonality is intentional and is derived from the specific product platform (Simpson et al., 2014). Product family design targets a variety of different market segments despite involving high numbers of common ‘elements’ (e.g., components, modules, subsystems, fabrication processes, and assembly operations) (Pirmoradi et al., 2014). Moreover, product family design also helps to propose and produce different product designs and configurations (e.g., Shafiee et al., 2022; Zhang et al., 2020).

Specific AI and GAI applications—which include automated replenishment, autonomous vehicles, automotive insurance, predictive maintenance, and supply chain optimization—are part of SPP and help to expand the product family of automobiles. According to Birlasoft (2022), GAI and AI are not just an option but a necessity for car manufacturers to stay competitive. It added that they enable predictive vehicle maintenance, real-time quality control, process optimization, and the development of functional vehicle prototypes. This ultimately helps to produce environmentally friendly products for the circular economy (Hettiarachchi et al., 2022; Wang et al., 2023). In light of this discussion, we argued that SPP is revolutionizing the automotive industry’s efficiency and effectiveness by reducing costs and making it more sustainable. Hence, we proposed the following hypothesis.

H3. Smart product platforming powered by artificial intelligence and generative artificial intelligence leads to environmentally friendly products for the circular economy.

2.3.4. The mediating role of smart product platforming

The literature (e.g., H1, H2, and H3) supports the important role played by SPP in the manufacturing of environmentally friendly products for the circular economy, and the presence of multiple interlocks between ABDAs and SPP. In today's rapidly evolving technological landscape, the integration of SPP and the development of environmentally friendly products have become central to strengthening sustainability through SPP. The overarching goal of SPP powered by AI and GAI is to identify areas in which the interlocks between ABDAs and environmentally friendly products for the circular economy can be improved at the design and production levels by making informed decisions, optimizing processes, and developing eco-conscious product offerings—a route to a sustainable economy and to new innovative business models that maximize societal and environmental benefits (Akhtar et al., 2023; Hettiarachchi et al., 2022; Hilbolling et al., 2021; Wang et al., 2023). Giudice et al. (2021), Hilbolling et al. (2021), and Jamali et al. (2020) posited that one of the key advantages of SPP is its ability to capture real-time data from connected devices and sensors embedded within products. The pertinent collected data are fed into a unified platform, enabling firms to continuously assess the eco-friendliness of their products, identify areas for improvement, and connect and manage various aspects of a product's lifecycle—from design and development to manufacturing and distribution.

Furthermore, SPP enhances the efficiency of product development and customization aimed at meeting sensitive customer demands. The valuable information and insights provided by SPP can be used to tailor products suited to meet specific environmental preferences and market demands. Moreover, SPP offers greater transparency in the supply chain, enabling companies to make informed and timely decisions pertaining to sourcing and materials. With SPP, businesses can trace the origins of raw materials, assess their environmental impact, and select eco-friendly alternatives. This level of transparency is not only aligned with the principles of sustainability but also enables companies to meet the growing demand for environmentally responsible products (e.g., Centobelli et al., 2022; Jalali et al., 2022; Hilbolling et al., 2021). The mediating role played by SPP is crucial in bridging the ABDAs and the development of environmentally friendly products for the circular economy. This synergy empowers businesses to harness the full potential of data-driven insights and translate them into tangible, sustainable product offerings. We thus suggested the following.

H4. Smart product platforming powered by artificial intelligence and generative artificial intelligence plays a mediating role between the applications of big data analytics and environmentally friendly products for the circular economy.

2.3.5. The moderating role of machine learning

Machine learning techniques—which are applied to large volumes of structured and unstructured data collected from different sources such as smart devices, sensors, and websites—have many operational and production applications in relation to strengthening performance outcomes. These applications have the potential to moderate the relationship between big data applications and environmentally friendly products, strengthening the circular economy. This is because machine learning, as an Industry 4.0 application, assists in the accurate prediction of patterns that can be utilized to better understand the processes and to make pertinent data-driven decisions suited to improve outcomes (Akhtar et al., 2023). Nascimento et al. (2019) investigated how Industry 4.0 technological applications strengthen the circular economy for manufacturing firms, including the reuse and recycling of products. Machine learning applications possess the ability to identify patterns in data, improve, make decisions based on a set of performance criteria, and optimize the relative outcomes (Gambella et al., 2021). As a result, machine learning applications enhance reliability and provide insights according to specific customer requirements, helping firms to leverage the information to develop and implement environmentally friendly products or circular economy practices. Furthermore, with the help of pre-determined machine learning algorithms measured based on performance metrics, designers can refine design schemes according to customers' environmental preferences learned from the data and integrated with historical data matched with product sales, market demand, and user characteristics. As such, designers can devise products that make use of recycled materials, and sustainable manufacturing processes that unlock the circular economy. Therefore, in line with this reasoning, we hypothesized:

H5. Machine learning applications play a moderating role between the applications of big data analytics and environmentally friendly products for the circular economy.

