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Artificial intelligence and the reconfiguration of NPD Teams: Adaptability and skill differentiation in sustainable product innovation

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ABSTRACT

Sustainable product innovation (SPI) is increasingly central to New Product Development (NPD) teams, aligning with global sustainability goals and industry expectations. However, the factors associated with SPI at team level remain underexplored. This study examines the roles of team skill differentiation and team adaptability in fostering SPI, proposing that these factors support teams in the pursuit of sustainability-oriented innovation more effectively. Furthermore, we investigate the moderating role of generative artificial intelligence (GenAI) in shaping the strength of these relationships. Drawing on the double diamond framework and its AI-augmented adaptation, we hypothesize that skill differentiation expands the range of potential solutions in the divergent phase of innovation, while adaptability enhances responsiveness in the convergent phase. GenAI is posited to enhance these effects by augmenting knowledge recombination and real-time strategic adaptation. To test our hypotheses, we conducted a multi-industry survey of NPD teams engaged in sustainability initiatives, applying multiple regression analysis to assess the proposed relationships. All our hypotheses were empirically supported. Overall, this study contributes to SPI research by integrating team capability theory with AI-driven innovation frameworks. The findings highlight the need for firms to cultivate multidisciplinary teams with adaptive capacities while leveraging GenAI as an amplifier rather than a substitute for human expertise. The results also underscore that effective SPI requires both internal knowledge diversity and external responsiveness, alongside AI tools that enhance creativity and sustainability-driven decision-making. Finally, this research provides insights into how NPD teams can enhance their engagement in sustainable innovation, aligning with the broader objectives of Sustainable Development Goals (SDGs) 9 and 12.

1. Introduction

Traditionally, organizational teams primarily focused on efficacy, efficiency, and market performance by streamlining design and production to sharpen their competitive edge. Today, however, firms engaged in innovation are increasingly expected to tackle grand societal challenges, including environmental sustainability, ethical sourcing, circular economy principles, and social responsibility (Albitar et al., 2023; Kimsey et al., 2023; Qin et al., 2025). This shift aligns with the broader objectives of the Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation, and Infrastructure) and SDG 12 (Responsible Consumption and Production) (United Nations, 2015).

Accordingly, New Product Development (NPD) teams are increasingly focusing their efforts on sustainable product innovation (SPI) (Melander, 2017), aiming to develop "a new or significantly improved product that provides positive environmental and societal benefits as well as economic benefits" (Calik, 2024, p. 102882). To achieve this, NPD teams must consider the enablers and constraints of SPI. However, despite the growing urgency to understand team-level drivers of sustainable innovation, empirical knowledge on this topic remains limited. In this study, we argue that teams must integrate two complementary dimensions—internal skill differentiation and external adaptability—to successfully accomplish sustainability objectives in product innovation.

Internally, skill differentiation allows teams to integrate expertise from design, engineering, environmental science, and market insights, balancing technical feasibility, regulatory compliance, and consumer expectations. A diverse knowledge base supports creative solutions such as circular design, resource efficiency, and ethical sourcing, helping

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teams address sustainability challenges. Externally, adaptability enables teams to respond to regulatory shifts, evolving consumer preferences, and technological advancements. By absorbing new information and adjusting strategies, teams can align innovation with sustainability standards, ensuring they remain relevant in a changing market while enhancing environmental and societal impact.

In this context, Generative Artificial Intelligence (GenAI)—defined as "a class of machine learning technologies that have the capability to generate new content that resembles human-created output, such as images, text, audio, and videos" (Grimes et al., 2023, p. 1617)—is reshaping NPD teams by accelerating eco-friendly material development, resource optimization, and circular design. Tools such as Autodesk's generative design software, Google DeepMind's AlphaFold, and OpenAI's GPT models allow firms to experiment with bio-based materials, closed-loop manufacturing, and modular product designs that improve recyclability. Nike and Adidas use GenAI to develop sustainable footwear, while Unilever applies AI-driven simulations to test biodegradable packaging. Patagonia leverages GenAI to assess garment life cycles, and Tesla and Northvolt explore next-generation battery materials to reduce reliance on rare earth elements. GenAI also streamlines design iterations, reducing material use, costs, and development time across automotive, aerospace, and consumer goods (McKinsey & Company, 2023a; 2023b). However, its integration presents challenges. It reshapes team dynamics, potentially displacing human expertise and altering creative processes, while also reinforcing biases that might cause teams to overlook sustainability trade-offs (Amankwah-Amoah et al., 2024). Dependence on GenAI raises concerns about energy-intensive computing infrastructure (Chu et al., 2024) and algorithmic transparency in decision-making (Larson et al., 2024; Raisch and Krakowski, 2021). As firms integrate GenAI into NPD, its role as both a driver of sustainability and a disruptor of established processes requires careful consideration. As GenAI becomes more embedded in NPD processes, organizations must critically assess its role at all levels.

Relatedly, we argue that while skill differentiation and adaptability are key drivers of sustainability-oriented innovation, their effectiveness may depend on the extent to which AI is integrated into the NPD process. Accordingly, we pose the following research question:

Do team skill differentiation and team adaptability foster sustainable product innovation, and to what extent does the team's use of GenAI moderate these relationships?

To address this question, the present study leverages the double diamond framework (Marion and Fixson, 2019) and its AI-augmented adaptation (Bouschery et al., 2023), which distinguish between divergent and convergent thinking in the innovation process. Drawing on this framework, we derive a set of hypotheses about how team skill differentiation, team adaptability, and GenAI use influence SPI. First, although prior studies have highlighted the downsides of multifunctionality in team-based work (van den Beukel and Molleman, 2002), we propose that team skill differentiation positively affects SPI. Sustainability-oriented innovation requires integrating diverse expertise (Ortiz-Avram et al., 2024), which enables teams to generate creative solutions to challenges such as circular design and resource efficiency. The original double diamond framework structures innovation through iterative cycles of divergence and convergence (Marion and Fixson, 2019). In the initial phase, a broad exploration of problems and opportunities occurs, while in the subsequent phase, solution options are developed before converging on viable outcomes. This process benefits from diverse expertise and skills. Such diversity expands the range of ideas explored and enhances integration during the refinement phase, enabling teams to navigate technical feasibility, regulatory constraints, and market demands more effectively.

Second, although prior research suggests that excessive adjustment can be detrimental—potentially leading to mission drift and short-termism in our context (Mumtaz and Nadeem, 2020)—we argue that team adaptability positively affects SPI. Given the dynamic nature of sustainability demands, adaptable teams can rapidly integrate external signals and adjust their strategies to align with evolving regulations and market expectations. Adaptability enhances convergent thinking by ensuring that teams can refine and implement sustainability solutions that remain viable amid shifting industry conditions. Additionally, adaptability allows teams to experiment with sustainability-driven innovations and recalibrate based on external feedback.

