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The innovation payoff of AI in production: evidence from German manufacturing

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ABSTRACT

This study examines the relationship between the implementation of artificial intelligence (AI) in production processes and product innovation outcomes in manufacturing firms. It contributes to the literature by providing empirical evidence on the role of AI in innovation while accounting for firm-level heterogeneity in established innovation drivers, including R&D intensity, workforce qualifications, human-centric practices, and structural characteristics. Using data from 1,334 firms in the 2022 German Manufacturing Survey, we find that AI implementation in production is positively associated with innovation-enhancing processes that complement existing organisational resources and capabilities. However, this relationship is limited to product innovations that are new to the firm and does not extend to innovations that are new to the market. Furthermore, distinguishing between product innovation types relevant to the twin transition, we find that AI implementation is primarily associated with a higher likelihood of digital product innovations, whereas eco-oriented product innovations are more strongly linked to the adoption of human-centric practices. These findings suggest that AI in production should be viewed not merely as an operational technology but as a strategic capability whose innovation potential depends on its integration with complementary organisational resources and capabilities.

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AI in production; product innovation; digital product innovation; eco product innovation; manufacturing; *German Manufacturing Survey*

1. Introduction

Artificial intelligence (AI) is understood as a transformative general-purpose technology that fundamentally enhances firms' ability to create and purposefully use knowledge (Broekhuizen et al. 2023; Lin and Wu 2025; Paschen, Kietzmann, and Kietzmann 2019), as well as improve processes that are central to innovation (Füller et al. 2022). By processing and interpreting large-scale and heterogeneous data, AI contributes to innovation activities across critical stages of the innovation process, including opportunity identification, idea evaluation and selection, concept and solution development as well as commercialisation (Bahoo, Cucculelli, and Qamar 2023; Broekhuizen et al. 2023; Füller et al. 2022; Truong and Papagiannidis 2022; Verganti, Vendraminelli, and Iansiti 2020). Therefore, beyond the role of AI in process automation and operational efficiency within manufacturing environments, recent research in production and innovation studies has begun to examine how AI implementation influences different types of product innovation, including innovations that vary in their degree of novelty, such as new-to-firm and new-to-market products (Rammer, Fernández, and Czarnitzki 2022). In parallel, the transformation of industrial systems is increasingly shaped by the so-called twin transition, which aims to advance digital transformation and sustainability goals simultaneously (Montresor and Vezzani 2023). This perspective highlights that firms are not only expected to innovate but also to develop products that contribute to digitalisation as well as to environmental sustainability. Consequently, two specific forms of product innovation have gained increasing attention in recent research: digital-oriented product innovation (Li, Liu, and Yang 2025) and eco-oriented product innovation (Cassânego et al. 2025; Lin et al. 2024; Montresor and Vezzani 2023; Shariq et al. 2026).

Despite these advances, there are still significant gaps in the literature. First, existing studies often approach AI from a technological perspective by focusing on specific AI technologies, such as machine learning or Large Language Model (LLM)-based solutions (Balasubramanian, Ye, and Xu 2022; Shrestha, Krishna, and von Krogh 2021). Less attention has been paid to the broader organisational use of AI across the enterprise, particularly regarding the application areas in which AI is implemented. AI applications in manufacturing environments and production-related processes have received limited attention in the literature (Heimberger, Horvat, Jäger, et al. 2026). Such applications include, for example, quality control, production process management,

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predictive maintenance, and inbound logistics, where AI can contribute to improved efficiency, stability, and responsiveness of production systems (Buchmeister, Palcic, and Ojstersek 2019; Plathottam et al. 2023). Second, these production-related AI applications can be interpreted as significant process innovations that may enhance firms' broader innovation capabilities (Alzoubi et al. 2024; Rammer, Fernández, and Czarnitzki 2022). In terms of innovation management, AI in production may support knowledge creation and learning processes that are relevant for innovation activities (Truong and Papagiannidis 2022). However, existing studies have largely neglected the role of production-related AI applications for product innovations in manufacturing firms and empirical evidence on this relationship remains scarce. Third, from the perspective of manufacturing companies' strategies in the context of the twin transition, it remains unclear how AI in production may contribute to the development of products with digital and/or eco-oriented characteristics. For instance, AI-enabled production systems may provide information about product usage, production efficiency, or environmental performance (Waltersmann et al. 2021), which could support the development of both digital-oriented and eco-oriented products. However, empirical insights into these mechanisms are still very limited. Finally, innovation research has traditionally focused on well-established determinants of product innovation, such as research and development (R&D) investments, workforce competencies, and involvement of employees in innovation processes (Horvat, Moll, et al. 2019; Pacheco et al. 2017; Rammer, Fernández, and Czarnitzki 2022). While these factors remain important, evidence is limited as to whether AI in production contributes to product innovation in addition to these factors (Mariani, Machado, and Nambisan 2023; Rammer, Fernández, and Czarnitzki 2022). Overall, there is still little empirical evidence to demonstrate the extent to which the use of AI in production is associated with a higher likelihood of manufacturing firms generating product innovation, or, more specifically, introducing various types of innovation, such as digital or environmentally friendly products, as well as products with varying levels of novelty (Füller et al. 2022; Rammer, Fernández, and Czarnitzki 2022). To address these gaps, this paper investigates the following research question:

> Is the implementation of AI in production positively associated with the product innovation capability of manufacturing firms, even when traditional firm-level innovation determinants, such as R&D activities, workforce qualifications, and human centricity, are simultaneously considered?

To answer this question, we develop a research model that examines whether the use of AI in production-specific application areas is associated with a higher likelihood that manufacturing firms introduce product innovations. We draw on the concept of absorptive capacity (AC) as a theoretical lens (Cohen and Levinthal 1990; Weidner, Som, and Horvat 2023; Zahra and George 2002) that sheds light on the role of AI in the innovation process. Prior research suggests that AI can support firms in acquiring, assimilating, and transforming new knowledge, thereby facilitating its translation into valuable innovation outcomes (Fu, Ni, and Fang 2025; Grilli and Pedota 2024; Lin and Wu 2025; Pedota 2024). Building on this line of reasoning, we argue that the implementation of AI in production-specific application areas can enhance both knowledge generation and knowledge utilisation, ultimately strengthening the innovation capability of manufacturing firms. Based on this theoretical logic, we propose that the use of AI in production is positively associated with the likelihood that manufacturers introduce new products. When analysing product innovation, we distinguish between product innovations that are characterised by digital and environmentally oriented product features. Furthermore, we differentiate between innovations that are new to the firm and those that are new to the market.

To test our hypotheses, we conduct an empirical analysis based on a representative sample of manufacturing firms in Germany; the 2022 wave of the *German Manufacturing Survey* (GMS) provides data for 1334 randomly selected manufacturing firms. Acknowledging that AI implementation does not occur in isolation, when examining the use of AI in production in relation to the diffusion of product innovation, we also consider established firm-specific determinants of innovation into our modelling framework, with particular emphasis on R&D activities, investments in training for production employees, and workforce involvement in innovation processes. Additionally, we control structural firm characteristics, including firm size, sectoral affiliation, batch size, and product complexity. Overall, this approach enables us to empirically investigate whether the use of AI in production is associated with a higher likelihood that manufacturing firms introduce various types of product innovation, while controlling known differences in innovation determinants and structural characteristics at the firm level.

The findings of this study carry several important implications for research on AI-enabled innovation in manufacturing. First, the results suggest that AI implementation in production should not be viewed merely as a tool for operational efficiency, but rather as an organisational capability that enhances firms' innovation capacity through improved knowledge generation, assimilation, and utilisation. By theoretically linking AI-enabled production processes with the concept of AC, the study contributes to a more nuanced understanding of how AI-driven technologies support organisational learning and, in turn, accelerate innovation processes in manufacturing firms. Second, the findings indicate that AI use in production is more strongly associated with incremental and firm-level product innovations than with radical market novelties, highlighting the need for future research to distinguish more clearly between different types of innovation outcomes and to further investigate the mechanisms through which AI influences them. Third, the study contributes to the emerging literature on the twin transition by demonstrating that AI-enabled production processes are associated with both digitally oriented and eco-oriented product innovations, although in different ways. Manufacturers with strong digital and AI capabilities tend to leverage them not only to optimise production processes but also to support digital product development, whereas eco-oriented product innovations appear to depend more strongly on R&D activities and human-centric organisational practices. These findings underscore the importance of examining the interplay between AI-enabled processes, R&D activities, and human-centric organisational practices, as the observed patterns suggest that innovation increasingly emerges from the integration of AI-driven insights with human knowledge and expertise rather than from isolated technological investments alone. Consequently, the study opens promising avenues for future research on socio-technical configurations of AI capabilities in manufacturing context.

For practitioners, our findings provide empirical evidence that firms with AI-enabled production processes are more likely to generate new product innovations, particularly digital product innovations. This positions AI not only as an operational tool in manufacturing but also supports the view of it as a strategic lever for innovation. At the same time, it is clear that the importance of human expertise or R&D cannot be replaced and must not be overlooked. AI might provide additional support for the knowledge and creativity processes required for product development and product design within a company. However, successful product innovation requires combining AI-generated insights with human expertise and integrating them effectively into R&D processes. Firms that are able to establish and manage such knowledge flows gain a competitive advantage in developing digital and eco-oriented product innovations.

2. Theoretical background

2.1. Literature on AI and product innovation

The theoretical foundation for understanding how advanced digital technologies such as AI influence a firm's innovativeness lies in the interplay between process and product innovation. Within the broader landscape of advanced digital technologies, AI has emerged as one of the most transformative technologies in manufacturing. Due to its ability to learn from data, detect complex patterns, and support or automate decision-making, AI has considerable potential to enhance manufacturing processes (Gabsi 2024; Papadopoulos et al. 2022). AI-enabled applications are increasingly used in areas such as process control, quality assurance, predictive maintenance, and internal logistics, where they contribute to improved efficiency, stability, and responsiveness of production systems (Buchmeister, Palcic, and Ojstersek 2019; Plathottam et al. 2023). When integrated across multiple production domains, AI can significantly increase operational efficiency and adaptability while also supporting broader innovation activities within firms (Alzoubi et al. 2024; Rammer, Fernández, and Czarnitzki 2022). In this way, AI contributes to strengthening firms' competitiveness in highly digitalised industrial environments (Heimberger, Horvat, and Schultmann 2026; Sanchez, Exposito, and Aguilar 2020). Recent developments further indicate that AI-driven applications are evolving towards increasingly smart, autonomous, and self-optimising production systems (Gao et al. 2024). These developments suggest that AI in production does not only improve operational performance but may also create new opportunities for innovation beyond the production domain. Therefore, beyond the role of AI in process automation and operational efficiency within manufacturing environments, the interest in the relationship between AI and product innovation has increased in recent years (Mariani, Machado, Magrelli, et al. 2023; Mariani and Dwivedi 2024).

