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From spark to launch – An empirical study of how AI shapes organizational innovation capability across new product development stages

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ABSTRACT

This study examines how artificial intelligence (AI) shapes organizational innovation capability across three stages of new product development (NPD)—concept development, product development, and implementation—and investigates whether employees' AI competence amplifies these effects. Drawing on a cross-sectional survey of 400 managers in Germany, we find that greater AI usage intensity is associated with higher innovation capability at each stage, with the strongest gains in concept development. Benefits decrease in later stages, where successful progress demands more human expertise, physical interaction, and emotional intelligence, areas in which current AI tools remain comparatively weak. These results challenge assumptions of uniform AI utility throughout NPD and argue for fit-to-task deployment. Furthermore, employees' AI competence significantly strengthens the relationship between AI use and innovation capability, underscoring the need to pair technology investments with workforce upskilling. Thus, managers should allocate AI resources strategically to match stage-specific demands, prioritize concept development for near-term impact, and cultivate skills that unlock AI's value in product development and implementation. This study advances the literature on AI-enabled innovation by offering a stage-contingent perspective and highlighting human–AI complementarity as key driver of innovation outcomes. Overall, the findings provide guidance for organizations seeking to maximize innovation via targeted AI strategies.

1. Introduction

In today's rapidly evolving market landscape, the need for organizations to innovate effectively and efficiently has never been greater. Yet, despite significant technological advances, an estimated 70–75% of new products still fail commercially (Cooper & Brem, 2024; Knudsen et al., 2023). These persistent failure rates highlight the urgent need for more robust, forward-thinking approaches to new product development (NPD) (Barczak et al., 2009; Knudsen et al., 2023). These challenges are amplified in industrial and business-to-business (B2B) contexts, where longer innovation cycles, greater complexity, higher investment volumes, multi-stakeholder dependencies, and narrower customer bases mean that product failures carry far-reaching consequences, further reinforcing the need for strong innovation capabilities (Amankwah-Amoah et al., 2024; Ehret et al., 2024; Najafi-Tavani et al., 2023).

Amid the ongoing challenge of enhancing NPD performance, artificial intelligence (AI) has emerged as a transformative technology promising to accelerate development, boost efficiency, and improve innovation outcomes (e.g., Cooper, 2024a, 2024b; Cooper & Brem, 2024; Pescher & Tellis, 2025; Piotrowski, 2024). For example, initial findings indicate that the use of AI in NPD can cut development times by more than 50% while simultaneously boosting customer satisfaction and achieving significant cost efficiencies (Cooper, 2024b). Moreover, AI tools are highly versatile, supporting a wide range of activities across the

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entire NPD process, including ideation, market analysis, prototyping, and fostering customer engagement (e.g., Cooper & McCausland, 2024; Cubric & Li, 2024; Marion et al., 2025; Pescher & Tellis, 2025).

Despite these promising benefits, the actual adoption of AI in NPD remains surprisingly low, with only 31% of organizations worldwide integrating AI tools into their processes (Singla et al., 2025). This gap between AI's potential and its practical implementation suggests that many organizations still lack clarity on how to apply AI effectively in the NPD process and what benefits they can realistically expect. This uncertainty is mirrored in academic literature, which reveals crucial gaps in understanding how the use of AI in NPD affects innovativeness of organizations.

First, while prior studies acknowledge AI's potential to enhance specific aspects of NPD (e.g., Cooper & Brem, 2024; Pescher & Tellis, 2025), existing insights remain fragmented. In particular, there is limited empirical evidence on how AI usage across the different stages of NPD—conceptual development, product development, and implementation—affects an organization's overall innovation capability. This gap is critical because the tasks and challenges differ substantially across NPD stages, making it likely that AI's effectiveness also varies by stage. Moreover, findings from prior research on the effectiveness of conventional IT tools in the different stages (e.g., Durmuşoğlu & Barczak, 2011) are not readily transferable, as AI operates fundamentally differently, with distinct capabilities and limitations (Tekic & Füller, 2023; Verganti et al., 2020). Clarifying stage-specific effects of AI is therefore essential to reduce the uncertainty that currently hampers adoption and to enable organizations to allocate AI resources more strategically for maximum innovation impact.