Third, we argue that GenAI use strengthens the relationship between team skill differentiation and SPI by expanding the problem and solution spaces in which NPD teams can operate (Bouschery et al., 2023). GenAI allows teams to access and generate larger volumes of knowledge, supporting knowledge recombination in the divergent phase and structured integration in the convergent phase (Chiarello et al., 2024; Magistretti et al., 2024). Within the GenAI-augmented double diamond framework, these tools allow teams to explore broader problem and solution spaces while facilitating more connections between them (Bouschery et al., 2023). This, in turn, enhances their ability to develop sustainability-focused innovations that align with both technical and economic requirements.

Fourth, we propose that GenAI use enhances the relationship between team adaptability and SPI by enabling real-time sensing and response. GenAI-driven analytics improve a team's ability to identify trends, anticipate customer needs, and generate technology forecasts (Bouschery et al., 2023; Chiarello et al., 2024). By augmenting teams' capacity to process large volumes of information efficiently, GenAI supports more agile adjustments to external shifts and market dynamics (Gama and Magistretti, 2025). By streamlining knowledge extraction and accelerating decision-making, GenAI reinforces adaptability as a driver of sustainability-oriented innovation, enabling teams to refine and scale sustainable solutions in dynamic environments.

To empirically examine our theoretical arguments, we conducted a multi-industry survey targeting NPD teams in manufacturing firms engaged in sustainable innovation. Data were collected through a structured questionnaire administered to NPD managers overseeing product development decisions. To test our hypotheses, we applied multiple regression analysis (Aiken et al., 1991; Hayes, 2022) using Stata MP 18.0. Our analysis, including a series of robustness checks, consistently provided empirical support for all four hypotheses.

Overall, this study advances the literature on sustainable product innovation (Calik, 2024; de Guimarães et al., 2021) by integrating team capability theory and AI-driven innovation frameworks. By framing SPI as a function of skill differentiation and adaptability, it highlights the dual competencies needed to address sustainability challenges. The findings reinforce the role of team diversity in fostering sustainability-driven innovation (Garcia Martinez et al., 2017; Hewlett et al., 2013; Weiss et al., 2018) and emphasize adaptability in responding to evolving regulations and market dynamics. By incorporating AI as a moderating factor, this study extends the double diamond framework (Marion and Fixson, 2019) and its AI-augmented adaptation (Bouschery et al., 2023), providing empirical evidence on how GenAI enhances both divergent knowledge generation and convergent problem-solving. At a practical level, this study offers insights for SDG 9 and SDG 12, showing how team capabilities and AI integration can drive sustainable innovation. It underscores how skill differentiation and adaptability help firms align with responsible production practices and resource efficiency, strengthening industrial resilience and circular economy strategies.

2. Theoretical background and hypothesis development

2.1. The double diamond and AI-augmented double diamond frameworks

The double diamond framework structures innovation as an iterative process of divergence and convergence, guiding how NPD teams navigate both problem identification and solution development (Marion and Fixson, 2019). When NPD is viewed as a process, each stage is designed to gather information to reduce uncertainty and manage risk (Balzano and Marzi, 2023; Cooper, 2023, 2024). The first diamond represents the search for problems or opportunities, beginning with a divergent phase in which teams explore a broad set of possible issues before converging on a specific, viable challenge. The second diamond follows a similar pattern, expanding the range of potential solutions before selecting the most effective solution for development and implementation. This structured approach focuses on innovation emerging through managed cycles of exploration and refinement.

Rooted in design thinking (Magistretti et al., 2025), the framework distinguishes between the problem space and the solution space, ensuring that NPD teams balance open-ended exploration with structured decision-making (Calabretta and Gemser, 2015; Micheli et al., 2019). The initial divergence allows teams to generate diverse perspectives, incorporating insights from multiple domains, while the convergence phases filter and refine ideas based on feasibility, strategic alignment, and market constraints (Carlgren et al., 2016). This process aligns with broader theories of innovation management by illustrating how NPD teams integrate diverse expertise, absorb external knowledge, and iteratively refine ideas through structured development (Cai et al., 2023). The ability to shift between exploratory and refining activities is central to design thinking (Balzano and Bortoluzzi, 2024; Brown, 2008), ensuring that teams can navigate uncertainty while progressing toward commercially viable and impactful solutions (Mortati et al., 2023; Nagaraj et al., 2020). Applying this framework to sustainable product innovation highlights how structured iteration supports the integration of sustainability principles into new product development (Sahakian & Ben Mahmoud-Jouini, 2023), enabling teams to systematically explore sustainability-oriented solutions. This approach ensures that the relationships between knowledge integration, problem-solving flexibility, and sustainability-driven innovation result from a structured innovation process rather than from ad hoc team dynamics (Magistretti et al., 2022; Verganti et al., 2021).

The AI-augmented double diamond framework extends this structured model by integrating artificial intelligence to enhance both problem exploration and solution development (Bouschery et al., 2023). GenAI can swiftly produce novel product ideas and analyse large data sets to generate insights for product design, leading to more tailored products that meet customer needs (Bilgram and Laarmann, 2023). AI-powered tools predict market trends, sales, pricing, and costs while monitoring competitors' activities to provide real-time insights into their strategies. GenAI also assists in financial analysis and risk assessment, helping project teams anticipate risks and propose mitigating actions (Vargas and Nieto-Rodriguez, 2023). However, GenAI does not replace the core principles of design thinking. Instead, it expands the operational scope of these principles by leveraging AI-driven data processing, insight extraction, and novel recombinations of knowledge. AI's role is particularly pronounced in augmenting the divergent phases, allowing NPD teams to explore broader problem spaces and generate a wider range of potential solutions (Sjödin et al., 2023).

In the context of SPI, this framework offers a structured way to examine how GenAI interacts with knowledge processes in NPD teams. GenAI expands problem spaces by synthesizing large volumes of environmental, regulatory, and consumer data, allowing teams to identify emerging sustainability challenges and to reveal connections that might otherwise remain obscured. In solution spaces, GenAI facilitates idea generation, encouraging teams to explore material optimizations, lifecycle assessments, and alternative design strategies derived from both structured and unstructured knowledge sources (Joosten et al., 2024). The AI-augmented model thus allows NPD teams to navigate sustainability challenges with greater precision and adaptability. This perspective provides a rationale for considering AI's moderating role in the relationships between team skill differentiation, team adaptability, and sustainable innovation outcomes. By structuring problem identification and solution development with AI support, the framework promotes NPD teams to systematically analyse how GenAI enhances both exploratory creativity and structured refinement—pillars of design thinking. Rather than replacing human expertise, AI extends the cognitive and analytical capacity of teams, helping them synthesize diverse inputs and adjust dynamically to evolving sustainability objectives.

2.2. The impact of team skill differentiation in sustainable product innovation

In NPD, teams operate within an iterative process of divergence and convergence, where ideas are first expanded and explored before being refined into viable solutions (Marion and Fixson, 2019). The iterative nature of SPI means that teams must cycle through divergence and convergence multiple times, making the ability to synthesize diverse inputs into actionable solutions particularly valuable (Bunderson and Sutcliffe, 2002). This cyclical structure necessitates cross-functional collaboration at different stages, as early-phase divergence relies on exploratory creativity, while later-phase convergence requires structured integration and feasibility assessment (Griffin and Hauser, 1996). Designers, engineers, marketers, and strategists each contribute domain-specific expertise, allowing NPD teams to generate a broad array of potential solutions and systematically refine them into market-ready innovations (Brown and Eisenhardt, 1995).