Existing studies have begun to examine how AI adoption influences different types of product innovation, including innovations that vary in their degree of novelty, such as new-to-firm and new-to-market products (Rammer, Fernández, and Czarnitzki 2022). In addition, a growing body of literature investigates the role of AI in enabling specific innovation orientations, particularly digital product innovation (Li, Liu, and Yang 2025) and eco-oriented or green product innovation (Cassânego et al. 2025; Lin et al. 2024; Montresor and Vezzani 2023; Shariq et al. 2026). These developments reflect the strategic orientations of companies in an environment characterised by digitalisation and increasing sustainability requirements. Table 1 provides an overview of current studies regarding the role of AI in product innovation.

Despite growing interest in this topic, prior research has paid limited attention to the specific organisational contexts in which AI technologies are implemented, instead predominantly examining the general use of AI at the enterprise level. In particular, AI applications in manufacturing environments and production-related processes have received comparatively little scholarly focus, despite their potential importance for firms' broader innovation capabilities. This gap is noteworthy, as innovation in production processes plays an important role in shaping knowledge creation and organisational learning, contributing thereby to product innovation. Moreover, from the perspective of the twin transition strategies increasingly pursued by manufacturing companies, it remains insufficiently understood how the use of AI in production supports the development of products characterised by digital and environmentally oriented features. Addressing these gaps, this study focuses on the use of AI in production and examines how production-related AI applications influence the innovation capability of manufacturing firms.

2.2. AI enabled absorptive capacity

To understand how AI in production contributes to the broader innovation capability of manufacturing firms, we draw on AC theory from management literature. AC refers to a set of organisational capabilities that enable firms to identify, acquire, assimilate, transform, and exploit external knowledge for commercial purposes (Cohen and Levinthal 1990; Horvat, Dreher, et al. 2019; Weidner, Som, and Horvat 2023; Zahra and George 2002). By linking external knowledge sources with internal learning processes, AC facilitates the transformation of knowledge into new or improved products, services, and processes, thereby strengthening a firm's innovation capability (Zahra and George 2002).

Following the two-dimensional concept of Zahra and George (2002), a major stream of the AC literature differentiates between potential AC (PACAP) and realised AC (RACAP)

Table 1. Literature overview on AI and its link to product innovation.

Study	Type of product innovation analysed: New-to-the-firm innovation	New-to-the-market innovation	Digital-oriented innovation	Eco-oriented innovation	Industry sector in focus	Research approach	Underlying theories	Main results
Mariani, Machado, Magrelli, et al. (2023)	✗	✗	✗	✗	Cross-sectoral approach	Systematic Literature Review	n/a	General analysis of AI in innovation research • Identification of factors as drivers of AI adoption and as outcomes
Rammer, Fernández, and Czarnitzki (2022)	✓	✓	✗	✗	Cross-sectoral approach	Empirical study	No specific theory in focus; innovation production function approach	• AI use boosts innovation, especially world-first outcomes • Broader, long-term AI adoption further increases innovation output
Lin et al. (2024)	✗	✗	✗	✓	Agricultural industry	Empirical study	Dynamic capability theory	• AI use improves environmental performance via green product/process innovation • Green culture strengthens AI's effect, especially through product innovation
Shariq et al. (2026)	✗	✗	✗	✓	Manufacturing industry	Empirical study	Organisational Information Processing Theory	• Generative AI strengthens business intelligence and supports green product innovation • Green product innovation alone does not directly improve carbon performance
Cassânego et al. (2025)	✗	✗	✗	✓	Cross-sectoral approach	Empirical study	Dynamic capability theory	• AI capabilities boost green product innovation, especially when combined with open innovation partnerships • The impact is positive but weaker than for green process innovation
Montresor and Vezzani (2023)	✗	✗	✓	✓	Cross-sectoral approach	Empirical study	No specific theory in focus; Knowledge recombination perspective	• AI investments have the strongest positive effect on eco-innovation • Digital technologies alone do not guarantee eco-innovation • Combining multiple digital technologies boosts eco-innovation
Li, Liu, and Yang (2025)	✗	✗	✓	✗	Technology/ innovation enterprises in China	Mixed-method study	Dynamic capability theory	• AI capability enables digital product innovation through online value-creation and digital resilience
Mariani and Dwivedi (2024)	✗	✗	✗	✗	Cross-sectoral approach	Mixed-method study	No specific theory in focus	• GenAI will enhance incremental and radical innovation • GenAI will reshape creativity, new product development and organisational innovation
Present study	✓	✓	✓	✓	Manufacturing industry	Empirical study	Absorptive capacity	• Positive relationship between AI adoption in production and incremental product innovation • AI in production as key factor for digital-oriented product innovation

(Camisón and Forés 2010; Horvat, Dreher, et al. 2019). PACAP refers to an organisation's ability to identify, acquire, and assimilate new knowledge from diverse external sources, enabling the recognition of emerging patterns and opportunities. RACAP, in contrast, reflects the organisation's ability to transform and integrate newly acquired knowledge with existing organisational knowledge and to apply it to concrete value-creation activities. These two dimensions of AC closely align with March's (1991) distinction between exploratory and exploitative learning (Lane, Koka, and Pathak 2006). PACAP embodies exploratory learning, as it involves the search for, acquisition, and understanding of novel external knowledge. RACAP, on the other hand, is associated with exploitative learning, in which assimilated knowledge is transformed, operationalised, and strategically applied within the organisation.

In this context, the transformative potential of AI lies in its ability to strengthen both dimensions. On the one hand, AI can enhance explorative learning through the acquisition and assimilation of new knowledge (i.e. a firm's PACAP) by improving the detection and analysis of external knowledge signals through automated pattern recognition and data-driven insights (Agrawal, Gans, and Goldfarb 2018; Neirotti, Pesce, and Battaglia 2021). On the other hand, AI can also enhance the exploitation of this knowledge (i.e. a firm's RACAP) by facilitating knowledge integration and transfer within the organisation, thereby further strengthening the innovation process (Lin and Wu 2025; Pedota 2024).

Recent work on the automation–augmentation paradox further emphasises that AI can simultaneously substitute for and augment human cognition, thereby fundamentally changing how organisations search for, combine, and recombine knowledge (Raisch and Krakowski 2021). Two mechanisms highlighted by Pedota (2024) help explain how AI and AC interact to drive innovation. First, cognitive ambidexterity, defined as the ability to combine domain-specific human expertise with AI-based analytical capabilities, enables organisations to more effectively acquire, assimilate, and exploit knowledge generated through human–AI collaboration. Second, the virtualisation of tacit knowledge refers to the process of uncovering, codifying, and digitally capturing previously tacit know-how so that it becomes accessible across the organisation. This allows AI-supported systems to extend knowledge utilisation beyond the expertise of individual employees and enables broader organisational learning. Together, these mechanisms illustrate how AI can complement rather than replace human cognition, strengthening firms' learning capabilities and accelerating innovation cycles. In doing so, AI-enabled production systems may not only enhance process performance but also contribute to the development of stronger product innovation capabilities in manufacturing firms.

3. Hypotheses

3.1. AI in production and product innovation

The ability of firms to introduce product innovations depends strongly on their capacity to generate, process, and exploit knowledge (Su et al. 2013). In this context, the concept of AC provides an important theoretical perspective for understanding how firms transform information and knowledge into innovation outcomes. Namely, the use of AI in production can strengthen firms' AC by enhancing their ability to generate and process knowledge from production-related data. On the one hand, AI-generated insights from activities such as process monitoring, quality management, and predictive maintenance can create new knowledge through advanced analytics, pattern recognition, and data-driven experimentation (Cockburn, Henderson, and Stern 2018; Neirotti, Pesce, and Battaglia 2021; Verganti, Vendraminelli, and Iansiti 2020). AI systems are particularly effective in analysing large volumes of heterogeneous data and identifying signals or relationships that might remain unnoticed by human analysts alone (Jordan and Mitchell 2015). In terms of AC, these capabilities support the exploration through recognition, acquisition, and assimilation of new knowledge (PACAP) that can inform and stimulate innovation processes within the firm. For instance, insights derived from production data may reveal product design weaknesses, previously unnoticed performance patterns, or new technological opportunities that can feed directly into product development activities.

On the other hand, AI can also enhance the RACAP by supporting the transformation and exploitation of newly acquired knowledge. Access to detailed production data enables firms to integrate new insights with existing organisational knowledge and apply them in concrete innovation activities, such as product redesign or the development of new functionalities (Lichtenthaler 2019). In this process, AI solutions act as decision-support tools that help organisations manage, interpret, and utilise large volumes of data in a timely and relevant manner (Joshi et al. 2010). Hence, by facilitating knowledge integration and informed decision-making, AI can accelerate the translation of operational insights into new product concepts and improvements.

Overall, the use of AI in production expands firms' capabilities to generate and exploit knowledge from operational processes, thereby strengthening the knowledge base available for innovation activities. Through its contribution to both PACAP and RACAP (Lichtenthaler 2019; Zahra and George 2002), and thereby to exploration and exploitation learning (Lane, Koka, and Pathak 2006; March 1991). AI adoption in production environments can increase the chance that firms identify innovation opportunities and successfully develop new products.

H1: *AI in production is positively associated with the likelihood that manufacturing firms introduce* ***product innovations****.*

3.2. AI in production and digital and eco-oriented product innovation

While product innovation represents a central outcome of firms' technological and organisational capabilities, recent research in production and innovation studies increasingly emphasises that not all product innovations are alike in their strategic orientation. In particular, the ongoing transformation of industrial systems is strongly shaped by the so-called twin transition, referring to the simultaneous digital and green transformation of manufacturing and industrial ecosystems (Cassânego et al. 2025; Li, Liu, and Yang 2025; Montresor and Vezzani 2023; Shariq et al. 2026). This perspective highlights that firms are not only expected to innovate but to develop products that contribute either to the digitalisation of products and services or to environmental sustainability.

Against this background, two specific forms of product innovation have gained particular attention: digital-oriented product innovation (Li, Liu, and Yang 2025) and eco-oriented product innovation (Cassânego et al. 2025; Lin et al. 2024; Montresor and Vezzani 2023; Shariq et al. 2026). Digital-oriented product innovation refers to the introduction of products with enhanced digital functionalities, connectivity, or data-based features. Such innovations are closely linked to the broader digitalisation of manufacturing and the increasing integration of software, sensors, and data-driven services into physical products. Eco-oriented product innovation, in contrast, focuses on products that reduce environmental impacts across their lifecycle, for instance, through improved energy efficiency, reduced material use, recyclability, or the use of environmentally friendly materials.

In the contemporary digital economy, digital product innovation has become a central driver of value creation and a core component of business model development (Meyer et al. 2018; Nambisan et al. 2017). Lyytinen, Yoo, and Boland (2016, 49) define digital product innovation as *'significantly new [...] products or services that are either embodied in information and communication technologies or enabled by them'*. This understanding captures two key innovation pathways: the development of fundamentally new ICT-based products and services, and the digital enhancement of existing physical products through the integration of software, connectivity, sensors, or embedded intelligence. Digital product innovation therefore reflects not only technological novelty, but new forms of digital resource recombination in product innovation processes (Nambisan 2013; Nambisan et al. 2017).