Second, there is limited understanding of which factors enable organizations to translate AI use into greater innovation capabilities. Prior research on digital technologies highlights employee skills as a critical determinant of whether technological benefits materialize in the NPD process (e.g., Pavlou & El Sawy, 2006), suggesting that similar factors are likely to shape AI's impact on innovation capabilities. Building on this insight, AI competence, which describes employees' proficiency in effectively leveraging AI tools, emerges as a likely determinant of how effectively AI contributes to innovation capabilities. However, this factor has received little empirical attention to date, and it remains unclear how the level of AI competence within an organization influences the benefits that can be derived from AI use across the different stages of NPD. Understanding this role is important, as it can inform workforce development initiatives and help companies build the competencies needed to fully exploit AI technologies.

This study addresses these gaps, which are particularly critical in industrial and business-to-business (B2B) contexts where organizations face complex and dynamic innovation processes, making the early integration of AI into NPD essential (Ehret et al., 2024; Lievens & Blažević, 2021; Tsai & Hsu, 2014). Thereby, we integrate theoretical insights into the fundamental characteristics of AI and its functions (originator vs. facilitator) with the specific demands of the NPD stages—concept development, product development, and implementation. Based on this foundation, we propose that AI tool usage in all NPD stages enhances an organizational innovation capability, defined as a firm's capacity to identify and exploit innovation opportunities through effective coordination, market responsiveness, and alignment of internal processes (Forsman, 2011; Gold et al., 2001; Lawson & Samson, 2001). In this perspective, innovation capability extends beyond the success of individual projects to reflect the organization's overall adaptability and innovativeness, representing a more strategic perspective on the implementation of AI in NPD.

Furthermore, we argue that the benefits of AI usage across the NPD stages are not uniform but follow a pattern of diminishing marginal returns. Because of changing demands throughout NPD and the capabilities of AI tools, we expect the effects of AI usage intensity on organizational innovation capability to be strongest during concept development, declining progressively in the product development and implementation stages. We explain this pattern by noting that in the early stages, AI's value lies in its dual role as both originator (e.g., autonomously generating novel ideas) and facilitator (e.g., analyzing unstructured data). As projects advance, the need for AI as an originator diminishes, while the demand for human expertise, physical interaction, and emotional intelligence increases, thereby limiting the benefits of AI tools.

In addition, we introduce employee AI competence as a potential contingency factor that moderates the relationship between AI usage intensity and innovation capability across the NPD stages. We hypothesize that higher levels of AI competence increase the benefits of AI tool usage across all NPD stages.

To test our research model, we conducted an empirical study surveying 400 employees in management positions with deep insights into their organization's NPD processes. Participants reported on AI tool usage across NPD stages, employees' AI competence, and their organization's innovation capability, along with other individual- and company-level control variables. Data analysis using partial least squares structural equation modeling supported our central propositions.

Overall, our study provides three central contributions. First, we provide robust empirical evidence that AI usage intensity across NPD stages significantly enhances organizational innovation capability. Prior research has typically examined individual AI tools, overall adoption levels, or single stages (e.g., Cooper, 2024a, 2024b; Marion et al., 2024, 2025; Pescher & Tellis, 2025). By contrast, our stage-spanning perspective shows that systematically embedding AI throughout the NPD process delivers cumulative benefits, improving coordination, responsiveness to market demands, and efficiency. This offers a comprehensive, empirically validated account of AI's multi-stage impact and answers recent calls for more granular insights into AI in NPD (Cooper, 2024a).

Second, we identify a previously underexplored dynamic: the diminishing marginal effect of AI usage as projects progress through the NPD process. AI has the greatest impact during concept development—where it serves as both originator (e.g., generating novel ideas) and facilitator (e.g., analyzing unstructured data)—with progressively smaller effects in product development and implementation. This contrasts with findings on conventional IT tools in NPD, which tend to be most beneficial in product development (Durmuşoğlu & Barczak, 2011). The results challenge assumptions of uniformly high AI effectiveness across stages and underscore the need for stage-contingent theorizing. For managers, particularly in resource-constrained settings, they emphasize prioritizing AI where it creates the most value—especially in creativity-intensive early stages—while recognizing reduced incremental benefits later.