When the focus shifts to SPI, sustainability-oriented challenges introduce additional dimensions—environmental impact assessments, life cycle analysis, circular design principles, and regulatory compliance—which could be addressed throughout both the divergence and convergence phases (Wilkerson and Trellevik, 2021). The ability to integrate sustainability-related knowledge with traditional NPD expertise is therefore critical. In this context, team skill differentiation enhances SPI by supporting both the exploratory and integrative functions of innovation.

The double diamond framework (Marion and Fixson, 2019) provides a structured lens for understanding how skill differentiation enhances SPI. In the divergent phase, where teams explore a broad range of sustainability-related challenges, diverse expertise allows for a wider search space in identifying opportunities and potential solutions. Engineers, designers, marketers, and environmental specialists contribute distinct insights, expanding the scope of problem exploration (Silk et al., 2021). This cross-functional input ensures that sustainability constraints and opportunities are recognized early, preventing late-stage design conflicts and aligning sustainability goals with technical feasibility and market viability (Genç and Di Benedetto, 2015).

In the convergent phase, where teams refine and integrate solutions into viable products, skill differentiation strengthens problem-solving capacity by allowing teams to synthesize insights from multiple domains. Regulatory specialists help ensure compliance, engineers evaluate technical feasibility, and market strategists assess consumer adoption potential. This structured integration enhances the team's ability to align sustainability-driven innovations with industry standards and commercial viability, ensuring that SPI efforts are both creative and implementable. In this perspective, skill differentiation enhances both the generation and execution of sustainability innovations, equipping NPD teams to navigate technical, market, and regulatory complexities more effectively. Therefore, we propose.

Hypothesis 1. NPD team skill differentiation positively affects sustainable product innovation.

2.3. The impact of team adaptability in sustainable product innovation

We argue that team adaptability enhances SPI by enabling NPD teams to integrate external signals, adjust strategies, and refine sustainability-driven solutions in response to shifting industry conditions. Given the dynamic nature of sustainability demands, adaptability ensures that teams remain responsive to regulatory changes, evolving market expectations, and technological advancements.

In this context, team adaptability refers to the collective capability to modify strategies, processes, and behaviors in response to external changes (Grass et al., 2020). In SPI, where sustainability imperatives continuously evolve, adaptable teams can rapidly incorporate new environmental standards, emerging circular economy principles, and consumer-driven sustainability preferences (Edmondson and Nembhard, 2009; Sosa, 2011). This ability enhances both strategic flexibility and execution, ensuring that sustainability efforts remain innovative and commercially viable.

Highly adaptable NPD teams exhibit superior environmental scanning capabilities, continuously monitoring policy changes, market trends, and technological innovations (Grass et al., 2020). This proactive responsiveness allows teams to identify sustainability opportunities early and adjust their design choices, supply chain configurations, and material selections accordingly (Gao et al., 2021). Whether responding to new eco-regulations or adapting to shifts in consumer demand for sustainable products, adaptability helps teams maintain alignment with evolving industry expectations while sustaining innovation momentum (Sivasubramaniam et al., 2022).

This adaptability is closely linked to iterative learning and experimentation, characterized by continuous refinement instead of rigid planning (Liedtka et al., 2024). Teams fostering a culture of psychological safety—where members are encouraged to experiment, iterate, and incorporate real-time feedback—are more effective in refining sustainability solutions (Edmondson and Lei, 2023). This iterative approach ensures that sustainability innovations are not only aligned with evolving market conditions but also optimized through cycles of feedback and recalibration (Birkinshaw et al., 2022).

Moreover, adaptability strengthens the interplay between divergent and convergent phases of innovation. In the divergent phase, adaptable teams explore multiple sustainability pathways, leveraging emerging environmental insights, evolving technological capabilities, and shifting stakeholder expectations. In the convergent phase, they refine and integrate these insights into actionable, scalable solutions (Ployhart and Turner, 2023). This ability to transition seamlessly between exploration and refinement ensures that sustainability-driven innovations remain viable, impactful, and responsive to external shifts (Baldassarre et al., 2024). By fostering agility in decision-making, adaptable NPD teams sustain a competitive advantage in dynamic environments, ensuring that sustainability-driven innovations remain strategically viable and market-relevant (DeFillippi et al., 2022). This leads us to propose.

Hypothesis 2. NPD Team adaptability positively affects sustainable product innovation.

2.4. The interplay of team skill differentiation and GenAI use

Building on the AI-augmented double diamond framework (Bouschery et al., 2023), our argument suggests that integrating GenAI into NPD teams can amplify the effects of team skill differentiation, leading to enhanced SPI outcomes through three principal mechanisms. First, during the problem phase of the double diamond framework, divergent thinking is crucial for identifying a variety of innovation possibilities. GenAI can significantly boost this stage by sifting through extensive structured and unstructured datasets to uncover insights beyond human cognitive limits. Recent studies have shown that GenAI can facilitate the identification of hidden patterns and connections often overlooked by human teams (Zhao et al., 2023a). Integrating AI tools into this phase allows teams to leverage their diverse skills more effectively and facilitates a deeper exploration of potential solutions. This enhanced ideation process is expected to yield more innovative outcomes by revealing new connections among diverse information sets and stimulating team creativity (Bouschery et al., 2023).

Moreover, AI-driven tools can simulate various scenarios, allowing teams to explore the potential environmental and economic impacts of different solutions early in the innovation process (Lee and Kumar, 2024). In the framework's solution phase, the focus shifts to refining options and deciding on the most feasible solutions. Here, GenAI's ability to analyse vast amounts of data and provide evidence-based insights can significantly enhance decision-making. For teams characterized by skill diversity, GenAI can deliver personalised, data-driven feedback tailored to each member's expertise, ensuring that decisions are based on a comprehensive analysis of all available data. GenAI becomes fundamental in environments where the complexity of data exceeds human processing capabilities, making AI an indispensable tool for integrating diverse perspectives into a coherent strategy (Smith et al., 2024).

By facilitating both the divergent and convergent phases of the double diamond framework, GenAI effectively enhances the innovation process within NPD teams. GenAI's capacity for processing vast amounts of data and its predictive capabilities are instrumental in maintaining the relevance and sustainability of innovations over the long term. Recent studies highlight how GenAI can assist teams in anticipating future trends, identifying potential challenges, and adjusting their approaches accordingly (Johnson et al., 2024). At the same time, GenAI facilitates a continuous learning environment in which team members can dynamically apply their diverse skills to new and emerging challenges. This allows teams to constantly adapt and refine their approaches in response to real-time data and insights provided by GenAI tools (Smith and Johnson, 2023). For instance, GenAI can help team members identify which aspects of their expertise are most applicable to current challenges, thereby optimising the allocation of skills and ensuring that the collective knowledge of the team is fully leveraged. Overall, we propose the following hypothesis.