A critical prerequisite for digital product innovation is the firm's ability to assemble, mobilise, and deploy digital resources across all stages of the innovation lifecycle (Chae, Koh, and Prybutok 2014; Nwankpa and Datta 2017). Digital technologies in manufacturing provide essential infrastructures for digital experimentation, real-time sensing, and data-driven problem solving, thereby facilitating innovation processes in manufacturing settings (Barrett et al. 2015). However, traditional automation technologies remain constrained to pre-programmed routines and improve performance only within predefined operational parameters, lacking interpretive flexibility or generative learning capability. In contrast, AI-enabled process innovation establishes organisational learning loops that connect production operations with product innovation functions (Cooper 2024). AI introduces learning-based adaptivity, enabling systems to autonomously interpret complex data, refine decision logic, and generate design-relevant knowledge for product innovation that extends beyond static programming boundaries (Grech, Mehnen, and Wodehouse 2023). In other words, by converting operational data into reusable innovation knowledge, firms increasingly generate digital product ideas grounded in real system behaviour and usage intelligence rather than relying exclusively on conventional R&D activities. AI allows firms not only to automate existing workflows but also to detect latent patterns, reconfigure processes, personalise product features or service offerings, and accelerate responses to dynamic market or environmental conditions, strengthening both efficiency-oriented and innovation-oriented performance outcomes (Paschen, Pitt, and Kietzmann 2020; Raisch and Krakowski 2021). Building on the same logic of technological uniqueness and organisational complementarity from the *H1*, we propose the following hypothesis with respect to digital product innovation:

H2a: *AI in production is positively associated with the likelihood that manufacturing firms realise* ***digital-oriented product innovation*** *instead of traditional non-digital product innovation.*

Sustainability has emerged as a pivotal element in modern manufacturing, particularly within the framework of Industry 4.0, Industry 5.0, and the twin transition (Rehman et al. 2023; Sebo et al. 2025). The integration of AI technologies into production processes not only improves operational efficiency but also plays a crucial role in fostering eco-oriented product innovation. First, AI in production generates valuable data relevant to sustainability issues such as optimising resource efficiency, reducing waste, and promoting circular economy principles (Mukhitdinov et al. 2025; Waltersmann et al. 2021). This data acquisition enhances the AC of firms, enabling them to assimilate and implement sustainability-related insights effectively (Dzhengiz and Niesten 2020). As companies become more capable of leveraging this knowledge, their potential for eco-oriented product innovation increases. By integrating AI-driven analytics, manufacturers can identify and exploit energy-efficient production methods, optimise material utilisation, and innovate product designs that minimise environmental impacts. Second, AI enhances the sustainability of production processes themselves (Waltersmann et al. 2021). Through continuous monitoring and optimisation, manufacturers can improve their processes towards greater sustainability, thus enhancing their capabilities to innovate in eco-oriented ways (Dou and Gao 2023). Improvements in production methodologies not only contribute to sustainability goals but also bolster the firm's overall innovation capabilities. Combining these insights with traditional innovation-related factors, such as R&D activities, workforce qualifications, training, and employee involvement, creates a robust environment for fostering eco-oriented product innovation. Hence, we conclude that the effective interplay between AI solutions and these traditional factors may significantly enhance the likelihood of a manufacturing firm realising eco-oriented innovations rather than merely focusing on traditional, non-eco-oriented products. Based on this rationale, we propose the following hypothesis:

H2b: *AI in production is positively associated with the likelihood that manufacturing firms realise* ***eco-oriented product innovation*** *instead of traditional non-eco-oriented product innovation.*

3.3. AI in production and market-novel product innovation

When considering product innovation, it is essential to differentiate between new products that are new to the company and products that are new to the market, i.e. 'do what we do better' vs. 'do something different' (Joe and John 2013). Innovations classified as new to the firm primarily involve incremental improvements, optimising existing products, services, or processes to enhance specific features for a defined customer base. This type of innovation is often characterised by lower complexity and greater certainty, as both target markets and customer needs are well understood (Robertson, Casali, and Jacobson 2012). Established production processes typically use existing technology that does not significantly differ from current practices. As a result, companies can leverage their existing knowledge, minimising the risks associated with innovation while improving efficiency, product quality, and reducing production costs without necessitating fundamental structural changes. Hence, the exploitation of existing knowledge plays a crucial role in this kind of innovation. This type of innovation is crucial for competitiveness, as it enables companies to respond flexibly to market changes and maintain their position in the market (Valle and Vázquez-Bustelo 2009).

However, opening new markets by creating completely new products, services, or technologies that are revolutionary for both the company and the overall market, comes with various innovation process relevant challenges. This form of innovation is characterised by a high degree of uncertainty and complexity, as the technological requirements and customer needs are often still unclear and can change rapidly (Slater, Mohr, and Sengupta 2014; Valle and Vázquez-Bustelo 2009). Companies pursuing this level of novelty must embrace significant risks and be adaptable to evolving conditions (Slater, Mohr, and Sengupta 2014). These innovations have the potential to disrupt existing market structures by introducing new business models and value chains that outperform traditional offerings (Garcia and Calantone 2002; Meyer et al. 2018). Consequently, their implementation demands a profound level of learning, flexibility, and adaptability. AI solutions in manufacturing can play a crucial role in fulfilling these tasks.

Drawing on these arguments, we conclude that AI implemented in production environments enhances knowledge exploration and implementation in innovation processes. Rather than merely automating established tasks, AI facilitates knowledge exploration by enabling firms to uncover previously hidden data structures, recombine work routines, tailor solutions for specific applications, and respond more swiftly to shifting markets and technological conditions. This capability strengthens both operational performance and innovation outcomes. Moreover, AI-driven process innovation increases production adaptability and supports the development of intricate product system designs, expanding the solution space for viable product concepts. Consequently, this directly facilitates the creation and market introduction of novel product offerings. By amplifying firms' ability to generate, internalise, and deploy new knowledge through manufacturing operations, AI equips production companies with enhanced capabilities to transform process-level insights into successful market innovations. Thus, we hypothesise that:

H3: *AI in production is positively associated with the likelihood that manufacturing firms realise* ***product innovations that are new to the market*** *instead of only new to the firm.*

3.4. Conceptual research model

Based on the theoretical framework presented above, this study examines relationships between the use of AI in production and different types of product innovation outcomes in manufacturing firms. Figure 1 summarises our conceptual research model.

With H1, we first investigated the general relationship between the use of AI in production and the likelihood that firms introduce product innovations. This analysis is motivated by the assumption that the use of AI technologies in production can improve firms' capabilities to process data, optimise production processes, and generate knowledge about products and operations. Subsequently, H2a and H2b distinguish between specific types of product innovation. For these hypotheses, we examine whether the use of AI in production is associated with the likelihood that firms will introduce digitally oriented (H2a) or environmentally oriented product innovations (H2b), and, thus, focus exclusively on product innovators. Given the increasing strategic relevance of both digitalisation and sustainability for manufacturing firms, examining these two types of product innovation allows for a more nuanced understanding of how AI adoption in production relates to firms' innovation activities. Furthermore, in H3, we examine the degree of novelty of product innovation outcomes and analyse whether AI in production is positively associated with the likelihood that manufacturing firms introduce market-novel product innovations.

Nevertheless, we situate AI in production within the firm's broader innovation context. Product innovation outcomes are typically shaped by a wider set of organisational capabilities and resources that have been widely discussed in the innovation management literature as key determinants of product innovation. We do not assume that AI alone guarantees product innovation outcomes; rather, we view AI in production as a complementary factor that may be associated with higher likelihoods of product innovation alongside other firm-level capabilities. Accordingly, the empirical model also accounts for structural characteristics of firms and their production context. Specifically, we consider R&D activities, human-centricity, and workforce qualifications as well as firm

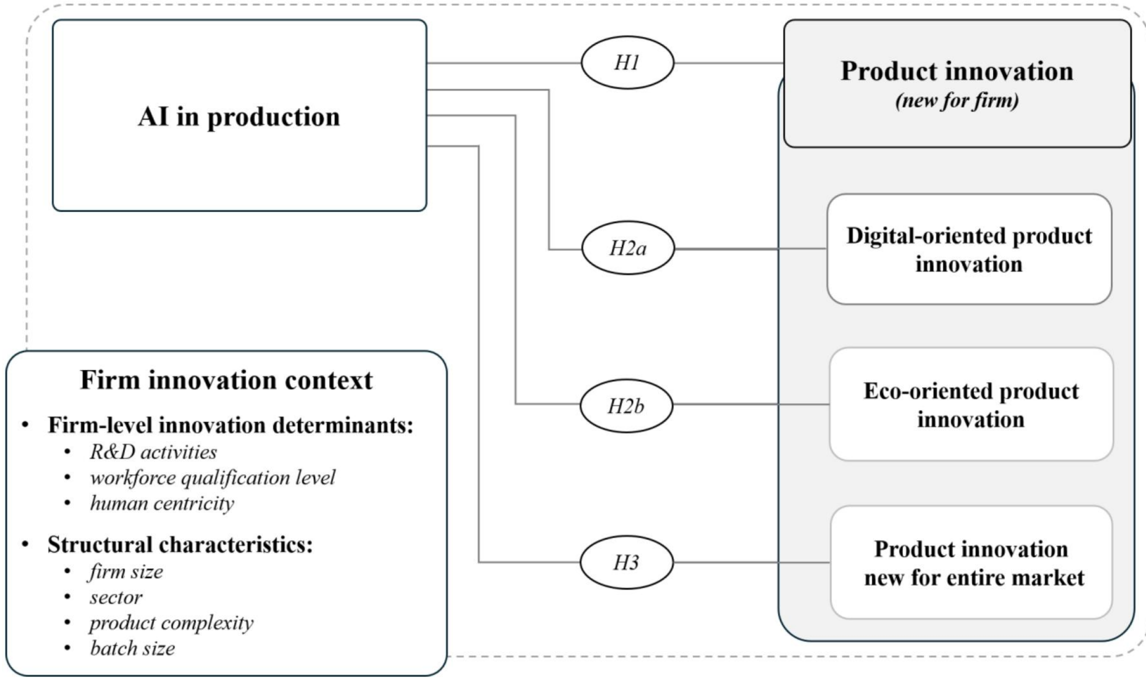

Figure 1. Research model.

size, industry affiliation, product complexity, and production batch size, which are commonly linked to firms' innovation activities and technological adoption in manufacturing.