2.3.6. The moderating role of flexibility

Flexibility signifies a firm's responsiveness in terms of adapting, changing, and adjusting to new knowledge and product features. Flexibility in SPP ultimately assists in tackling any uncertainty and enhancing customization as per customer demand (Hilbolling et al., 2021; Jalali et al., 2022; Suh et al., 2007). Flexible product platforming provides operational advantages in terms of, inter alia, reducing risk, customizing, and counteracting any productivity obstacles (Van et al., 2018). To achieve the circular economy, firms need to align sustainability value across their production lines by integrating flexibility in their manufacturing.

However, environmental regulations or requirements may differ across the value chain and evolve. To comply with updated environmental standards without having to engage in any significant overhaul, firms strive to anticipate future needs and establish plans for the adaptation and modification of technological components or subsystems in the platform. At the same time, flexibility provides a solution to SPP with enhanced modular components without the need to replace entire product units when initial designs do not meet some circular economy requirements or customization. Flexibility in SPP enables firms to adjust their sustainability features or recycling materials to bring them more in line with customer demands than they would as a result of any ample generated unstructured solutions. In this way, firms simulate and optimize the behaviors of different products within product families, thus reducing any unnecessary production actions in relation to circular economy goals. Flexibility ultimately enhances the effectiveness of SPP by enabling adjustment or adaptation to resources with a low environmental impact and to technological solutions that minimize waste and increase product lifecycles for easy disassembly and recycling, promoting flexible manufacturing concepts

(Sarkar and Bhuniya, 2022; Kulak et al., 2016). Thus, we present our final hypothesis and, in Figure 1, we depict the graphical representation of our hypotheses.

H6. Flexibility in smart product platforming plays a moderating role in the production of environmentally friendly products for the circular economy.