Hypothesis 3. NPD team AI use strengthens the relationship between team skill differentiation and sustainable product innovation.

2.5. The interplay of team adaptability and GenAI use

In this section, we posit that the deployment of GenAI amplifies the interplay between team adaptability and SPI. Indeed, recent advancements in GenAI underscore its role in enhancing a team's ability to swiftly process large volumes of data and analyse complex trends. These capabilities significantly boost teams' capacity to recognise and adapt to shifts in the external landscape. For instance, by delivering real-time insights into market dynamics, consumer behaviour, and technological developments, GenAI allows teams to remain agile and responsive. According to Jiao et al. (2020), deploying AI tools in market analysis allows for a more nuanced understanding of consumer preferences and emerging trends, facilitating the timely adjustment of strategies to maintain competitive advantage.

First, GenAI systems provide up-to-date data and predictive analytics that allow teams to quickly adapt to new sustainability standards, evolving market demands, and emerging technological advancements. Zong and Guan (2024) observed that AI-driven predictive analytics can preemptively identify shifts in consumer behaviour related to sustainability, allowing firms to adjust their innovation processes proactively. Kulkov et al. (2024) highlighted that AI tools can also streamline the integration of new technologies into product development cycles, ensuring that teams can swiftly incorporate the latest advancements into their sustainability strategies.

Second, the AI-augmented double diamond framework highlights AI's role in enhancing both the divergent and convergent phases of the innovation process. In the divergent phase, AI tools significantly improve the team's ability to explore a wide range of possibilities by analysing vast amounts of external data. Zhao et al. (2023b) have shown that AI-driven data mining and pattern recognition can reveal subtle shifts in consumer behaviour and industry trends, thus allowing innovation teams to adapt their strategies in real time. In the convergent phase, AI narrows the options to the most viable and impactful solutions. By leveraging predictive analytics and simulation models, AI can assess

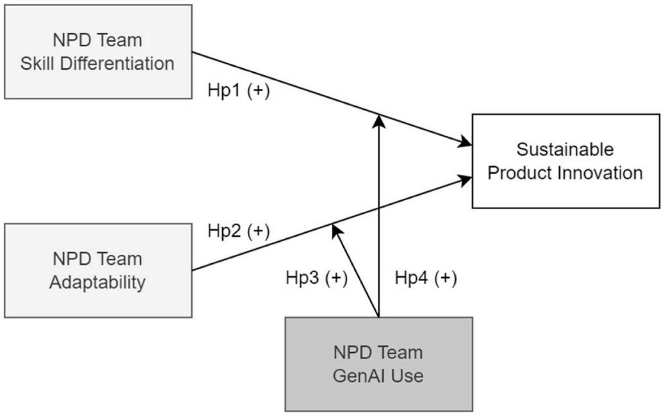

Fig. 1. Research model.

the feasibility and sustainability of different innovation paths. For instance, Langer et al. (2021) emphasize that AI can evaluate the environmental impact and practicality of proposed solutions, ensuring that innovation efforts are both actionable and aligned with sustainability goals.

Through the AI-augmented double diamond framework, teams can enhance their adaptability in two ways. On one hand, teams can identify and adapt to emerging trends sooner by expanding their ability to explore the opportunity landscape more thoroughly. On the other hand, by focusing on the most feasible and sustainable solutions, they can ensure that their innovation efforts are relevant and capable of driving long-term value. Relatedly, GenAI facilitates quick prototyping by assisting teams in creating, testing, and refining models more quickly and accurately than traditional methods. AI-driven simulations allow teams to experiment with different design variables and predict outcomes without physical prototypes, saving time and resources. Bouschery et al. (2023) propose that AI tools like generative design and machine learning algorithms can rapidly generate and assess multiple design iterations, allowing teams to explore various possibilities and make informed decisions on the most promising prototypes. Interestingly, Nguyen et al. (2023) found that teams leveraging AI in this way show superior adaptability and resilience, particularly in environments characterised by rapid technological advancements and shifting market demands. GenAI thus serves as a key facilitator of team adaptability, enhancing teams' responsiveness to external changes and enriching their innovation methodologies. By improving environmental awareness, streamlining the exploration of opportunities, and expediting iterative development, GenAI strengthens the link between team adaptability and sustainable product innovation. Accordingly, we put forth the following hypothesis.

Hypothesis 4. NPD team AI use strengthens the relationship between team adaptability and sustainable product innovation.

In Fig. 1, we present our research model.

3. Methods

3.1. Sample and setting

To test our hypotheses, we focused on the manufacturing industry. Data collection was conducted via a structured questionnaire distributed by mail, ensuring a broad, representative sample. Confidentiality and anonymity were assured to encourage candid responses from participants. The questionnaire aimed to gather detailed insights into team dynamics, GenAI integration, and SPI practices within participating firms. To prevent acquiescence bias and minimize response distortions, we employed balanced scales, varied question phrasing, and included reverse-coded items where appropriate. Additionally, three attention checks were incorporated to assess respondent engagement and ensure data quality by identifying inattentive or random responses.

To ensure the questionnaire's content validity, an initial version was evaluated by two managers, a field expert, and two academics. Based on their feedback, the instrument was refined. In particular, this process allowed us to verify the relevance and clarity of the items and to refine how the constructs were adapted to the study's context. Feedback from managers ensured practical applicability, the field expert provided domain-specific insights, and the academics assessed conceptual rigor and alignment with existing literature. This iterative evaluation helped refine wording, structure, and measurement scales, improving both

Table 1
Sample characteristics.

Teams' characteristics					
Team experience (years)			Team size (number of team members)		
1–5	117	35.35 %	Less than 5	10	3.02 %
6–10	150	45.32 %	6–10	91	27.49 %
More than 10	64	19.34 %	15–20	120	36.25 %
			20–25	27	8.16 %
			More than 20	83	25.08 %
Team stability (number of team members changed during the duration of the last NPD project).			*Last NPD project duration (months)*		
0	55	16.62 %	6–12	148	44.71 %
1–3	154	46.53 %	12–24	63	19.03 %
4–6	66	19.94 %	More than 24	120	36.25 %
7–9	44	13.29 %			
More than 9	12	3.63 %			
Firms' characteristics					
Size (employee number)			*Manufacturing Sector*		
5–20	59	17.82 %	Computer and Electronics	42	12.69 %
21–50	44	13.29 %	Electrical and Machinery	113	34.14 %
51–250	87	26.28 %	Metallic	38	11.48 %
251–500	130	39.27 %	Motor vehicles and transports	68	20.54 %
>500	11	3.32 %	Pharmaceutical	35	10.57 %
			Plastics and non-metallic	24	7.25 %
Technological Level					
High-Tech	210	63.44 %			
Low-Tech	121	36.56 %			
Grand Total	**331**				

Table 2
Items and reliability of latent variables.