4. Methodology

4.1. Data base

This study draws on empirical data from the *German Manufacturing Survey* (GMS), a well-established quantitative survey of industrial firms in Germany (Fraunhofer Institute for Systems and Innovation Research ISI 2025). Initiated in 1993 (Lay and Maloca 2004), the GMS has been conducted every three to four years and represents Germany's contribution to the *European Manufacturing Survey*. Since 1995, the objective of this survey has been to systematically monitor manufacturing industries in Germany and their modernisation trends, focusing on various practices related to production processes, products, services, and organisational aspects. When operationalising these dimensions, the focus is on factual questions in order to capture the firm's actual situation rather than management's perception of it. GMS data have been used in several firm-level research articles (Armbruster et al. 2008; Horvat, Jäger, and Lerch 2025; Lerch and Jäger 2024). The survey addresses firms in Germany with 20 or more employees from all manufacturing sectors, i.e. NACE Rev. 2, 10–33 (EUROSTAT 2008).

For our analysis, we utilise the most recent dataset from the GMS 2022 round, conducted between fall 2021 and spring 2022 (Jäger and Maloca 2022). The survey was contacted with the support of the Zentrum für Sozialforschung Halle/Saale (zsh), a university institute that provides data collection services for CATI and CAPI surveys. A gross sample of 15,299 manufacturing sites in Germany was initially randomly selected using a proportional stratified sampling procedure considering the distribution in the population, including firm size, region, and sector. The sampling frame was based on address data from the Hoppenstedt/Dun & Bradstreet database, which achieves relatively high coverage of the industry in Germany and includes over 90% of manufacturing sites in Germany. For each firm one specific respondent was identified and personally asked to complete the questionnaire for the respective site. The aim was to address one informant who managed production at the highest level and therefore had organisational, technical, and strategic insights into the operation. Depending on the firm size, we approached either the production manager, CTO, or CEO of the production site (Jäger and Maloca 2022).

We conducted a survey using a mixed-methods approach, which began with an initial invitation sent by post to ensure a representative sample and was designed to use a CAPI survey as the main method. This approach was supplemented by a 'push-to-web' telephone procedure, email reminders where possible, and the option to participate using pen and paper as an alternative (Sakshaug, Vicari, and Couper 2019). For methodological rigour and following the multistep procedure for respondents receiving mailed invitations, they were reminded several times by different mailing methods (Bavdaž et al. 2020). Special effort was made to provide transparency regarding the anonymity of the survey and simultaneously keep the utmost comfort for respondents fully due to ethical reasons and with the aim to minimise potential method biases. The field period lasted a total of four months (Jäger and Maloca 2022).

In total, a net sample of 14,045 firms was contacted, with the survey being addressed to the production managers or chief technical officers of these firms (Jäger and Maloca 2022). Of these, 1,334 returned valid questionnaires with at

Table 2. Basic descriptions for GMS 2022 and for the German manufacturing industry.

# of firms	$n = 1.334^{(a)}$	$N = 46.158^{(b)}$
Firm size (# of employees)		
up to 49 employees	44.5%	51.0%
50–99 employees	21.1%	21.4%
100–499 employees	28.8%	23.6%
500 and more employees	5.7%	4.0%
Sector (Nace rev. 2)		
Metal industry (24–25)	21.8%	19.9%
Rubber and plastics; glass and stone products (22–23)	15.7%	14.3%
Machinery (28)	20.6%	13.7%
Food and beverages (10–12)	8.8%	13.4%
Products of wood, paper etc. (16–18)	6.1%	7.1%
Electrical products (27)	3.6%	4.9%
Chemicals and pharmaceuticals (20–21)	5.0%	4.5%
Electronic products (26)	4.6%	4.3%
Automotive and transport equipment (29–30)	4.3%	3.7%
Textile, leather, clothing industry (13–15)	3.1%	2.2%
Other sectors	6.4%	11.9%

Source: (a) *German Manufacturing Survey* 2022, (b) Federal Statistical Office (2022). Own calculation.

least 75% of questions filled in, yielding a 10% response rate. The realised dataset reflects the structural characteristics of the German manufacturing sector in terms of firm size, and region. The industry structure is also well represented, especially the core sectors, the only exception being a lower share of returns by food producers (Jäger and Maloca 2022). Thus, GMS 2022 can be regarded as representative in these aspects. Furthermore, a successive wave analysis to assess a potential non-response bias (Duszynski et al. 2022) comparing the firms that responded early in the survey period with those that responded later revealed no statistically relevant differences in key characteristics (Jäger and Maloca 2022). Table 2 summarises the key characteristics of the analysed sample and compares them with corresponding structural data for the population in the German manufacturing industry, broken down by firm size and sector, based on Federal Statistical Office information.

4.2. Key variables

For our analysis, we use variables and measures covering (1) product innovation, (2) AI in production, and (3) firm-level innovation determinants. We also include indicators of the (4) production context.

4.2.1. Product innovation types

To evaluate the innovative strength of manufacturing companies, we focus on four indicators of product innovation as our dependent variables (Horvat, Jäger, and Lerch 2025). First, we identify *product innovators* as firms that have introduced new products or significantly improved existing ones (e.g. through new materials or modified functions) in the last three years preceding the survey, in accordance with the definition set out in the Oslo Manual of the OECD and Eurostat (OECD/Eurostat 2018). Following prior research, we consider these innovations to provide new benefits, even if their changes and impacts are limited (Benner and Tushman 2003; Guisado-González, Vila-Alonso, and Guisado-Tato 2016; Varadarajan 2009). Second, we assess the digital dimension of product innovation by distinguishing between firms that have incorporated digital extensions or significant improvements to existing digital elements in their new products, i.e. *digital-oriented product innovators*, and those firms that have not. We assume these digital innovations have substantial potential for enhancing functionality (Lyytinen, Yoo, and Boland 2016; Matt, Hess, and Benlian 2015; Nylén and Holmström 2015; Pesch, Endres, and Bouncken 2021). Third, we analyse eco-oriented product innovations, differentiating between firms that have significantly improved the environmental impact of their new products during use or disposal and those product innovators with new products that showed no significant improvements (Dangelico and Pujari 2010; Paparoidamis et al. 2019; Pujari 2006). The survey covers six dimensions that can be identified as environmental improvements in the new product: (a) a reduction in health risks during use, (b) lower energy consumption, (c) minimised emissions or environmental pollution during use of the product, (d) better recycling properties, (e) a longer product life, and (f) easy maintenance or retrofitting. Firms that achieved improvements in at least two of these sustainability aspects were classified as *eco-oriented product innovators*, whereas those with fewer or no such improvements were considered non-eco-oriented product innovators. Finally, we investigate whether the new products have led to market innovations. The firms reported whether their new products included any products that they had launched on the market for the first time. The indicator distinguishes between *market innovators* and firms whose new products did not include market innovations. We posit that these market innovations reflect greater innovative strength than those that are merely new to the company (Guisado-González, Vila-Alonso, and Guisado-Tato 2016; Kyriakopoulos, Hughes, and Hughes 2016; Mosey 2005).

4.2.1.1. AI adoption in production. In our study, the indicator *AI adoption in production* captures, in a dichotomous form, the implementation of AI solutions in technical production processes (Heimberger, Horvat, Jäger, et al. 2026). Firms were asked whether they use AI-based self-learning software solutions, defined as algorithms that recognise patterns and offer actionable recommendations, and to specify it in relation to five production-related areas:

1. management of production processes (e.g. process monitoring)
2. quality control (e.g. defect detection)
3. maintenance of machinery and equipment (e.g. condition monitoring)
4. management of internal logistics (e.g. warehouse management and transport)
5. improvement or innovation of product processes.

Based on this specific information, the indicator makes a binary distinction between AI adopters (firms that use AI in at least one possible production application area) and non-AI adopters (those firms that do not use AI in any of the five areas). Such a binary classification is commonly used in other studies on AI adoption (Dahlke et al. 2024; Heimberger, Horvat, Jäger, et al. 2026; Zhan et al. 2024). The underlying assumption is that the use of AI in even a single application area signals the presence of AI-related capabilities within the firm. Not all application areas are necessarily relevant or economically meaningful for every company. Our analysis therefore focuses on identifying firms that use AI in at least one production context, emphasising whether firms use AI at all. The scope or intensity of its use was not of interest (Heimberger, Horvat, Jäger, et al. 2026).

4.2.1.2. Firm-level innovation determinants. To capture the firm's product innovation context, we consider three firm-level innovation determinants. Table 3 displays the indicators and measurement levels of these three determinants. First, we consider the *R&D activities* of manufacturing firms, as these are known to positively influence product innovation (Becker and Dietz 2004; Bianchi et al. 2016; Un, Cuervo-Cazurra, and Asakawa 2010). To assess R&D activities, we examine on the one hand whether firms conduct R&D internally or outsource it. On the other hand, we also examine whether a firm collaborates with other companies, or research institutions on R&D topics. Both indicators are dichotomous variables and are considered independently of each other. In order to assess the significance of R&D activities as such, the influence of the two indicators on the construct are considered jointly. Secondly, we control for the *workforce qualification level* assuming that a certain degree of knowledge and specific skills among employees positively impacts the capabilities to realise product innovation (Herrmann and Peine 2011; Kach, Azadegan, and Wagner 2015; Romano 1990). The indicator is based on the proportion of highly qualified employees, i.e. employees with an ISDEC level of at least 5 (including university graduates, technical college graduates, technicians, or master craftsmen) and is taken into account as a centred value in the regressions.

Third, we consider firms' *human-centricity*, focusing on two dimensions: targeted employee training and production employees' involvement. Specific training initiatives can enhance employee competences for using AI (Baumgartner et al. 2024) and boost product innovation capabilities (Manresa, Bikfalvi, and Simon 2018; Romano 1990), while the dedicated involvement of production employees is recognised as another key driver of product innovation (Abu El-Ella et al. 2013; Rangus and Slavec 2017). In order to assess the training opportunities available to production employees, we use an ordinal indicator to distinguish between firms that do not offer any training at all, firms that offer cross-functional training as well as creativity-focused training for production employees, and firms that offer training for their production employees but not both specific training. For involving employees in innovation, we distinguish between firms that actively involve employees in innovation and product development by applying organisational concepts, such as dedicated working time or formalised sessions for idea generation, and those firms that do not apply such concepts.

4.2.2. Production context variables

In our analysis, we also consider other variables that reflect structural characteristics and production specifics which set the operational framework for both the adoption of AI and the scope for product innovation. A key contextual variable is *firm size*, measured by the total employee count. For regression models, this indicator is logarithmically transformed to adjust for decreasing marginal costs. In descriptive analyses, the metric information is classified into distinct groups. As noted in previous studies, larger firms typically have more resources and often implement innovation-enabling measures (s.a. R&D) to drive product innovation (Ettlie and Rubenstein 1987; Shefer and Frenkel 2005). However, small businesses can also excel due to their dynamism and agility (Ettlie and Rubenstein 1987; Romano 1990; Stock, Greis, and Fischer 2002). In addition to firm size, we take into account the *industry affiliation*, which reveals specific

Table 3. Operationalisation of firm-level innovation determinants.