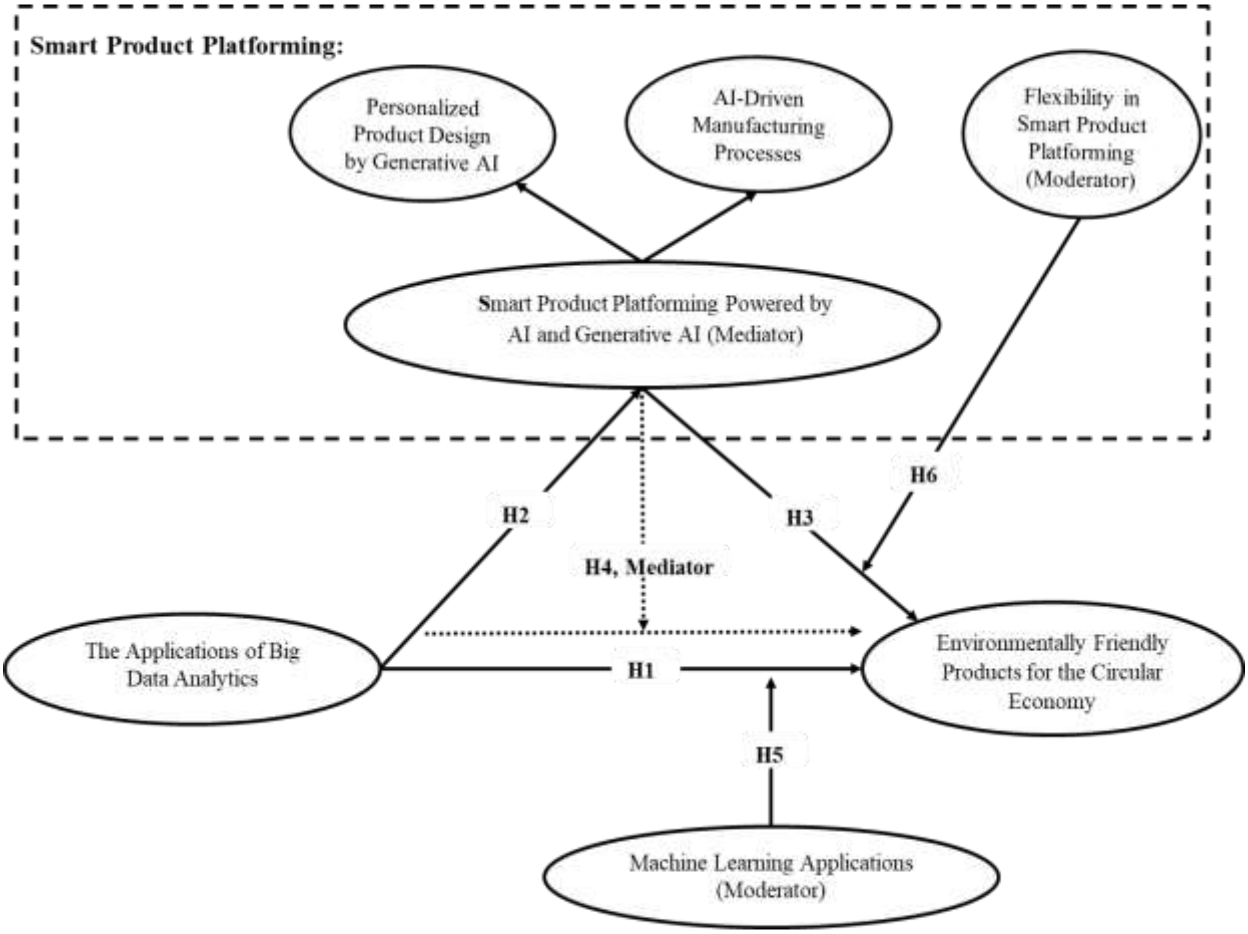

Fig. 1. Relationships among the underlying constructs.

3. Methodology

3.1. Research approach and context

For our research, we took a quantitative approach and adopted a cross-sectional survey design to examine the relationship between the variables and constructs. Creswell and Clark (2017) suggested that quantitative research supports investigators in collecting data from a large sample population to investigate specific questions. Hair et al. (2016) also posited that quantitative research is appropriate for the testing of hypotheses and theories, and for exploring the relationships between constructs. We measured all variables measured based on primary data collected through a self-administered online survey.

The context for our study was the Chinese automotive manufacturing industry, which is actively contributing to the development of eco-friendly products for the circular economy. China's automotive manufacturing, which ranks among the country's top ten industries, is a significant contributor to its economic growth (Yu et al., 2022). According to the latest figures published by the China Association of Automobile Manufacturers (CAAM, 2023), Chinese automakers produced 27.02 million units in 2022, marking a 3.4% growth from the preceding year and leading the world (being ranked number 1 in terms of EV production units and sales). Concurrently, sales increased by 2.1%, to 26.86 million units. The substantial scale of production recorded within the automotive sector offered a rich ground to investigate the challenges faced by Chinese automobile businesses, including the applications of SPP powered by AI and GAI, flexibility in SPP, applications of big data analytics, machine learning applications, and eco-friendly products for the circular economy.

3.2. Participants, data, and common method bias

Table 1 presents our research participants' characteristics. To gather diverse perspectives from a sizeable dataset, we selected multiple managers associated with the automotive industry.

Table 1
Demographic profiles of the respondents

Individual Demographics		Frequency	Percentage Rounded
Gender	Male	162	79
	Female	44	21
Subtotal		*206*	*100*
	Junior college	15	7
	Bachelor	119	58
	Master's or above	72	35
Subtotal		*206*	*100*
Job Title	Product design managers	84	41
	Manufacturing managers	42	20
	Operation managers	27	13
	IT/Analytics managers	36	18
	CEO/COO/CTO	8	4
	Others	9	4
Subtotal		*206*	*100*
Experience	3 to 5 years	55	27
	6 to 10 years	116	56
	11 years and more	35	17
Subtotal		*206*	*100*
Total		206	100

Before distributing our survey questionnaire, we obtained our potential respondents' consent. We chose our participants through purposive sampling, adhering to the following inclusion criteria: (i) being top and middle-level managers with relevant knowledge and practice, and (ii) being employed in relevant operations, production, product design, data/analytics, and IT departments. Following the exclusion of any non-viable responses, our final usable sample size was 206 out of 1,000, generating a response rate of 20.6%.

We used two methods to assess the quality of our data. First, to test for non-response bias—as proposed by Armstrong and Overton (1977)—we performed an independent t-test in which we compared our first respondents and last 20 respondents on all variables. The results confirmed that there was no significant variance between the early and late respondent subsamples, thus indicating the absence of non-response bias. Second, to examine the potential presence of common method bias in the data, we took the marker variable approach. In our study framework, we included an unrelated variable (organizational culture) for correlational analysis (Lowry and Gaskin, 2014; Simmering et al., 2015). We found the correlational values to range from low (MV > EFPCE = 0.028) to moderate (MV > ABDA = 0.59), corroborating a low likelihood of any common methods bias. Additionally, we addressed common bias at the questionnaire design and survey execution stages by adopting an affective survey design strategy. This strategy involved avoiding double-barreled questions and not using negative and complex statements. We also included multiple respondents with different operational levels.