Think about the last projects (last year) you participated in relation to the development of a new product:	Cronbach's Alpha	AVE
Sustainable Product Innovation (adapted from Calik, 2024)	0.928	0.500
In the last year, our company has been designing and developing products that consume as little energy as possible.		
In the last year, our company has been designing and developing products that consume other resources (water, oil, etc.) as little as possible.		
Our new products have fewer pollutant emissions or wastes during the life cycle than our competitors' products.		
Our new products consume fewer other resources (water, oil, etc.) during their lifecycle than our competitors' products.		
In the last year, our company has been trying to use natural and biodegradable materials in our products.		
In the last year, our company has been redesigning and improving its products to be able to comply with new environmental guidelines and criteria (such as WEEE and ROHS documents).		
In the last year, our company has been increasing the durability of our products.		
Consumers perceive our new products as more ergonomic than our competitors' products.		
In the last year, our company has been considering end-of-life activities (disassembly, remanufacturing, recycling, disposal, etc.) when designing new products.		
In the last year, while designing new products, our company has considered the effects of products on the health and safety of customers during the product life cycle.		
In the last year, our company has continuously developed and commercialized new products that provide environmental and societal benefits.		
In the last year, our company has gained/is gaining patents/utility models related to sustainability for its new products.		
In the last year, our company has been continuously increasing its expenditures for product innovations that provide environmental and societal benefits.		
NPD Team Skill Differentiation (adapted from Morgeson and Humphrey, 2006)	0.803	0.505
Inside our NPD team(s), there are people with a wide variety of skills.		
Our NPD projects require the use of a variety of different skills to complete the job to be done.		
Our NPD projects require the use of a number of complex or highly specialised skills.		
Our NPD projects require the use of a number of diverse skills.		
NPD Team Adaptability (adapted from Hyatt and Ruddy, 1997; Morgeson and Humphrey, 2006)	0.861	0.509
We regularly take time to figure out ways to improve our NPD teams' work processes in spite of environmental changes.		
Our NPD teams frequently seeks new information outside the company, leading us to make important changes.		
We invite people from outside the NPD teams to present information or have discussions with us.		
In our NPD teams, someone always makes sure that we leverage external stimuli to fine-tune the team's work process.		
Our NPD teams monitors external shifts to implement business decisions and ensure customer requirements are met.		
Our NPD teams use external data to revise work group processes.		
NPD team GenAI Use (adapted from Marzi et al., 2023)	0.873	0.637
We regularly use GenAI in our NPD projects.		
We plan continuous use of GenAI in our NPD projects.		
We recommend using GenAI in NPD projects.		
We keep integrating GenAI into our NPD projects.		

content validity and construct operationalization.

Subsequently, the survey was administered to a group of NPD managers in manufacturing firms who held decision-making authority over their organisation's NPD processes. A total of 331 responses were received, each representing a distinct NPD team. All responses met the criteria for validity, as verified through manipulation checks. As shown in Table 1, the sample covers a wide array of team and firm characteristics pertinent to NPD projects. The teams in our sample had varying levels of experience, with many possessing moderate to substantial experience in the field. Team sizes varied significantly: many teams had a moderate number of members, while relatively few were much larger or much smaller.

Another key factor is team stability: almost half of the teams reported only minor changes in composition during their most recent NPD project, while a smaller portion of teams experienced more significant membership changes. The timeline for NPD projects also varies, with a number of projects being completed within one year, although many extended beyond this duration.

In terms of firm characteristics, the sample comprises companies of varying sizes, ranging from small to large, with a significant representation of medium to large enterprises. These firms represent a broad spectrum of manufacturing sectors, and their technological sophistication also varies significantly.

3.2. Measures

The dependent variable of this study is SPI, which measures how well firms' product innovations adhere to sustainability criteria. This variable is operationalized using a 7-point Likert scale adapted from Calik (2024), where respondents assess the degree to which sustainability is integrated into their NPD processes.

The two main independent variables are NPD team skill differentiation and NPD team adaptability. NPD team skill differentiation is measured using a 7-point Likert scale adapted from Morgeson and Humphrey (2006), where higher scores reflect a broader range of skills among team members. This measure captures the complexity of sustainable innovation, which requires a blend of technical, managerial, and creative skills to successfully navigate the challenges associated with developing sustainable products. NPD team adaptability, on the other hand, assesses the team's ability to adjust strategies and operations in response to environmental and market changes. This variable is measured using a 7-point Likert scale adapted from Hyatt and Ruddy (1997) and Morgeson and Humphrey (2006), with higher scores indicating greater adaptability. This reflects the dynamic nature of sustainable innovation, where teams must respond fluidly to shifting regulations, changing consumer preferences, and emerging technologies.

The moderating variable in this study is NPD team GenAI use, which measures the extent to which generative artificial intelligence is integrated into the NPD team's processes. This is also captured through a 7-point Likert scale, adapted from Marzi et al. (2023). Several control variables are included in the analysis to account for additional factors that may influence outcomes. These controls include firm size (measured on a 1–5 scale); team experience (captured on a 1–3 scale to reflect collective expertise in sustainable innovation); a binary indicator for technological intensity (differentiating between high-tech and low-tech firms); team stability (measured on a 1–5 scale to evaluate the consistency of team membership); manufacturing sector (to analyse sector-specific dynamics of sustainable innovation); and NPD project duration (measured on a 1–3 scale) to assess the influence of project

Table 3
Correlation matrix.

	Mean	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Sustainable Product Innovation	5.033	1.045	1.000	7.000	1.000									
(2) NPD Team Skill Differentiation	4.857	1.073	1.000	7.000	0.212***	1.000								
(3) NPD Team Adaptability	5.174	0.951	1.000	7.000	0.292***	−0.054	1.000							
(4) NPD Team AI Use	5.462	1.041	1.000	7.000	0.174**	−0.116*	0.228***	1.000						
(5) Firm Size	2.970	1.173	1.000	5.000	−0.023	−0.033	−0.074	−0.057	1.000					
(6) NPD Team Size	3.248	1.193	1.000	5.000	−0.009	−0.050	−0.014	0.110*	0.044	1.000				
(7) NPD Team Experience	1.840	0.723	1.000	3.000	0.110*	0.037	0.049	0.068	−0.006	0.120*	1.000			
(8) High-Tech/Low-Tech	1.366	0.482	1.000	2.000	0.070	−0.085	0.021	0.059	0.245***	−0.037	0.029	1.000		
(9) NPD Team Stability	3.592	1.030	1.000	5.000	0.059	−0.021	−0.024	0.111*	−0.138*	0.060	−0.080	0.027	1.000	
(10) Manufacturing Sector	3.172	1.625	1.000	7.000	0.133*	0.073	0.007	−0.000	0.120*	0.048	0.052	0.012	−0.239***	1.000
(11) NPD Project Duration	1.915	0.897	1.000	3.000	−0.000	−0.021	0.037	−0.036	0.096^{+}	0.198***	0.091^{+}	−0.040	−0.116*	0.407***

$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. n = 331.

length on sustainable innovation outcomes.