Innovation determinants	Indicators	Measurement level
R&D activities	• Performed R&D or awarded R&D contracts to external partners in 2021	Yes-no dummy
	• Cooperated in R&D with another firm or a research institution	Yes-no dummy
Workforce qualification level	• Share of highly qualified employees	Centred value of the share
	• (ISDEC level > =5) on the all employees	
Human centricity	• Involvement of production employees in the development of products or processes	Yes-no dummy
	• Cross-functional and creativity training for production employees	Ordinal variable (3 groups)
	◦ No training offered for production employees	
	◦ Other training offered for production employees, but not these two specific offers	
	◦ Training offered for production employees at least on both topics: creativity and innovation (e.g. problem solving, idea generation, brainstorming techniques) and with interdisciplinary focus (e.g. project management, team leadership, language courses)	

characteristics such as automation or competitive pressure that are known to influence innovation activity. This indicator is of crucial importance since manufacturing sub-sectors vary in technological intensity (e.g. high tech vs. low tech) and innovative capacity (Romano 1990; Vega-Jurado et al. 2008). We categorise industries into eleven groups based on the NACE Rev. 2 classifications (as showed in Table 2). We also take into account the *batch size* of the firm's main product, as firms with smaller batch sizes often drive product innovation more than companies with larger series (Hobday 1998). We distinguish between single-item production, small- to medium-series production, and large-batch production. Furthermore, we consider the *product complexity*, as companies with highly complex products typically involve more intricate innovation processes and require enhanced collaboration (Caniato and Größler 2015; Hobday 1998).

4.3. Statistical methods and model specification

As a first step, univariate analyses are presented to describing the manufacturing sector regarding core concepts and key indicators, supplemented by bivariate group comparisons highlighting structural differences. Given the data's representativeness, these analyses provide an initial insight into product innovation in German manufacturing. Group comparisons further illustrate the links between the use of AI in manufacturing and product innovation in its various forms, using Kruskal–Wallis tests for multiple-group and Mann–Whitney U tests for dichotomous comparisons to assess the statistical robustness of the observed differences.

Finally, the hypothesised relationships were then tested using multiple logistic regression models, allowing examination of associations while controlling for relevant factors. As product innovation and the various types of product innovation are measured using binary indicators, standard logistic regression models were estimated separately for each outcome, including not only AI use in production but also the other structural and innovation-determinants.

For H1, data from all manufacturers with complete information on included variables were used ($n \approx 970$). A comparison between the data used in the multi-indicator analyses and the observations excluded from these multivariate analyses revealed no statistically significant differences regarding structural characteristics, supporting the assumption that missingness is sufficiently random. Similarly, no statistically significant differences were found for most other key variables. However, a slight bias was observed for firms conducting R&D (OR $= 0.71$, $p = .039$) and using AI (OR $= 0.75$, $p = .035$), suggesting that missingness is not completely at random for these variables. For H2a, H2b, and H3, the sample was restricted to product innovators only ($n \approx 430$). As expected, this subgroup differs from non-innovators in both innovation-related and structural characteristics, with the exception of batch size.

For all models, we report odds ratios (ORs) along with corresponding significance levels to facilitate the interpretation of effect sizes across the individual indicators. In addition, we also reports $\Delta-2$LL as the reduction in -2 log-likelihood when moving from the reduced to the full model for assessing the impacts of the different factors, not only at item-level. Goodness-of-fit diagnostics (-2 log-likelihood, two pseudo-R^2 statistics) indicate overall explanatory power. Regarding model prerequisites, multicollinearity is low (all VIF < 2.5; bivariate correlations < 0.4, mostly < 0.2), Hosmer–Lemeshow tests indicate acceptable fit (all $p > .05$), and influence diagnostics reveal no problematic outliers. However, given the cross-sectional design and the lack of temporal separation between predictors and outcome, endogeneity through reversed causality, simultaneity, or omitted variables cannot be ruled out. As no instrumental variables are available, these concerns also cannot be statistically addressed beyond grounding the model in theory. Consequently, the results will be interpreted as associations, controlling for the included covariates, rather than as evidence of causal effects.

5. Results

5.1. The spread of product innovations

To examine the link between product innovation and the adoption of AI in production, we first present descriptive findings on the prevalence of product innovation in its various forms within Germany's manufacturing sector and describe how the determinants of innovation have spread. First, we examine how widespread product innovations are in the manufacturing sector. In 2022, 45% of manufacturers in Germany had launched a new product that had not previously been available within the firm, as shown in Figure 2. When broken down by type of product innovation, a more nuanced picture emerges: more than a quarter of product innovators launched new products that were based on a digital product extension or a major improvement of existing digital product elements. Relative to the total population, this corresponds to 13% of all manufacturers. Similarly, 13% of all manufacturers introduced eco-oriented product innovations. Furthermore, almost half of all product innovators claimed to have introduced product innovations that were new to the entire market, which means that 22% of all manufacturers are market innovators. These results illustrate the willingness of manufacturers in Germany to invest in various types of product innovations, with a surprisingly high share of market innovations.

As shown in Table 4, the bivariate analyses of the various types of product innovators also reveal some interesting structural features. When examining firm size, it is noticeable that large manufacturers (with 500 or more employees) are predominantly product innovators. Three-quarters of large firms (75%) introduced new products in the three years prior to 2022. In contrast, only about a third of small firms with fewer than 50 employees introduced new products. Additionally, 39% of large product innovators focused on digital-oriented product innovations; among small product innovators, the share was 31%. Moreover, a substantial share of large product innovators pursued eco-oriented product innovations (43%), whereas only a quarter of the small product innovators (25%) launched such products. However, no

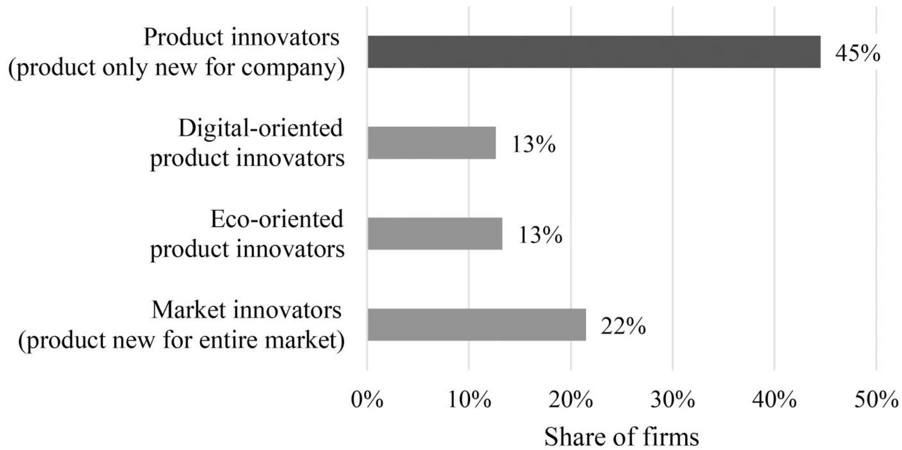

Figure 2. Share of product innovators in German manufacturing.
Sources: Own calculation.

statistically significant differences in the share of market innovators were identified between firm-size groups.

There are also striking differences across sectors and across product complexity classes, while batch-size groups showed no statistically significant differences. Regarding sectoral differences, some sectors stand out as particularly active product innovators, with strong variation by product-innovation type: for digital-oriented innovations, the electronics industry leads with 63% of product innovators developing digital-oriented new products, followed by the machinery sector at 42%. In contrast, eco-oriented innovations are especially evident among innovators from the wood and paper industry (48%). Regarding product complexity, manufacturers of complex products are, in particular, more oriented towards product innovation across all types than firms offering simple or moderately complex products.

5.2. Manufacturers' potential for innovation

In addition to describing these key indicators on product innovation, the next step is to take a closer look at the three well-established determinants of innovation. As shown in Table 5, this descriptive analysis reveals further interesting insights into the current innovation landscape in German manufacturing.

In terms of R&D, only 37% of companies appear to conduct in-house R&D or outsource R&D to external contractors. This suggests that the majority of German manufacturers (63%) did not invest in R&D in 2021, which could indicate a reluctance to pursue an innovation strategy. However, when looking at R&D collaborations with other companies or with research institutions, a large proportion of companies (54%) actively enter into partnerships that go beyond pure business contracts to strengthen their innovative capabilities. In detail, 45% of manufacturers cooperate with research institutions, 39% cooperate on R&D topics with customers or suppliers, and 27% cooperate on these topics with other companies. Regarding the second factor, the qualification level of the workforce, the analysis shows that, on average, 22% of personnel in German manufacturing firms (median = 18%) are considered highly skilled with an educational background at least ISCED level 5, i.e. employees who have graduated from a university or technical college, or who hold a technician or master craftsman certificate. The third innovation factor, human-centricity, is also important for strengthening the innovative capacity of manufacturing firms. As shown in Table 4, 46% of manufacturers have organisational practices in place to involve their employees in innovation processes. When it comes to training measures to promote creativity and innovation or to boost cross-functional skills, the results show that only 18% of manufacturers in Germany offer dedicated training for both areas to their production employees. A further 63% offer training to production staff, but these programs do not cover the cross-cutting topics. In addition, 16% of manufacturers in Germany do not offer their production employees any further training opportunities. Specifically, only 26% of firms offer training to promote creativity and innovation, e.g. problem-solving, idea generation, or brainstorming techniques. This could hinder the development of innovative ideas. In contrast, cross-functional training focused on project management, team management, or language courses is somewhat more widespread, with 43% of firms offering such programs and thus promoting the integration of different disciplines into the innovation process.

5.3. Use of AI in production

Another key aspect of our analyses is determining the extent to which AI is used in production by German manufacturers. The GMS data provide insights into the 2022 situation. Figure 3 shows the AI adoption rate in five production application areas analysed for Germany's manufacturing industry, as well as the overall AI adoption rate defined as AI use in at least one of these five areas. In 2022, 8% of firms used AI to manage their production processes, 7% for quality control, another 7% for internal logistics. Additionally, 6% used AI for machines and equipment maintenance, and 4% for improving or innovating production processes. Overall, 16% of the manufacturing firms in Germany used AI in at least one of the five production-specific application areas in 2022. While this adoption rate may appear relatively low, it is consistent with earlier empirical research: Rammer, Fernández, and Czarnitzki (2022) report AI adoption of up to 11% in the

Table 4. Different types of product innovators depending on selected structural characteristics.