3.3. Instruments and procedures

Based on a comprehensive literature review, we identified the relevant concepts and measures of variables to use in our study. We operationalized all variables as multi-item measures and adapted them to suit our study context, namely the Chinese automotive manufacturing sector. To ensure the accuracy of our data and prevent any possibility of instrument misspecification, we incorporated screening questions into our questionnaire. In collecting the primary data for our variables, we used a five-point Likert-type scale in which 1 stood for *strongly disagree* and 5 for *strongly agree*. We also submitted our constructs to comprehensive statistical procedures by performing exploratory factor analyses and establishing reliability and validity [e.g., composite reliability (CR), and average variance extracted (AVE)].

We measured the degree of AI/GAI used in personalized product design and product manufacturing processes. This was a two-dimensional, second-order construct in which *personalized product design* indicated the degree to which the teams employed GAI to develop personalized product designs. Moreover, the *product manufacturing process* referred to the degree to which the teams took an AI approach to the manufacturing processes. Both dimensions involved four items. We measured *personalized product design* using scales suggested by Zhu and Luo (2022) and Ghoreishi and Happonen (2020) and product manufacturing processes using those devised by Hyunjin (2020) and Leoni et al. (2022). We found the internal consistency of the respective variables' scales to be 0.786 and 0.875. To measure *flexibility in SPP*, we adopted guidelines from previous studies (Sarkar and Bhuniya, 2022; Van et al., 2018), and found internal consistency to be 0.891. The *applications of big data analytics* (ABDAs) variable referred to the efficient utilization of the latest data analysis techniques and contemporary technologies to extract valuable real-time information from large datasets. This helps in developing and implementing business strategies suited to support operations and fulfill customer requirements. We measured this variable by means of five items from Awan et al. (2022). We found the internal consistency of the construct to be 0.839.

The *machine learning applications* variable (MLA) referred to the application and integration of machine learning technology in production and operations to enhance firms' decisions and operational outcomes. This variable was measured utilizing five items from Leoni et al. (2022). We found the internal consistency of the construct to be 0.882. The *environmentally friendly products for the circular economy* variable reflected the utilization of sustainable and recycled resources to produce eco-friendly products. It involved the assimilation of sustainable practices in production processes and product design to achieve a firm's sustainability objectives. We measured it using eight items from Katsikeas et al. (2016) and Awan et al. (2021). We found the internal consistency of this construct to be 0.889. To summarize, we found that all internal consistency values for our constructs fell above the minimum recommended threshold of 0.70, demonstrating the reliability of our constructs (Akhtar et al., 2018; Hair et al. 2016). The details of our constructs and items are given in Appendix A.

4. Results

4.1. Measurement model results, validity, and reliability

To ensure the effectiveness of systematic measurements, it is crucial to assess the key factors of validity and reliability (Kuehnl et al., 2019). We evaluated convergent validity through loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Hair et al. (2016), recommended an acceptable minimum loading value of 0.60. Moreover, AVE values have been recommended to fall above 0.5, as this helps gauge the relationship within the construct (Wang et al., 2023). Our findings yielded loading values greater than 0.6. We also found our CR and Cronbach's alpha values to significantly exceed the minimum recommended threshold of 0.70. Furthermore, we found our AVE values for the constructs to exceed the minimum threshold of 0.50. We thus found our measurement model results to meet all the criteria recommended for the key factors of validity and reliability. We performed the HTMT test as a more robust method to assess discriminant validity by measuring the ratio of correlation among the constructs (Rönkkö and Cho, 2022). The maximum threshold for HTMT is 0.85 (Hair et al., 2021). We found our results for all the constructs to fall below such a threshold. Therefore, we found the constructs in our model to demonstrate sufficient discriminant validity, with each differing from the others. The details of these assessments and their values are listed in Table 2 and Figure 2.