Third, we highlight the moderating role of employees' AI competence in amplifying AI's positive effects across all NPD stages. In line with the resource-based view (Barney, 1991, 2001), our findings show that technological and human resources must be jointly developed to unlock AI's full potential. By empirically validating this relationship in the NPD context, we extend prior work on IT and AI adoption (e.g., Gallivan et al., 2005; Pan et al., 2022) and address calls for more research on organizational competences for AI-based innovation (Baumgartner et al., 2024; Brem et al., 2023). The results stress that human–AI synergy requires not only technical skills but also the contextual judgment to decide when and how to deploy AI tools and interpret outputs in light of domain goals. This underscores the need to invest in workforce AI competence to fully realize AI-driven innovation benefits.

The remainder of this article is structured as follows. We first present the theoretical background, outlining the NPD process and its stage-specific demands, as well as the characteristics of AI and its differences from conventional IT. Building on this, we develop our conceptual model and propose hypotheses on the effects of AI usage intensity and the moderating role of employee AI competence. We then describe the empirical study conducted to test these propositions. The article concludes with a discussion of theoretical and practical implications, limitations, and avenues for future research.

2. Theoretical background

2.1. New product development process

NPD can be understood as a cross-functional process encompassing the conception, design, development, and commercialization of new goods or services that deliver novel value to the market (Marzi et al., 2021; Parry et al., 2009). NPD involves a variety of distinct steps and tasks and is, for clarity, often organized into distinct, manageable stages (Browning & Ramasesh, 2007; Cooper, 2019; Han et al., 2025; Sihvonen & Pajunen, 2019). These stages guide innovation projects through decision points, providing actionable recommendations and addressing barriers as well as complexities (Cooper, 1990, 2008, 2019; Hartley et al., 2013).

Although NPD models vary in the number of stages and terminology—ranging from three-stage models (Chiesa et al., 2009; Ernst et al., 2010; Hansen & Birkinshaw, 2007; Munck et al., 2020; Pillai et al., 2002) to seven-stage frameworks (Feeney & Pierce, 2018)—most converge on three core stages: concept development, product development, and implementation (Sommer et al., 2015). To maintain clarity and focus, this study adopts this widely recognized three-stage framework (Chiesa et al., 2009; Ernst et al., 2010; Munck et al., 2020; Pillai et al., 2002).

The concept development stage focuses on defining a new product's strategic goals, generating ideas, and analyzing market trends, changes, and growth potentials. Often referred to as the "fuzzy front end," it is highly digital and knowledge-intensive, involving creative ideation, identification of market gaps, and rapid iteration (Marion et al., 2025; Takey & Carvalho, 2016). This stage also includes selecting promising ideas, narrowing the scope from broad exploration to focused concepts, and estimating the required resources, timelines, and potential risks before finalizing written concepts that define the project's strategic foundation and direction (Ernst et al., 2010; Munck et al., 2020; Song & Parry, 1997). As such, it plays a pivotal role in the NPD process, with the selected concepts forming the basis for all subsequent stages (Takey & Carvalho, 2016).

In the product development stage, the concept transitions into a tangible product through the translation of abstract ideas into manufacturable prototypes, requiring both design feasibility and alignment with technical constraints (Lu et al., 2024). This stage involves engineering and design refinement, prototype development, and iterative testing to ensure functionality, quality, and compliance with standards. Customer tests and test marketing provide critical insights that guide adjustments to the product's features, usability, and market positioning. In parallel, detailed commercialization planning—including production processes, supply chain setup, and cost optimization—ensures readiness for scale. The stage concludes with an evaluation of market acceptance and the formulation of the overall market launch strategy (Ernst et al., 2010; Munck et al., 2020; Song & Parry, 1997).

The implementation stage marks the product's official market entry, focusing on executing the launch and driving adoption. Targeted sales, advertising, and distribution efforts are complemented by sales enablement, customer onboarding, service training, and partner coordination—tasks that rely heavily on empathy, improvisation, and interpersonal communication (Luo et al., 2021; Munck et al., 2020; Song & Parry, 1997; Stone et al., 2020). Many activities in this stage, particularly in sales, distribution, and after-sales, depend especially in B2B markets on relationship capital, such as trust-based ties with key accounts, distributors, and partners.