	Product innovators (new for firm) [all firms]		Digital-oriented product innovators [Product innovators only]		Eco-oriented product innovators [Product innovators only]		Market innovators (new for market) [Product innovators only]	
Structural features	yes	no	yes	no	yes	no	yes	no
Firm size (# of employees)	***		*		*		n.s.	
up to 49 employees	34%	66%	31%	69%	25%	75%	45%	55%
50–99 employees	47%	53%	23%	77%	28%	72%	53%	47%
100–499 employees	52%	48%	26%	74%	32%	68%	48%	52%
500 or more employees	75%	25%	39%	61%	43%	57%	48%	52%
Sector groups (NACE rev. 2)	***		***		***		n.s.	
metal products	27%	73%	24%	76%	23%	77%	37%	63%
textile, clothing and leather industry	46%	54%	11%	89%	21%	79%	63%	37%
wood products, paper, cardboard industry	36%	64%	24%	76%	48%	52%	48%	52%
machinery	59%	41%	41%	59%	34%	66%	53%	47%
rubber and plastics industry	39%	61%	16%	84%	25%	75%	41%	59%
food and beverage industry	42%	58%	4%	96%	9%	91%	48%	52%
chemical and pharmaceutical industry	58%	42%	8%	92%	43%	57%	39%	61%
electronic industry	62%	38%	63%	37%	33%	67%	50%	50%
electrical equipment industry	58%	42%	32%	68%	41%	59%	68%	32%
automotive industry	53%	47%	29%	71%	35%	65%	47%	53%
other sectors	48%	52%	33%	67%	23%	78%	50%	50%
Batch size	n.s.		n.s.		n.s.		n.s.	
single lot	40%	60%	28%	72%	31%	69%	49%	51%
small/medium lot	45%	55%	29%	71%	28%	72%	49%	51%
big lot	47%	53%	21%	79%	33%	67%	41%	59%
Product complexity	***		***		***		**	
simple products	29%	71%	10%	90%	13%	87%	38%	62%
medium complex products	43%	57%	28%	72%	30%	70%	46%	54%
complex products	56%	44%	36%	64%	36%	64%	55%	45%

Note: Statistical significance level of group comparison: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$, n.s. not statistically significant with $p >= 0.1$. *Sources:* Own calculation.

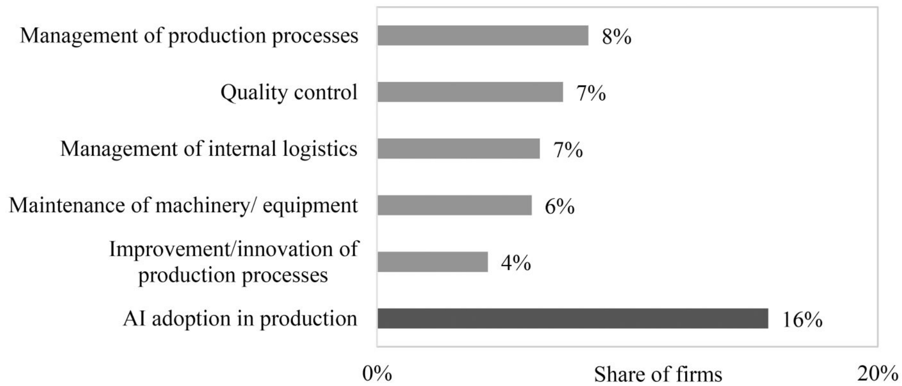

Figure 3. AI adoption in production by application area.
Sources: Own calculation.

Table 5. Utilisation of firm-level innovation determinants across manufacturing firms in Germany.

Firm-level innovation determinants	Indicators	Share of firms	mean (in %)
R&D activities	R&D performed internally or outsourced	37%	–
	R&D cooperations with another firm or a research institution	54%	–
Workforce qualification level	Share of highly qualified personnel	–	22%
Human centricity	Measures for employee involvement	46%	–
	Training in creativity and innovation and with cross-functional focus:		–
	• No training offers	16%	
	• Some training offers but not those both specific ones	66%	–
	• training with cross-functional focus and training for creativity and innovation	18%	

Sources: Own calculation.

Table 6. Correlation between the adoption of AI and product innovations in manufacturing firms.

Type of product innovation	AI adopters	Non-AI adopters
Product innovators (products new for firm) [among all manufacturers] **	52%	43%
Digital-oriented product innovators [among product innovators] ***	42%	25%
Eco-oriented product innovators [among product innovators] ***	48%	26%
Market innovators (products new for entire market) [among product innovators] n.s.	52%	48%

Note: Statistical significance level of group comparison: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$, n.s. not statistically significant with $p >= 0.1$.
Sources: Own calculation.

German electrical equipment industry (2018 data), and McElheran et al. (2024) find an adoption rate of around 12% for the overall manufacturing industry in the USA (2018 data). Unlike these studies, our measure focuses explicitly on AI application areas in production, suggesting that the observed adoption level accurately reflects AI adoption in production processes.

5.4. Linking AI use in production and product innovation

To gain an initial insight into the relationship between product innovation and the use of AI in manufacturing, Table 6 shows the shares of product innovators across the four types of product innovations analysed, by AI adoption in production. A comparison of the proportions among AI adopters and non-adopters yields initial insights. Across all four types, AI-adopting firms in production have a higher share of product innovators. Between 2019 and 2022, 52% of AI adopters introduced new products that were new to the firm, compared with 43% of non-adopters. The differences are particularly pronounced for digital-oriented and eco-oriented product innovations. Here, 42% of AI adopters with product innovations introduced digital-oriented new products, versus 25% among non-AI adopters. A similar pattern is seen for eco-oriented innovations: 48% of AI adopters with new products developed eco-oriented innovations, compared with 26% among non-AI adopters who implemented new products. This suggests that AI-enabled capabilities in production place firms in a better position to generate and deliver innovations. For market innovations, however, there were no statistically significant differences. Roughly half of the product innovators introduced market innovations, regardless of AI adoption in production.

However, this initial impression that AI adopters have a higher share of product innovators may not provide a balanced view. The observed correlation could be misleading, as differences in other characteristics have not been controlled for. Therefore, we also tested our hypotheses using logistic regression analyses to further investigate the relationship between AI adoption and the implementation of product innovations. The results are presented in three steps. First, Table 7 summarises the results of these four logistic regression models in terms of the explanatory contribution of the factors analysed. For each model, the model improvement achieved by including the indicators for the factor is shown by the change in the model fit between the baseline model without the indicator(s) and the model with the indicator(s). The table reports $\Delta-2LL$ as the reduction in -2 log-likelihood when moving from the reduced to the full

Table 7. Explanatory power of the impact factors in the estimated logistic models for models A–D.

	Models			
	All manufacturers	All product innovators		
Population	Product innovator (vs. non-product innovator)	Digital-oriented product innovator (vs non-digital-oriented product innovator)	Eco-oriented product innovator (vs. non- eco-oriented product innovator)	Market innovator (product new to the market) (vs. non-market innovator)
Dependent construct	A (H1)	B (H2a)	C (H2b)	D (H3)
Factors	$\Delta-2$LL (df) sig.	$\Delta-2$LL (df) sig.	$\Delta-2$LL (df) sig.	$\Delta-2$LL (df) sig.
Firm size	10.61 (1) **	n.s.	n.s.	n.s.
Industry affiliation	32.14 (10) ***	31.49 (10) **	23.24 (10) ***	n.s.
Batch size	n.s.	n.s.	n.s.	n.s.
Product complexity	n.s.	n.s.	5.38 (2) *	n.s.
AI adoption in production	2.89 (1) *	7.40 (1) **	3.64 (1) *	n.s.
R&D activities	47.01 (2) ***	n.s.	n.s.	8.44 (2) **
Workforce qualification level	2.88 (1) *	n.s.	n.s.	n.s.
Human centricity	12.16 (3) **	6.58 (3) *	20.02 (3) ***	10.64 (3) **
N	968	429	427	429
−2-LL/Sig.	1123.915 ***	417.023 ***	438.240 ***	555.253 **
Cox & Snell R^2t	19%	16%	16%	8%

Notes: Logistic regression models. Model A included all manufacturers, models B, C and D only firms who were product innovators. For each construct the realised difference in the -2LL due to the indicators is displayed as well as the degree of freedom in brackets and the significance level for the model modification. Parameter of model fit: −2LL = −2 Log-Likelihood, N = number of cases. All models are statistically significant (Models A, B, C $p < 0.001$; Model D $p < 0.05$).
Significance level: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$, n.s. not statistically significant with $p >= 0.1$.
The authors are happy to provide more detailed information on all models upon request.
Sources: Own calculation.

model; positive values indicate an improvement in model fit. Taking into account the necessary degrees of freedom, this allows an assessment of the independent explanatory contribution for each explanatory factor. In addition, Table 8 lists the estimated odds ratios (OR) and the results of the statistical significance tests for the individual indicators of the various constructs of innovation factors. This clearly illustrates the relationship between the values of the various characteristics and the potential for production innovation, holding all other factors constant.

A comparison of the estimation models presented shows that the indicators taken into account make a relevant contribution to explaining the likelihood of a firm introducing product innovations, as well as the type of product innovation. As the Cox & Snell R^2 estimate of the explained variance shows, the explanatory power is significantly greater in the first three models. Overall, however, it should be regarded as moderate. Moreover, Table 7 shows that, in three of the four models, despite controlling for additional structural and traditional, primarily organisational innovation factors, a difference can be observed in the likelihood of product innovation between users of AI in manufacturing and non-users. However, this difference varies significantly. It also becomes clear that, in addition to the diverse R&D activities, human centricity plays an important role in predicting product innovation activities. Furthermore, industry-specific conditions continue to be a decisive factor in a manufacturer's product innovation activities. As summarised in Table 8, our estimated results for Model A show in detail that the adoption of AI in production processes is positively linked to the likelihood that product innovations are realised at all (OR = 1.4), even when important drivers for product innovations and structural characteristics are controlled for. However, this estimated difference is only statistically significant at the 10 percent level. R&D related activities are more decisive for being a product innovator with new products for the firm. Both the firms' own direct R&D activities (OR = 2.2) and the R&D cooperation with external innovation partners (OR = 1.7) increase the likelihood that a firm is a product innovator.

These findings indicate that, in the estimated regression model, the integration of R&D efforts is more strongly associated with the likelihood that a firm launches a new product than the use of AI in production processes. In addition, indicators for a human centricity make a relevant contribution. Firms that offer trainings for production employees are more likely to be product innovators than firms without such training offers (OR = 1.8). Moreover, firms that offer their production employees a training with a cross-functional focus and a creativity-related training demonstrate even greater innovative strength (OR = 2.0). However, organisational efforts to involve production employees in innovation processes are surprisingly not significantly associated with product innovation and do not improve the model's fit. In addition, firms with a larger share of highly qualified employees are more likely to be product innovators (OR = 1.2). Finally, from a structural perspective, the firm size and the industry are also significantly associated with the likelihood of product

Table 8. Estimated ORs for the indicators of innovation drivers in the estimated models A–D.

	Models							
	A (H1)		B (H2a)		C (H2b)		D (H3)	
Innovation drivers	OR	Sig.	OR	Sig.	OR	Sig.	OR	Sig.
AI adoption		*		**		*		
AI adoption in production [(1)]	1.438	*	2.372	**	1.791	*	1.052	n.s.
Qualification		*						
Share of highly-qualified personnel (z-centred)	1.156	*	1.232	*	0.952	n.s.	1.090	n.s.
Human centricity		**		*		***		**
Employee involvement in innovation and improvement [(2)]	1.271	n.s.	1.239	n.s.	1.785	**	1.510	*
Cross-functional and creativity training for production employees		**		n.s.		**		*
Some training, but not both [(3)]	1.830	**	4.479	*	3.925	*	0.808	n.s.
Cross-functional as well as creativity training [(3)]	2.000	**	4.398	*	8.066	**	1.490	n.s.
R&D activities		***						**
R&D activity (internal/external) [(4)]	2.159	***	1.145	n.s.	1.369	n.s.	1.677	**
R&D cooperation(s) [(5)]	1.745	***	1.122	n.s.	1.411	n.s.	1.379	n.s.