3.3. Constructs' reliability and analytical technique

To ensure the reliability of the latent constructs, the CLC Estimator, as described by Marzi et al. (2023), was applied. As shown in Table 2, the reliability of each construct was evaluated using Cronbach's Alpha (α) and Average Variance Extracted (AVE). For each construct, the standardised factor loadings exceeded the recommended threshold, indicating an adequate fit (Hair et al., 2010). Moreover, discriminant validity was supported by meeting the requirements of the Fornell–Larcker criterion (Fornell and Larcker, 1981).

To test our hypotheses, we employed multiple regression analysis (Aiken et al., 1991; Hayes, 2022) using Stata MP 18.0 for statistical computations. The regression analysis was conducted in a stepwise manner, beginning with a model that included only control variables. Additional variables were then incrementally introduced in subsequent models to enhance interpretability and assess their specific impact on sustainable product innovation. In addition to the main analysis, we performed a series of robustness checks to ensure the stability and reliability of the results.

4. Results

4.1. Hypothesis tests

Table 3 presents the key descriptive statistics. The correlation matrix highlights the relationships among the independent variables, with the highest correlations observed between NPD team adaptability and NPD team AI use ($r = 0.228$; $p < 0.001$), firm size and the high-tech/low-tech variable ($r = 0.245$; $p < 0.000$), and the manufacturing sector and NPD team stability ($r = -0.239$; $p < 0.000$). These correlations provide initial insights into potential multicollinearity and the interplay between variables within the context of the study.

To address potential multicollinearity issues, we calculated variance inflation factors (VIF) for each variable. The results indicated that all VIF values were well below the commonly accepted threshold of 10 (Gujarati, 2004), thereby mitigating concerns about multicollinearity. Table 4 presents the outcomes of the multiple regression analysis. Model 1 includes only the control variables, establishing a baseline. In Model 2, we introduce the first independent variable, NPD team skill differentiation, to observe its initial effect on sustainable product innovation. Model 3 adds the second independent variable, NPD team adaptability, while Model 4 incorporates both independent variables to capture the combined effects of skill differentiation and adaptability. Models 5 and 6 separately examine the interaction effects: Model 5 explores the interaction between NPD team skill differentiation and NPD team AI use, and Model 6 investigates the interaction between NPD team adaptability and NPD team AI use. Finally, Model 7, the full model, includes all variables and interaction effects. This model serves as the basis for hypothesis testing. To enhance the validity of our regression analysis, all variables were mean-centred, following the recommendations of Aiken et al. (1991), ensuring that multicollinearity from interaction terms was minimised. Additionally, robust standard errors were used to adjust for any potential heteroskedasticity in the data, ensuring the robustness of our results.

To begin with, Hypothesis 1 posits that NPD team skill differentiation positively affects sustainable product innovation. The analysis reveals that the estimated coefficient for team skill differentiation is positive and significant ($\beta = 0.197$; $p < 0.000$), thus providing support for our first hypothesis. Hypothesis 2 posits that NPD team adaptability positively influences sustainable product innovation. The results show that the estimated coefficient for team adaptability is positive and significant ($\beta = 0.324$; $p < 0.000$), thereby supporting our second hypothesis. Hypothesis 3 suggests that NPD team AI use strengthens the positive relationship between team skill differentiation and sustainable product

Table 4
Regression analysis with robust standard errors.

	Hp	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NPD Team Skill Differentiation	Hp 1		0.203***		0.232***	0.195***	0.235***	0.197***
			(0.053)		(0.051)	(0.051)	(0.050)	(0.051)
NPD Team Adaptability	Hp 2			0.289***	0.275***	0.272***	0.324***	0.324***
				(0.050)	(0.055)	(0.054)	(0.062)	(0.061)
NPD Team GenAI Use					0.118*	0.125*	0.123*	0.131**
					(0.053)	(0.051)	(0.050)	(0.049)
NPD team sk. diff. X NPD team GenAI use	Hp 3					0.190**		0.196***
						(0.058)		(0.058)
NPD team Adap. X NPD team GenAI use	Hp 4						0.091*	0.096**
							(0.038)	(0.034)
Firm Size		−0.040	−0.037	−0.014	−0.004	−0.003	0.012	0.014
		(0.059)	(0.058)	(0.057)	(0.056)	(0.056)	(0.056)	(0.056)
NPD Team Size		−0.020	−0.010	−0.014	−0.016	−0.011	−0.020	−0.016
		(0.059)	(0.058)	(0.057)	(0.055)	(0.054)	(0.054)	(0.053)
NPD Team Experience		0.114*	0.105+	0.102+	0.084+	0.076	0.089+	0.080
		(0.056)	(0.054)	(0.053)	(0.051)	(0.050)	(0.050)	(0.049)
High-Tech/Low-Tech		0.069	0.087+	0.056	0.069	0.065	0.070	0.067
		(0.053)	(0.052)	(0.050)	(0.048)	(0.047)	(0.049)	(0.047)
NPD Team Stability		0.098+	0.097+	0.106*	0.093+	0.103*	0.098+	0.108*
		(0.054)	(0.052)	(0.052)	(0.052)	(0.050)	(0.050)	(0.049)
Manufacturing Sector		0.181**	0.160*	0.184**	0.155*	0.169**	0.158**	0.173**
		(0.064)	(0.064)	(0.061)	(0.060)	(0.060)	(0.060)	(0.060)
NPD Project Duration		−0.062	−0.051	−0.076	−0.055	−0.059	−0.062	−0.067
		(0.066)	(0.064)	(0.063)	(0.060)	(0.060)	(0.060)	(0.059)
n		331	331	331	331	331	331	331
Adjusted R^2		0.028	0.066	0.109	0.165	0.189	0.176	0.202

+ $p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Standard errors in parentheses. The dependent variable is Sustainable Product Innovation.

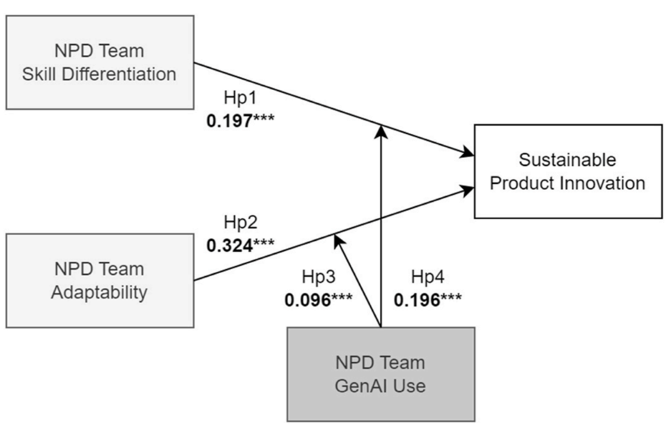

Fig. 2. Results of the full model.

innovation. The positive coefficient (β = 0.096; p < 0.000) indicates the interaction effect is significant, providing support for the third hypothesis. Hypothesis 4 posits that NPD team AI use strengthens the positive relationship between team adaptability and sustainable product innovation. The analysis yields a positive and significant interaction coefficient (β = 0.196; p < 0.000), which supports our fourth hypothesis. The likelihood-ratio tests indicate an improvement in model fit as additional variables are introduced, supporting the incremental gain in predictive accuracy of our models. In Fig. 2 we report the results of the full model (Model 7).