2.2. Artificial intelligence

The term "Artificial Intelligence" was introduced by McCarthy in 1956, who envisioned machines capable of learning and problem-solving, akin to human intelligence (Madanaguli et al., 2024; McCarthy et al., 2006; Sheikh et al., 2023). However, a universally accepted definition remains elusive due to the complexity of AI and debates on what constitutes "intelligence" in machines (Bhatnagar et al., 2018; Collins et al., 2021; Sheikh et al., 2023). For this work, we adopt a broad AI definition aligned with the European Commission's High-Level Expert Group on Artificial Intelligence (AI HLEG): "Systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals" (High-Level Expert Group on Artificial Intelligence, 2019). This definition allows for a comprehensive exploration of AI's vast scope without narrowing it unnecessarily, addressing concerns raised by others about the importance of inclusivity in defining AI (Madanaguli et al., 2024; Sheikh et al., 2023).

Although AI builds on conventional IT, it represents a qualitatively distinct class of technologies. Conventional IT operates deterministically, executing predefined routines based on standardized inputs (e.g., Gordon & Tarafdar, 2010; Reid et al., 2016). In contrast, AI processes ill-structured inputs and performs diverse tasks flexibly (e.g., Mariani et al., 2023; Marion et al., 2025). Unlike rule-based, non-adaptive IT systems, AI learns from data and adapts over time, improving performance (e.g., Babina et al., 2024; Durmuşoğlu & Kawakami, 2021).

User roles differ accordingly: conventional IT positions users as operators following predefined workflows, whereas AI involves supervisory or collaborative interaction, guiding and evaluating system outputs. These differences shape value creation: conventional IT primarily delivers efficiency and coordination, while AI augments creativity and knowledge, complemented by efficiency gains from rapid processing of unstructured tasks. AI functions can be broadly classified into originator functions (generating ideas or suggestions) and facilitator functions (enhancing speed and accuracy) (Brem et al., 2023).

Key contingencies also diverge. Conventional IT effectiveness depends on IT support, user training, and data availability (Barczak et al., 2008; Marion & Fixson, 2021). AI effectiveness hinges on data quality, absence of algorithmic bias, and user AI competence (Baumgartner et al., 2024; Chen & Tajdini, 2025; Zha et al., 2025). Table 1 summarizes these distinctions.

2.3. Conventional IT tools and AI tools in new product development

Prior research identifies numerous tools across NPD stages. Conventional IT tools (e.g., idea repositories, structured market research databases, and spreadsheet-based scoring models) support concept development; CAD and PLM systems aid product development; ERP and CRM systems facilitate implementation and launch (e.g., Durmuşoğlu & Kawakami, 2021; Kawakami et al., 2015). These tools are typically tailored to specific functions, offering limited flexibility. Empirical evidence suggests moderate, context-dependent benefits, with the strongest impact during product development (Barczak et al., 2007, 2008; Durmuşoğlu & Barczak, 2011).

AI introduces "smart" tools that operate autonomously and adapt dynamically (Durmuşoğlu & Kawakami, 2021). Examples include generative ideation and predictive modeling in concept development; generative design and rapid prototyping in product development; and adaptive launch strategies and post-launch feedback mining in implementation (e.g., Cooper, 2024b; Mariani et al., 2023; Marion et al., 2024). Early evidence indicates AI tools can reduce cycle times and improve efficiency by up to 50%, while enhancing concept novelty (Cooper, 2024b; Marion et al., 2024, 2025). However, systematic evidence on stage-specific impacts remains scarce. The following sections develop hypotheses and empirically test AI's influence across NPD stages.

Table 2 maps the stage-specific roles of conventional versus AI-based tools in NPD.

Table 1
Differences between conventional IT and AI tools.