Notes: Logistic regression models. Model A included all manufacturers, models B, C and D only firms who were product innovators. All models included also indicators for sector, firm size, product complexity and batch size.
Significance level: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$, n.s. not statistically significant with $p >= 0.1$.
Reference groups: (1) no AI adoption in production, (2) no organisational concept implemented to involve production employees in improvement and innovation processes, (3) no training offer for production employees, (4) no R&D performed, (5) no R&D cooperation with another firm or research institution.
The authors are happy to provide more detailed information on all models upon request.
Sources: Own calculation.

innovation, whereas production characteristics seem not to be significantly related to it in this model.

Next, we examined which factors are associated product innovators being more likely to launch digital-oriented products than traditional, non-digital product innovations. The reference group consists of firms that have introduced traditional product innovations, i.e. those that have entered the market with analog improvements (model B). Our results indicate that the adoption of AI in production processes is significantly associated with a higher likelihood that a firm introduces digital-oriented product innovations rather than traditional, non-digital new products (OR = 2.4). Compared to the other factors included in the model, AI adoption makes one of the largest contributions to model fit, which indicates that it is one of the strongest statistical predictors of this distinction. This means that AI users are much more likely digital-oriented product innovators which fosters the assumption that AI adoption in production promotes digital innovation processes and supports companies in the development of digitally enhanced products. A higher share of qualified employees also increases the likelihood (odds ratio OR = 1.2) that a firm will be a digital product innovator rather than a traditional product innovator; however, this effect is only significant at the 10% level. The human-centricity characteristics also show a weak association at the 10-percent significance level, in particular training programs for production staff, which are associated with whether a firm focuses more on digital product innovations. In contrast, the indicator for production employees' involvement in innovation is not statistically significantly associated with this type of product innovation and does not improve the model fit. R&D activity per se is also not significantly associated with this distinction between digital and traditional product innovations, which indicates that while R&D and the organisational changes it requires may be related to the overall development of new products, they are not clearly linked to the specific type of innovation in this model. From a structural perspective, the manufacturers' industry affiliation, which reflects different potentials for digitisation and digitalisation of the product across manufacturing industries, is significantly associated with the type of product innovation. Other firm and production characteristics, however, are not significantly associated with this distinction in the estimated model.

Model C analyzes which factors are associated with the likelihood that a firm introduces eco-oriented product innovations rather than non-eco-oriented ones. Our results indicate that AI adoption in production processes is positively associated with the likelihood of eco-oriented product innovations (OR = 1.8); however, this effect is only significant at the 10% level. In this model, human-centricity shows a stronger association with eco-oriented product innovations than AI adoption. Training measures to promote the innovative ability and cross-functional skills of production employees are strongly associated with a higher likelihood of eco-oriented product innovations (OR = 8.1); other training offerings are also positively associated with these odds (OR = 3.9). Additionally, the involvement of production employees in innovation processes is associated with a higher likelihood that a firm will introduce eco-oriented product innovations (OR = 1.8). In contrast, the qualification level of employees does not contribute to the model fit. R&D activity per se is also not significantly associated with the distinction between eco-oriented and non-eco-oriented product innovations. Structural firm information and production characteristics are of lesser importance; only the sector in which the firm operates is significantly associated with the likelihood of introducing eco-oriented product innovations.

Finally, Model D analyzes which factors are associated with the likelihood that a firm introduces a product that is new to the market (as opposed to a product that is only new for the firm). First, the results suggest that the likelihood is more strongly associated with R&D activities and human-centricity characteristics than with structural factors.

Moreover, AI adoption in production is not significantly associated with this distinction. Specifically, firms that engage in direct R&D activities are more likely to develop market innovations (OR = 1.7). Collaboration with other companies or research institutions in R&D, on the other hand, is not significantly associated with market innovations and does not improve the model fit. Furthermore, firms that offer cross-functional and creativity-related training for production employees are more likely (OR = 1.5) to be market innovators than firms that do not offer such training or that offer other forms of training. In addition, firms that involve their production employees in innovation processes are also more likely to be market innovators (OR = 1.5). However, both associations are significant only at the 10% level.

A comparison of our four models yields several interesting insights. While R&D activities and research partnerships are consistently associated with a higher likelihood of product innovations, they are not clearly linked to the specific type of innovation, such as digital or eco-oriented product innovations. In these distinctions, factors such as AI adoption in production and, in the case of eco-oriented innovations, human-centricity are more strongly associated. Furthermore, the findings highlight that structural factors are consistently related to a firm's overall innovation activity and to certain innovation pathways. Larger companies tend to be more frequently associated with product innovations, but firm size is not strongly related to whether a firm pursues digital or eco-oriented product innovations. This pattern aligns with the idea that larger firms often benefit from greater resources and capabilities for general product innovation, whereas the specific type of innovation tends to reflect strategic orientation rather than firm size alone. Finally, industry affiliation is consistently associated with innovation patterns across all types of innovation. Different industries exhibit varying propensities for traditional, digital, or eco-oriented product innovations, which may reflect industry-specific regulations, technological advances, and market demand structures.

6. Discussion and conclusions

This study provides empirical insights into how the implementation of AI solutions in production-specific application areas is associated with manufacturing firms' product-related innovation patterns. The study builds on absorptive capacity (AC) theory (Cohen and Levinthal 1990), particularly the stream that distinguishes between potential (PACAP) and mphasiz AC (RACAP) as two core modes of mphasizingal learning: exploration and exploitation (Horvat, Dreher, et al. 2019; Jansen 2005; Lane, Koka, and Pathak 2006; Zahra and George 2002). In addition, the study draws on the emerging literature on AI-enabled AC (Fu, Ni, and Fang 2025; Grilli and Pedota 2024; Lin and Wu 2025; Pedota 2024). Our results show that the use of AI in production, beyond established firm-level innovation determinants such as R&D activities, human-centric practices, and structural firm characteristics, is associated with a higher likelihood that firms introduce product innovations. By emphasizing the role of AI in production as data-driven knowledge generator, this study contributes to a more nuanced understanding of the extent to which successful product innovation is prevalent in contemporary manufacturing contexts in conjunction with the use of AI in production. In doing so, the study contributes to current academic debates in both production research and industrial innovation studies, while also providing sound empirical findings with implications for managerial practice.

6.1. Theoretical implications

6.1.1. AI in production as a driver for variety and new types of product innovation

Our empirical analysis indicates that the implementation of AI in production is significantly associated with a higher likelihood that manufacturers introduce product innovations that are new to the firm (OR = 1.438). This finding is consistent with the argument that firms applying AI in critical production-related application areas are better positioned to generate, acquire, and utilise new knowledge, thereby strengthening their AC (Horvat, Jäger, and Lerch 2025; Lerch et al. 2024; Pedota 2024). Enhanced AC, in turn, supports both exploratory and exploitative modes of organisational learning (Lane, Koka, and Pathak 2006; March 1991), enabling firms to identify new innovation opportunities and effectively integrate and apply knowledge in product innovation processes (Cohen and Levinthal 1990; Weidner, Som, and Horvat 2023; Zahra and George 2002). More specifically, our findings suggest that the use of AI in production co-occurs with patterns of knowledge-related activities that encompass both the acquisition and assimilation of new knowledge related to production processes (Broekhuizen et al. 2023; Wu, Lou, and Hitt 2019) and the more effective application of such knowledge to innovation-related outcomes. This pattern aligns with the notion that AI in production can contribute to innovation-accelerating processes that complement existing firm-level innovation resources and capabilities. The significant positive association between production-related AI use and product innovation further underscores the relevance of AI-enabled knowledge dynamics for strengthening the innovation capability of manufacturing firms (Pedota 2024).

Furthermore, prior research suggests that once smart manufacturing reaches a certain level of maturity, it is associated with greater production flexibility and a higher likelihood of adopting advanced technologies such as additive manufacturing (Frank, Dalenogare, and Ayala 2019). This pattern, in turn, tends to co-occur with a higher variety and complexity of product designs and, more generally, with product innovation. Against this background, our findings indicate that AI-enabled production processes are more likely to associated with incremental forms of product innovation, including product modifications, customisations, and continuous improvements. These innovation patterns appear to coincide with ongoing R&D activities (OR = 2.159), which exhibit the strongest association with the introduction of product innovations in general. The incremental nature of AI-enabled patterns is further supported by the results for H3, which show no statistically significant association between AI use in production and the likelihood of introducing innovations new to the market (OR = 1.052). Such market novelties typically coincide with more radical innovation patterns that appear to be less tied to production-related learning effects and more closely related to exploratory R&D and strategic capability development.

Our results also contribute to the twin transition literature by indicating that AI-enabled processes are associated not only with a higher likelihood of product innovation in general, but also with a greater variety and the emergence of new types of product innovations. On the one hand, in the context of digitalisation (H2a), our findings show that manufacturers using AI in their production are significantly more likely to introduce digital-oriented product innovations (OR = 2.372) than firms without AI-enabled processes. In this analysis, AI use in production is the strongest associated factor. Human-centricity, especially the provision of cross-functional and creative training, is also strongly associated with the realisation of digital product innovations (OR = 4.398), though this association is only significant at the 10-percent level. This pattern is consistent with the idea that manufacturers developing or expanding digital capabilities tend to integrate them more widely across the firm, due to individual and organisational learning effects (Lenka, Parida, and Wincent 2017; Lerch et al. 2026). Furthermore, firms tend to assemble, mobilise, and deploy their digital resources across all stages of the innovation lifecycle (Chae, Koh, and Prybutok 2014; Nwankpa and Datta 2017). Since digital technologies in production often coincide with the conditions for AI adoption (Heimberger, Horvat, Jäger, et al. 2026), it is plausible that firms possessing both digital and AI capabilities apply them not only within production processes but also in product development (Frank, Dalenogare, and Ayala 2019). Over time, this pattern may be associated with the emergence of both smart product innovations and smart production systems.

On the other hand, in the context of sustainability (H2b), our results show that manufacturers adopting AI in production are more likely to implement eco-oriented product innovations (OR = 1.791). Here, employee involvement (OR = 1.785) and especially cross-functional training (OR = 8.066) are stronger associated with eco-oriented product innovations than AI use in production. However, the observed pattern may be linked to the broader dynamics of the twin transition, which combine digitalisation and sustainability efforts (Montresor and Vezzani 2023). Manufacturers are increasingly associated with environmentally friendly product development and the reduction of ecological impact (Rehman et al. 2023). In this context, it is conceivable that manufacturers could use information from their AI-enabled production processes to reduce waste and increase the resource efficiency and recyclability of their products (Waltersmann et al. 2021), which may in turn be reflected in the observed association with eco-innovations.