4.2. Robustness tests

To inspect the reliability of the results, three robustness checks were conducted to confirm that the findings are not overly sensitive to model specification, measurement techniques, or specific data points. The first robustness check utilized jackknife resampling techniques (Efron and Tibshirani, 1994; Miller, 1974). This method involves running the regression models multiple times, each time excluding different subsamples of the data. The goal was to assess whether specific subsamples had an undue influence on the overall model fit and parameter estimates. The results from these analyses confirmed the original findings, indicating that outliers or highly influential observations did not disproportionately drive the outcomes.

The second robustness check focused on the estimation of latent variables. While the primary analyses estimated latent scores using congeneric models, the robustness of these estimates was tested by employing parallel models as an alternative method (Jöreskog and Sörbom, 1996). Despite the different assumptions of these models, the results were consistent, providing further support for the robustness of the latent variables used in the study.

The third robustness check involved re-estimating the model without including the control variables (Bernerth et al., 2018). Even without these controls, the results remained aligned with the main findings, supporting that the relationships observed are not merely artefacts of confounding variables. Finally, to further substantiate the robustness of our conclusions, we applied the Sorted Effects Method (Chen et al., 2020; Chernozhukov et al., 2018). This method allows for detecting potential heterogeneous effects that might be overlooked when focusing solely on average estimates from regression analysis. Examining the impact of variables across different percentiles provided a more fine-grained view of how relationships vary at different levels of the dependent, independent, and moderator variables. The results showed that the regression model remained stable and consistent across various percentiles, reinforcing the model's validity under diverse conditions.

5. Discussion

5.1. Theoretical contributions

Our findings contribute to multiple streams of literature by integrating insights from innovation management, team dynamics, and generative AI-enhanced decision-making. Specifically, we extend research on sustainable product innovation, team capabilities, and AI-driven augmentation of NPD processes.

First, our finding that skill differentiation positively influences SPI extends prior work on team diversity and innovation (Bunderson and Sutcliffe, 2002; Edmondson and Nembhard, 2009). The literature has established that skill-diverse teams are more effective in problem-solving due to their ability to integrate multiple knowledge domains (Griffin and Hauser, 1996; Morgeson and Humphrey, 2006). However, research on SPI has not fully accounted for how team skill differentiation specifically facilitates sustainability-oriented outcomes. We contribute to this debate by applying the double diamond framework (Marion and Fixson, 2019) to sustainability-driven NPD. Our results suggest that skill differentiation is particularly valuable in sustainability-oriented innovation because it allows teams to navigate regulatory complexity, integrate eco-design principles, and balance economic feasibility with environmental goals. This contribution aligns with and extends prior studies on cross-functional innovation teams (Hewlett et al., 2013; Weiss et al., 2018) by showing that the breadth of knowledge within a team can enhance the creative exploration and feasibility evaluation of sustainability solutions.

Second, our study advances research on adaptability in team-based innovation (Eisenhardt and Martin, 2000; Grass et al., 2020) by highlighting its specific role in SPI. While adaptability has been linked to agility in dynamic environments (Ployhart and Turner, 2023), its function in sustainability-focused NPD remains underexplored. Our findings support the idea that adaptable teams are more effective at integrating evolving sustainability regulations, shifting consumer expectations, and technological advancements into their innovation processes. By extending the AI-augmented double diamond framework (Bouschery et al., 2023), we show that team adaptability facilitates sustainability-oriented innovation through both divergent exploration and convergent refinement. Prior studies have examined adaptability in traditional innovation settings (DeFillippi et al., 2022) but have not explicitly linked it to sustainability imperatives. Our study suggests that adaptability is not only beneficial for responding to uncertainty but is also key for maintaining alignment with evolving sustainability standards and circular economy principles.

The moderating effect of AI on skill differentiation contributes to the emerging literature on AI-driven innovation (Bouschery et al., 2023; Gama and Magistretti, 2025). While prior studies have suggested that AI can augment team capabilities (Smith et al., 2024), few have examined its specific impact on SPI. Our research builds on this foundation by supporting that AI acts as a cognitive amplifier, enhancing the ideation and solution development phases of sustainability-driven innovation. This extends the literature on cross-functional team effectiveness (Tushman and O'Reilly, 1997) by showing that AI can facilitate better knowledge recombination among diverse team members. AI expands the problem and solution spaces by integrating structured and unstructured sustainability data (Lee & Kumar, 2024), thereby helping teams leverage their diverse skills more effectively. This contribution aligns with studies on knowledge diversity in NPD (Bunderson and Sutcliffe, 2002) but adds the novel insight that AI strengthens these effects by improving the efficiency of knowledge integration.

Our study advances research on AI's role in enhancing organizational and team adaptability (Zhang et al., 2022). The ability of AI to provide real-time environmental scanning, predictive analytics, and rapid scenario testing assists teams to adapt more effectively to external sustainability shifts (Jiao et al., 2020). While prior studies have examined the role of AI in market responsiveness (Nieto-Rodriguez and Vargas, 2023), our findings highlight that AI-driven insights strengthen teams' ability to continuously recalibrate sustainability strategies.

We extend the AI-augmented double diamond framework by showing that AI facilitates teams to transition more fluidly between divergent exploration and convergent decision-making in response to sustainability challenges. Prior research has emphasized the importance of adaptability in fast-changing markets (Edmondson and Lei, 2023), but our study provides empirical support for the idea that AI amplifies adaptability's effect on sustainability outcomes. This insight is particularly relevant for firms navigating regulatory volatility and shifting consumer sustainability expectations.

Our overarching theoretical contribution is the conceptualization of AI as a multiplier of existing team capabilities in SPI. Rather than replacing human expertise, AI enhances both cognitive and operational aspects of team dynamics, reinforcing the role of skill differentiation and adaptability. This perspective aligns with recent discussions on GenAI as both an enabler and a disruptor of traditional innovation processes (Cooper, 2024), but we extend this argument to sustainability-oriented innovation. Our study position GenAI as a new wave of creative augmentation in NPD, supporting teams in navigating sustainability challenges. This contributes to the broader literature on technological innovation by showing how GenAI can facilitate both knowledge recombination and real-time adaptation in sustainability-driven contexts.

5.2. Practical implications

Our findings suggest that organizations aiming to enhance SPI may benefit from reconsidering how they structure teams, foster adaptability, and integrate GenAI into innovation processes. Given the increasing alignment of corporate strategies with global sustainability frameworks, including SDG 9 (Industry, Innovation, and Infrastructure) and SDG 12 (Responsible Consumption and Production) (United Nations, 2015), our results indicate that GenAI's role extends beyond process automation to empowering knowledge recombination and strategic decision-making in SPI.