Table 2
Results of Confirmatory Composite Analysis

Construct	Factor Loadings	Cronbach's Alpha	CR	AVE	HTMT
Smart product platforming powered by GAI and AI					
Personalized product design					
SPPAI1	0.790	0.786	0.791	0.543	< 0.85
SPPAI2	0.712				
SPPAI3	0.775				
SPPAI4	0.741				
Product manufacturing process					
SPPGAI5	0.752	0.875	0.889	0.685	< 0.85
SPPGAI6	0.892				
SPPGAI7	0.774				
SPPGAI8	0.863				
Flexibility in smart product platforming					
FSPP1	0.766	0.891	0.896	0.672	< 0.85
FSPP2	0.841				
FSPP3	0.876				
FSPP4	0.755				
Applications of big data analytics					
ABDA1	0.735	0.839	0.857	0.613	< 0.85
ABDA2	0.778				
ABDA3	0.821				
ABDA4	0.805				
ABDA5	0.782				
Machine learning applications		0.882	0.887	0.585	< 0.85
MLA1	0.756				
MLA2	0.787				
MLA3	0.719				
MLA4	0.897				
MLA5	0.861				
Environmentally friendly products for circular the economy		0.889	0.903	0.702	< 0.85
EFPCE1	0.825				
EFPCE2	0.864				
EFPCE3	0.886				
EFPCE4	0.746				
EFPCE5	0.873				
EFPCE6	0.817				
EFPCE7	0.752				
EFPCE8	0.788				

(n=206)
Legend: CR (composite reliability), AVE (average variance extracted), HTMT (hetero-trait-monotrait ratio of correlations)

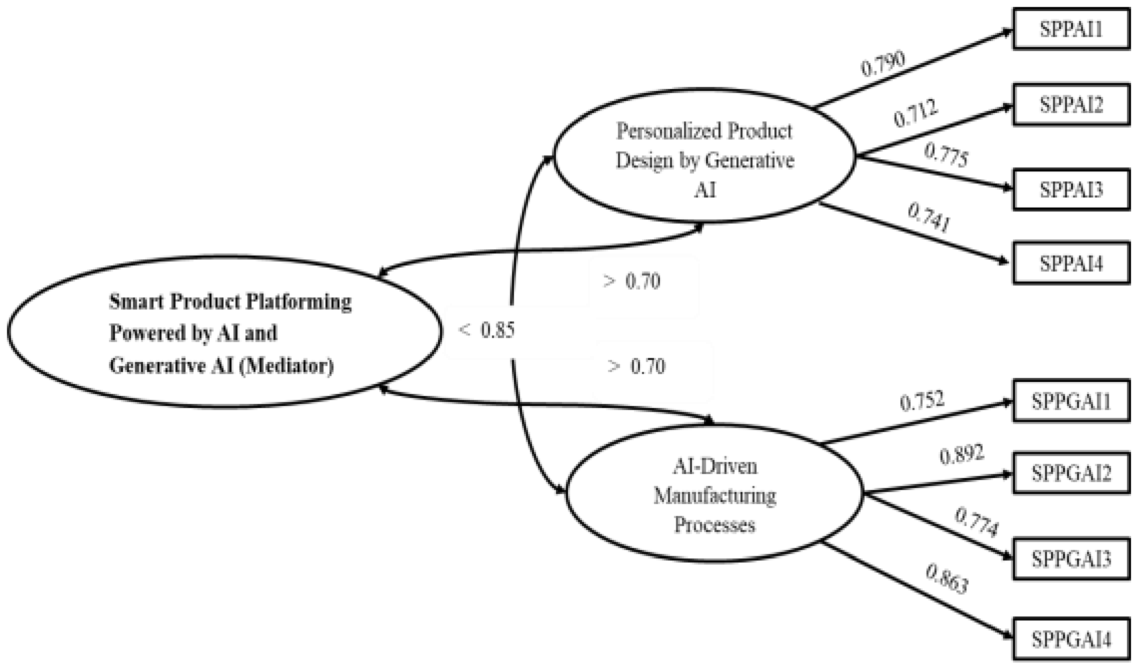

Fig. 2. The second-order construct of SPP powered by AI and GAI

4.2. Structural model and hypothesis results

As recommended by Hair et al. (2019) and Akhtar (2018), we adopted standardized procedures to report our results and to test our hypotheses for the structural model. We found ABDAs (H1) to be in a statistically significant direct relationship with EFPCE. Hence, we found H1 to be supported. Table 3 provides the β and t-values for all the underlying hypotheses. Furthermore, as a result of our hypotheses' testing, we found a significant direct relationship between ABDAs and SPP, thus confirming H2. The outcomes were also found to indicate a significant direct relationship between SPP powered by AI and GAI and EFPCE; thus, H3 was found to be supported. We took a forward statistical approach to test these relationships—which we found to be consistently significant in all four models—with control variables (e.g., organizational age and size). We performed a mediation analysis following Rungtusanatham et al. (2014). The SPP intervention in Model 4—compared to Model 1—exhibited t-values reduced from 6.616 (highly significant) to 3.188 (significant), demonstrating partial support for H4.