6.1.2. Market innovation – another story?

In contrast to product innovations that are new to the firm, our analysis reveals no statistically significant additional association between AI use in production and the realisation of product innovations that are new to the market (H3). Rather than indicating the absence of innovation effects, this finding may point to an important boundary condition of production-related AI applications. Specifically, AI-enabled production processes appear to be more closely associated with exploitation-oriented innovation activities aimed at improving, refining, and customising existing products than with exploratory innovation activities required for the development of market novelties (Benner and Tushman 2003; Jansen 2005; March 1991).

From an organisational learning perspective, this distinction reflects the difference between exploitation and exploration (Levinthal and March 1993; March 1991). Exploitation involves refinement, efficiency improvements, and the extension of existing knowledge, whereas exploration refers to search, experimentation, and generation of novel knowledge domains enabling the introduction of fundamentally new products and markets (Jansen 2005; Katila and Ahuja 2002; Lane, Koka, and Pathak 2006). AI systems embedded in production environments primarily operate on existing operational, process, and quality-related data. As a result, they support efficiency improvements, process optimisation, defect reduction, and incremental product adaptation (Buchmeister, Palcic, and Ojstersek 2019; Heimberger, Horvat, Jäger, et al. 2026; Plathottam et al. 2023; Wamba-Taguimdje et al. 2020). These learning mechanisms are consistent with exploitation-oriented innovation processes that strengthen firms' ability to refine and recombine existing knowledge, but are less directly aligned with exploratory search processes that underpin market novelties (Lane, Koka, and Pathak 2006). Consequently, AI use in production may contribute more strongly to incremental innovation outcomes than to radical innovations associated with market novelties.

Our descriptive results support this interpretation. Only 22% of manufacturing firms in our sample report introducing product innovations that are also new to the market, suggesting that market novelties remain comparatively rare and resource-intensive. The regression results further show that R&D activities (OR = 1.677) and human-centric organisational characteristics (OR = 1.510; OR = 1.490) are significantly associated with market novelties, whereas AI use in production is not. This pattern indicates that market innovations depend less on operational production knowledge and more on firms' ability to integrate external market intelligence, customer insights, and exploratory technological development efforts (Horvat, Dreher, et al. 2019; Jansen 2005).

From the perspective of AC theory, these findings suggest that distinct dimensions of AC (Horvat, Dreher, et al. 2019; Zahra and George 2002), and, by extension, different modes of organisational learning (Lane, Koka, and Pathak 2006; March 1991), may be differentially associated with innovation outcomes (Jansen 2005). Production-related AI appears to primarily enhance firms' ability to transform and exploit existing operational knowledge, thereby strengthening RACAP. In contrast, the development of market novelties seems to depend more strongly on exploratory learning and the integration of external knowledge sources, requiring a more balanced interplay between PACAP and RACAP. In this context, human-centric organisational practices and R&D activities may play a particularly important enabling role. They facilitate cross-functional knowledge integration across market insights, technological experimentation, and strategic learning processes, which are critical for achieving more radical innovation outcomes (Jansen 2005; Jansen, van den Bosch, and Volberda 2005).

6.1.3. Innovation beyond R&D: the interplay of AI-enabled processes and human centricity

Our findings indicate that R&D is strongly associated with both generic product innovations, which is new to the firm, and market innovations. This pattern is consistent with findings from earlier studies (Rammer, Fernández, and Czarnitzki 2022; Shefer and Frenkel 2005; Un, Cuervo-Cazurra, and Asakawa 2010). However, our analysis shows that R&D efforts are not significantly associated with the development of product innovations characterised by digital or environmentally oriented features (H2a/b). We therefore assume that most manufacturers' R&D activities remain primarily focused on traditional products.

In contrast, our analyses indicate that AI-enabled production processes and human-centric organisational practices tend to co-occur with emerging forms of product innovation, including smart and sustainable products. Building on these findings, we argue that while R&D activities are strongly associated with generic product innovation, AI-supported processes and human centric practices appear to broaden the scope and diversity of innovation outcomes by providing complementary sources of knowledge. More specifically, AI-enabled processes are more strongly associated with digital-oriented innovations, whereas human centricity show a stronger association with eco-oriented innovations. This pattern is consistent with the idea that the combination AI-driven insights and human expertise may support product innovations aligned with the twin transition, including digitally enabled and more sustainable solutions.

Finally, beyond AI-enabled processes, R&D and human-centric organisational practices, several contextual characteristics of manufacturers are also associated with innovation outcomes. In particular, industry affiliation is significantly associated with generic product innovations as well as with digital- and eco-oriented innovations. Manufacturers operating in technology-intensive sectors are more likely to introduce product innovations, which is consistent with prior research (Kirner, Kinkel, and Jaeger 2009). The share of highly qualified personnel is moderately associated with both generic product innovations and digital-oriented innovations, underscoring the relevance of human knowledge and skills in firms' innovation patterns. Interestingly, the results indicate no association between firm size and digital- or eco-oriented innovations, nor with market-novel innovations. Among production-related characteristics, only product complexity exhibits a positive association, specifically with eco-oriented product innovations. Overall, these findings suggest that sectoral technological intensity, the implementation of AI in production, and the effective integration of human knowledge tend to be more strongly associated with both generic and emerging forms of product innovation than with structural features of manufacturers' production systems and resource endowments.

6.2. Practical implications

Our findings also hold implications for practitioners and innovation managers in manufacturing companies. As our results show, AI-enabled processes in production are well capable of providing valuable information for product development and product design. Therefore, AI should be viewed as a strategic lever for innovation rather than merely an operational tool. When embedded in a broader innovation strategy, AI adoption in production processes can facilitate both digital and sustainable product development. To unlock this potential, firms should strategically invest in collecting, storing and analysing AI-generated data and learn how this information can be transferred into new product development.

Our study also highlights the importance of the interplay between R&D, human centricity, and AI-enabled production processes. According to our findings, it is not enough to rely solely on AI. For modern types of product innovation, it is crucial to combine human experience with AI-generated information, link this to new knowledge, and apply it in a targeted manner in R&D activities. Manufacturers who can master these factors and process them into a flow of information have a decisive advantage when it comes to product innovations and their various types. Interestingly, his is not only relevant for large firms, but particularly for small and medium-sized enterprises (SMEs), too. While company size typically has an impact on driving general product innovation (Ettlie and Rubenstein 1987; Shefer and Frenkel 2005), these effects do not significantly apply to digital or eco-oriented product innovation. This suggests that resource constraints may be less of a barrier in these domains, opening up new innovation opportunities for SMEs.

Moreover, our study highlights ways in which manufacturers can be specifically encouraged to pursue digital or eco-oriented innovations (Rehman et al. 2023). For digital-oriented product innovation, companies can harness AI capabilities such as predictive analytics, real-time monitoring, and smart product development to create digitally enhanced offerings. Eco-oriented innovation, in turn, can benefit from AI-driven approaches to improving resource efficiency, reducing waste, and supporting circular economy principles. These insights highlight the value of AI not only in enhancing innovation performance but also in aligning product strategies with broader sustainability and digitalisation agendas.

6.3. Limitations and future research

Our study holds some limitations that simultaneously present opportunities for future research.

First, although our study provides valuable insights into how the implementation of AI in production is associated with a higher likelihood of product innovation alongside other firm-level capabilities, it does not allow for causal inference. Rather than testing formally specified causal hypotheses, our regression models primarily serve to refine and qualify observed bivariate relationships. The data were collected through a single cross-sectional survey, meaning that all variables refer to the same point in time. Consequently, causal relationships cannot be identified, and endogeneity concerns remain. Unobserved firm-level characteristics, unmeasured determinants of innovation, or potential reverse causality may bias the estimated relationships. Moreover, due to item non-response in some variables, the multivariate models for H1 are based on a reduced analytical sample. A systematic comparison of included and excluded observations revealed that the excluded firms exhibit slightly higher rates of both AI adoption in production and R&D activity. Since both factors are positively associated with product innovation, their underrepresentation in the analytical sample suggests that the estimated odds ratios may be subject to a conservative bias, meaning that the true associations could be somewhat stronger than those reported. Given that both factors are positively associated with innovation outcomes, we interpret our findings as conservative estimates that likely represent a lower bound of the true associations. Future research should place greater emphasis on uncovering causal mechanisms. In particular, longitudinal designs could examine how ongoing R&D activities contribute to the development of a firm's AC and thereby enable the translation of AI-generated production insights into new product architectures. Additionally, research could explore how human-centric organisational practices support the diffusion of AI-derived knowledge across functions and facilitate the identification of new product opportunities rooted in operational experience. For such inquiries, research designs employing panel data or other data structures with lagged variables (e.g. matched datasets) would be particularly informative.

Second, our analysis focuses exclusively on physical product innovations, not looking at complementary innovations in areas such as product-related services and business model innovations, particularly in the context of global trends like digitalisation and sustainability. Future research should broaden the analytical scope to explore how AI facilitates a wider range of innovations, including product-service systems and platform-based business models. Investigating these areas could enhance our understanding of AI's transformative potential in production across various dimensions of industrial value creation.

Third, our analysis is confined to the production systems and innovation outcomes of individual manufacturers. However, modern innovations, especially those driven by AI, often emerge from collaborations across companies and within ecosystems. Our quantitative analyses did not capture the importance of inter-firm interactions. Therefore, we see potential for future studies that should explore how AI adoption interacts with external innovation ecosystems, including collaborations with start-ups, research institutions, and suppliers. Such analyses could provide a more comprehensive view of AI's role in networked innovation, illuminating how external partnerships can amplify or shape the innovation potential of AI technologies in production processes.

Fourth, while our findings are based on a large-scale survey utilising firm-level data and multiple regression analysis, we cannot provide insights into the strategies of individual manufacturers and their relationship with product innovations. This highlights the necessity for qualitative research designs, such as case studies and ethnographic methods, which are well-suited for exploring the organisational and contextual mechanisms underpinning the impact of AI-enabled production on manufacturers' innovation capabilities. These approaches could reveal how cultural, structural, and leadership factors mediate the relationship between AI implementation and innovation outcomes.

Finally, our findings relate exclusively to the manufacturing sector in Germany. While we utilised a representative dataset for our analyses, our results are country specific and should not be generalised to other countries. Conducting similar analyses in different national contexts would be valuable, especially in comparing developed and emerging economies. Cross-country comparative studies could provide insights into how national and regional contexts influence AI-driven innovation, considering factors such as regulatory frameworks, industry structures, digital infrastructures, and workforce skills. Expanding the geographic and institutional scope of this empirical research can enhance the generalisability and relevance of our findings.

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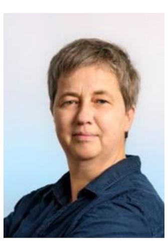

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