One implication of this study is that GenAI does not substitute for human expertise but amplifies it, particularly in expanding problem exploration and refining sustainability-driven solutions. Our findings highlight that skill differentiation enhances SPI by bringing together expertise from diverse domains, yet fully leveraging this diversity remains a challenge. In this regard, GenAI's capacity to process vast amounts of structured and unstructured data—such as sustainability regulations, market trends, and material innovations—suggests that AI-assisted knowledge recombination could allow teams to explore sustainability challenges more systematically (Bilgram and Laarmann, 2023; Zhao et al., 2023b). Rather than relying solely on individual expertise, teams can use AI-generated insights to identify connections between emerging technologies, regulatory shifts, and consumer expectations, potentially enhancing the creative ideation process (Bouschery et al., 2023). However, the effectiveness of this approach depends on the extent to which AI-generated insights are critically evaluated and integrated into decision-making, reinforcing the idea that AI should complement, rather than replace, human judgment (Nieto-Rodriguez and Vargas, 2023).

Similarly, our results indicate that team adaptability plays a central role in SPI, suggesting that firms operating in dynamic sustainability landscapes may benefit from embedding mechanisms that enhance teams' ability to integrate new information and adjust strategies accordingly. The increasing need for sustainability-oriented innovation, coupled with regulatory uncertainty and evolving stakeholder expectations, implies that teams need to remain responsive to external shifts (Edmondson and Nembhard, 2009; Ployhart and Turner, 2023). GenAI's predictive analytics and real-time scenario modeling appear to offer potential advantages in this regard, particularly in helping teams anticipate market trends, regulatory developments, and supply chain disruptions (Jiao et al., 2020; Zhang et al., 2022).

Another implication of our study concerns the role of organizations in shaping the conditions under which AI enhances SPI. While much of the focus on AI adoption in innovation centers on technical implementation, our findings suggest that organizational factors—such as AI literacy, governance mechanisms, and cross-functional collaboration—play a key role in determining the extent to which AI complements team capabilities (Amankwah-Amoah et al., 2024). Firms investing in AI for SPI may consider approaches that go beyond the deployment of technical tools to include structured initiatives that enhance teams' ability to critically interpret AI-generated insights and integrate them into iterative innovation processes (Smith et al., 2024).

The interaction between AI and human expertise remains an open question, and further research is needed to explore how organizations can create conditions in which AI strengthens, rather than constrains, the creative and adaptive capacities of teams (Marion and Fixson, 2019).

Moreover, our results point to a broader strategic consideration: how firms align AI-enhanced SPI with long-term sustainability objectives. Traditional innovation metrics, often focused on efficiency, cost reduction, and speed to market, may not fully capture the value that AI brings to sustainability-driven innovation (McKinsey & Company, 2023a; 2023b). Our findings suggest that firms may benefit from incorporating sustainability-oriented performance indicators into their AI-driven innovation processes, such as assessments of circularity, projected carbon footprint reduction, and regulatory alignment (Calik, 2024). By embedding AI-assisted sustainability analytics into SPI frameworks, firms can develop a more structured approach to balancing economic, environmental, and social dimensions of innovation.

5.3. *Future research avenues*

Our findings open several promising avenues for future research, particularly in understanding the interplay between Generative Artificial Intelligence (GenAI), team capabilities, and sustainable product innovation (SPI). While this study highlights the potential of AI-augmented skill differentiation and adaptability, several unexplored mechanisms and strategic implications merit further investigation.

First, future research could explore the synergy between GenAI and human creativity within SPI teams. While AI can enhance the creative potential of teams by expanding the scope of problem-solving and ideation through advanced data processing and pattern recognition, the precise mechanisms through which GenAI interacts with human creativity remain unclear (Bouschery et al., 2023). Studies could investigate how AI tools can be designed to complement rather than replace human creativity, particularly in the divergent phases of the innovation process. This could involve examining the types of AI-driven interventions that most effectively foster creative collaboration among team members with diverse skill sets. Moreover, research could explore how different AI interfaces—such as visual, conversational, or predictive models—influence the creative processes within teams, potentially leading to new models of AI-human collaboration that enhance sustainability-driven innovation outcomes.

Second, the role of team adaptability in maximizing the benefits of AI integration in SPI remains an open question. Our findings suggest that adaptability is essential for responding to external changes, yet the extent to which AI enhances or constrains strategic adaptability over time is not well understood. Future studies could explore whether AI-augmented SPI teams develop more effective long-term learning mechanisms or whether reliance on AI for decision-making leads to an overemphasis on short-term adjustments. Moreover, research could investigate how organizations structure AI-assisted adaptability mechanisms to balance responsiveness with sustained strategic focus in SPI.

Third, while the short-term benefits of AI integration—such as increased efficiency, enhanced creativity, and improved decision-making—are well-documented, the long-term effects on sustainability performance, market competitiveness, and regulatory positioning remain uncertain (McKinsey & Company, 2023a). Longitudinal studies could track whether AI-augmented SPI leads to measurable improvements in firms' ecological footprints, resource efficiency, and alignment with evolving sustainability regulations over time. Research could also investigate whether firms that integrate AI into SPI experience enhanced stakeholder trust and regulatory advantages in industries facing stringent sustainability requirements.

6. Limitations and conclusions

The present study contributes to the literature on the intersection of AI and NPD, particularly in the context of SPI within the manufacturing sector. Our analysis of NPD teams offers insights into how these elements collectively enhance sustainable innovation. However, this study has limitations that present opportunities for future research and contextualisation of our findings within the broader scope of innovation studies. A primary limitation of the study lies in its focus on the manufacturing sector, which captures only a segment of the broader business landscape. Future research could extend this inquiry to other sectors and conduct comparative studies across industries and geographical locations to test the generalizability of our findings and identify sector-specific factors that may influence GenAI's effectiveness in enhancing sustainable innovation. Another limitation is the cross-sectional design, limiting our ability to infer causality or observe how relationships between variables evolve. Additionally, while this study includes various control variables, other factors were not examined but could significantly influence sustainable product innovation. Industry-specific challenges, such as supply chain constraints or the availability of skilled labour, may affect teams' ability to leverage GenAI effectively. By addressing the limitations identified in the present study, future studies can build on our findings to develop a better understanding of how GenAI can drive sustainable innovation across different sectors and over time. As GenAI and AI-based tools more in general continue to evolve and reshape the global business landscape, ongoing research will be increasingly salient to guide organizations toward more effective and sustainable innovation practices, ultimately contributing to broader SDG goals.

CRediT authorship contribution statement

Giacomo Marzi: Writing - review & editing, Writing - original draft, Investigation, Methodology, Conceptualization. **Marco Balzano:** Writing - review & editing, Writing - original draft, Investigation, Methodology, Conceptualization.

Data availability

The authors do not have permission to share data.

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