Table 3
Models, structural results, and fit indices.

Constructs/Hypothesis	Model 1	Model 2	Model 3	Model 4
ABDA→EFPCE (H1)	0.541 (6.616***)	0.314 (4.236***)	0.273 (3.479***)	0.206 (3.113**)
ABDA→SPP (H2)	-	0.459 (5.347***)	0.467 (4.551***)	0.559 (6.662***)
SPP→EFPCE (H3)	-	-	0.503 (6.001***)	0.373 (4.758***)
ABDA→ SPP →EFPCE (H4)	-	-	-	0.216 (3.188**)
MLA x ABDA→EFPCE (H5)	-	-	-	0.265 (3.468**)
FSPP x SPP→EFPCE (H6)	-	-	-	0.225 (3.226**)
R^2	0.295	0.375	0.410	0.496
χ^2/df	1.766	1.421	1.285	1.011
RMSEA	0.088	0.061	0.054	0.039
CFI	0.911	0.959	0.963	0.979
TLI	0.898	0.931	0.952	0.970
IFI	0.911	0.959	0.963	0.975

n=206
Note: statistically significant at $p < 0.01$ (***), and at $p < 0.05$ (**)

Finally, we took the product indicator approach employed by Ng and Chan (2020) to analyze the moderating effects of ML and FSPP, respectively. Our results were found to demonstrate that MLA has significant moderation effects on the association between ABDAs and EFPCE. Moreover, our results were also found to indicate that FSPP exerts statistically significant moderation effects on the association. To provide a visual interpretation of the relationship described in H5 and H6, we plotted a graphical representation. As shown in Figures 3 and 4, a high presence of machine learning and flexibility in SPP enhances EFPCE. Last, the results of the fit indices, as reported in Table 3, show that all indicator values, including R^2, χ^2/df, RMSEA, CFI, TLI, and IFI, are well past the acceptable threshold for fit values, indicating a good fit.

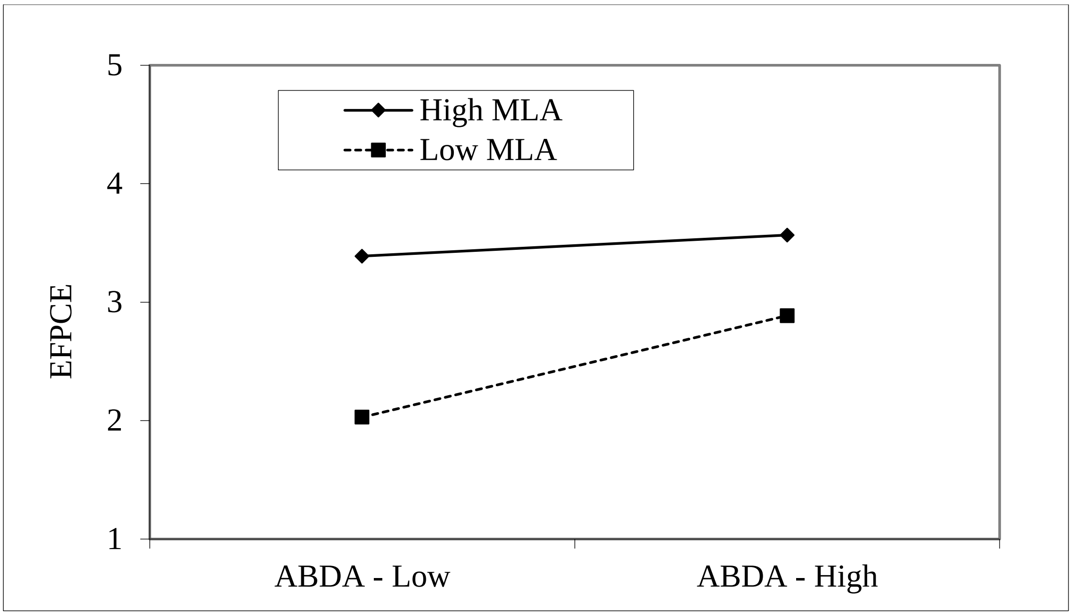

Fig. 3. Moderation effect of machine learning applications

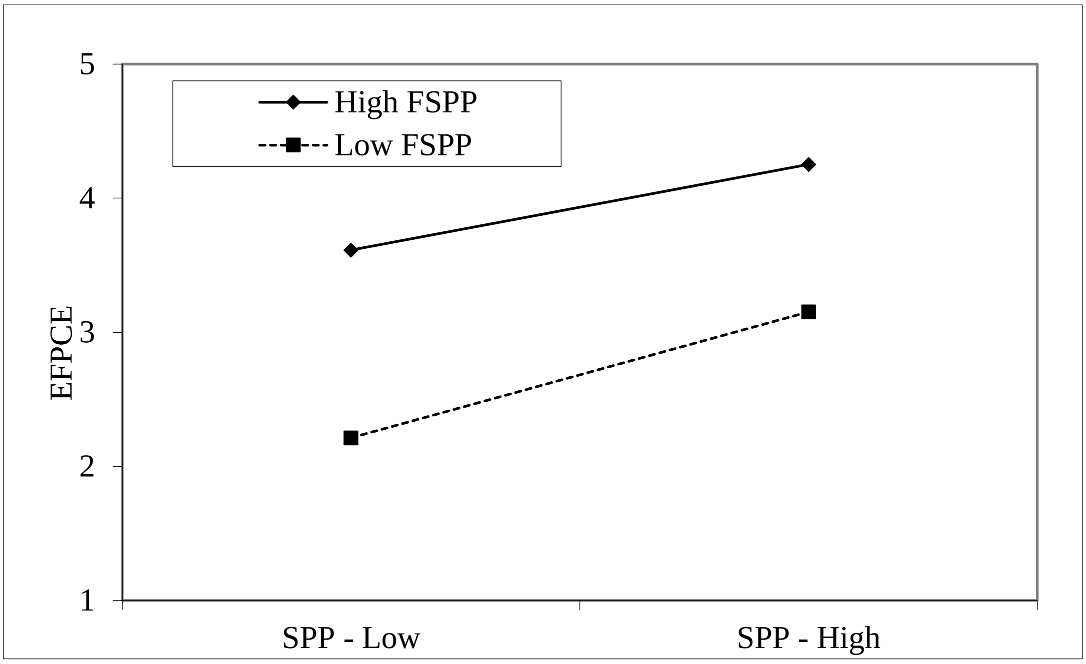

Fig. 4. Moderation effect of Flexibility in SPP

5. Discussion and conclusion

Our findings emphasize how SPP powered by AI and GAI, big data analytics, and machine learning interact in personalized product design and manufacturing, leading to environmentally friendly products for the circular economy. Our findings support the underlying constructs that are the key determinants in enabling the production of environmentally friendly products and strengthening circular economy implementations. The use of SPP with inherited flexibility and advanced technology—such as AI, GAI, big data analytics, and machine learning—plays a major role in effective and creative product design, consequently facilitating the related manufacturing processes.

5.1. Theoretical and practical implications

SPP powered by AI and GAI is an emerging field that strongly contributes to the dimensions of sustainability (Hettiarachchi et al., 2022; Wang et al., 2023). In particular, GAI came to the forefront in 2022, when ChatGPT hit the market (Wu et al., 2023). GAI models provide great opportunities to learn theoretical concepts both effectively and efficiently. Open AI could be one of the best tools for the creation and development of knowledge. These models involve an interplay between big data analytics, machine learning, algorithms, AI, and GAI, providing a comprehensive understanding of interdisciplinarity and related applications (Akhtar et al., 2023; Gozalo-Brizuela and Garrido-Merchan, 2023; Sætra., 2023). Designing products and facilitating their manufacturing using GAI can benefit the operational community and improve work productivity (Noy and Zhang, 2023). Flexibility in SPP is also important for the manufacture of environmentally friendly products for the circular economy, as it helps to facilitate the creation of closely related product families and achieve optimal results (Sarkar and Bhuniya, 2022; Van et al., 2018).

Big data, analytics, machine learning, AI, and GAI work jointly to support information and data processing operations to the end of achieving mutual goals in SPP and contributing to OIPT (Feuerriegel et al., 2024; Rashid et al., 2024). In particular, GAI has recently changed the game for SPP, with these joint technologies supporting it and ultimately promoting personalized product development. This assists in upscaling the circular economy for a better future. However, ethical issues related to the use of GAI should also be considered. The responsible use of GAI is crucial to address ethical issues and users need to understand the related obligations (Bartlett and Camba, 2024). Universities and schools should also play a role in educating new generations in regard to their responsibilities pertaining to the use of technology. Governments, particularly those of advanced countries, could also introduce new laws and regulations aimed at ensuring that groups and forces use such technologies responsibly.

From a practical standpoint, SPP with GAI models enables exponential timesaving. It assists in obtaining specific information and insights more quickly than search engines. If properly implemented with good user input, it also assists in improving the quality of work, ultimately enhancing productivity. Although managers can input detailed and specific questions, SPP/GAI cannot replace human intelligence, which features originality in thought and action in improving operational business procedures, whereas SPP/GAI/AI depends on user inputs to generate outcomes. For instance, designers can insert specific criteria (e.g., sustainable, sporty look, size, type) for car designs, and GAI can then generate an image. Designers can then add their originality and creativity by using iterative procedures to execute the final designs assisted by SPP. GAI/SPP is thus used as a process tool/platform.

The benefits of SPP are not devoid of practical challenges for managers. The security of the data inputted by users/managers is at risk when they operate on open AI/GAI platforms. Organizations and their employees thus need to be very careful when using them. They could develop their own AIGC models, but the required in-house expertise could challenge this approach. The skills required to use such models in the workplace are also challenging. Not all employees are IT-savvy, and the relatively traditional culture of some of them could hinder the workplace development and usage of SPP. However, in the long run, organizations could train their employees and invest in GAI/SPP to promote sustainability and circular economy concepts interlinked with contemporary technologies and SPP.

5.2. Limitations and future research

Our study is not devoid of limitations. Very few empirical studies have addressed the underlying topics and their links with environmentally friendly products for the circular economy, which is still in its infancy. We thus borrowed the literature on SSP from GAI/AI/interdisciplinary domains and its links with other underlying constructs. This offers valuable opportunities for future research to be based on our study while implementing the findings of other domains. For example, future research could focus on conducting case studies in different industries such as banking, retail, and IT. More studies could also be conducted in manufacturing. Although we did follow comprehensive methodological procedures, we did not make any causal claims. Furthermore, SPP may yet become more intelligent; thus, researching product platforms and their families could further benefit the business community and employees by enabling them to work smarter, rather than harder, reducing any unnecessary extra efforts, increasing their productivity, and bringing greater innovation at work with better sustainable outcomes. While we addressed our research questions with data collected from Chinese manufacturing firms, future research could consider samples drawn from other regions and countries. The nexus of the digital-led circular economy for sustainability is still in its infancy, particularly concerning the interlinks with contemporary technology like GAI; future studies could thus consider further unpacking the interlocks in SPP and promoting sustainability dimensions.

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Appendix A:
Constructs, brief item descriptions, and codes.

Constructs	Brief item descriptions
Smart product platforming powered by GAI and AI: 1) personalized product designs and 2) product manufacturing processes	1) Our product design team applies GAI [e.g., ChatGPT,] to develop personalized product design concepts. 2) Our product design team uses GAI-based product design innovation for personalization. 3) Our product design team employs GAI for personalized product design identification. 4) Our product design team utilizes GAI to upgrade our product designs as per customer requirements. 5) Our product manufacturing team integrates AI-based solutions to improve related manufacturing processes. 6) We consider AI to be our major strategy for product-related manufacturing innovation. 7) We use AI in our manufacturing processes to optimize product characteristics (e.g., product strengthening and material balancing). 8) We use robotic process automation in our manufacturing processes.
Flexibility in smart product platforming	1) We are flexible in our product family design 2) We are flexible in our product family manufacturing procedures 3) Our product platforming is flexible to adopt operational changes 4) We continuously update our product platform to align it with the latest technology
Applications of big data analytics	1) We apply big data analytics in our operations 2) The use of big data analytics is part of our business strategy. 3) We extensively employ big data analytics in our operations. 4) Big data analytical applications provide us with insights suited to understanding specific customer requirements. 5) Our top management encourages us to apply insights drawn from unstructured data for better customer solutions.
Machine learning applications	1) We apply machine learning-based analytics in our operations. 2) We integrate machine learning techniques in our analyses. 3) We encourage our teams to adopt machine-learning techniques.

	4) We implement insights drawn from deep learning applications. 5) We use insights drawn from neural networks.
Environmentally friendly products for the circular economy	1) Our products integrate recyclable materials for environmental benefits inherited in the circular economy 2) We use environmentally friendly resources in our products for the promotion of the circular economy. 3) We use recycled materials in our products to promote the circular economy 4) We perform lifecycle analyses to assess the impact of our environmentally friendly products on the circular economy. 5) Our environmentally friendly products help us to support our circular economy strategy. 6) Our products' reusability is a key part of our circular economy strategy. 7) Our circular economy guidelines enable us to produce durable environmentally friendly products. 8) Our circular economy directions drive our products to achieve our net-zero goals for an environmentally friendly future.