Feature/function	Conventional IT tools	AI-powered tools
Processing mode, task structure	Standardized inputs, deterministic, predefined routines (e.g., Gordon & Tarafdar, 2010; Reid et al., 2016)	Ill-structured inputs; probabilistic, flexible processing and outputs (e.g., Mariani et al., 2023; Marion et al., 2025)
Learning capability	None; rule-based and non-adaptive (e.g., Durmuşoğlu & Kawakami, 2021)	Data-driven and adaptive; learning enables performance improvement over time (e.g., Babina et al., 2024; Brem et al., 2023)
User role	Operates the tool by following predefined workflows (e.g., Mauerhoefer et al., 2017; Reid et al., 2016)	Interacts with the tool in supervisory or collaborative roles, guiding and evaluating system outputs (e.g., Baumgartner et al., 2024; Marion et al., 2025)
Value mechanism	Efficiency gains through automation and coordination (e.g., Marion et al., 2015; Mauerhoefer et al., 2017)	Creativity and knowledge augmentation, complemented by efficiency gains from rapid processing of unstructured tasks (e.g., Cooper, 2024b; Marion et al., 2025)
Key contingencies	IT support, user training, data availability (e.g., Barczak et al., 2008; Marion & Fixson, 2021)	Data quality, absence of algorithmic bias, and user AI competence (e.g., Baumgartner et al., 2024; Chen & Tajdini, 2025; Zha et al., 2025)
Typical examples	PLM- (Solidworks PLM), RM-systems (IBM Rational DOORS), E-mail (Microsoft Outlook) (e.g., Marion et al., 2016; Reid et al., 2016)	Generative AI (GPT-4), AutoML, recommender engines (e.g., Cooper, 2024b; Marion et al., 2024)

Table 2
Stage-specific roles of conventional IT vs. AI tools in NPD.

NPD stage	Role of conventional IT tools	Role of AI-based tools
Concept Development	Idea repositories, collaboration portals; support information sharing and coordination; structured market research databases; spreadsheet-based scoring models (e.g., Durmuşoğlu & Kawakami, 2021; Kawakami et al., 2015)	Generative ideation, real-time trend detection, NLP-based idea clustering, automated opportunity recognition and predictive modeling of concept success (e.g., Marion et al., 2024; Marion et al., 2025)
Product Development	PLM and CAD systems; structured design and version control; rule-based simulations and fixed testing protocols (e.g., Durmuşoğlu & Kawakami, 2021; Kawakami et al., 2015)	AI-driven generative design suggestions, parameter optimization, rapid prototyping from unstructured input, AI-based predictive defect detection (e.g., Cooper, 2024b; Marion et al., 2025)
Implementation & Launch	ERP, CRM, and supply chain tools; conventional forecasting and segmentation tools (e.g., Durmuşoğlu & Kawakami, 2021; Kawakami et al., 2015)	Predictive market analytics, adaptive launch strategies, dynamic pricing and personalization, post-launch feedback mining (e.g., Cooper, 2024b; Mariani et al., 2023)

3. Hypotheses development

3.1. AI usage intensity and organizational innovation capability

In this part, we develop hypotheses on the benefits of AI usage across NPD stages. We adopt a capability-based perspective, which focuses on the organizational prerequisites for innovation rather than project-level success. Accordingly, we focus on organizational innovation capability—a firm's ability to identify and respond to innovation opportunities through effective coordination, responsiveness to market demands, and reduction of internal inefficiencies (Forsman, 2011; Gold et al., 2001; Lawson & Samson, 2001). These capabilities span key innovation-enabling functions throughout the NPD process, including recognizing new business opportunities, coordinating development efforts across different units, and avoiding overlapping initiatives (Forsman, 2011; Gold et al., 2001; Lawson & Samson, 2001). This perspective is beneficial because it captures the enduring capacities that enable firms to repeatedly generate and implement innovations, offers a holistic view of how AI tools influence performance over time, and aligns with research emphasizing dynamic capabilities as central drivers of competitive advantage in innovation management (Rothaermel & Hess, 2007).

Prior work highlights the growing role of AI in enhancing analytical capabilities, decision-making, and coordination across NPD stages (e.g., Cooper, 2024a; Cubric & Li, 2024; Marion et al., 2025; Pescher & Tellis, 2025). AI tools are increasingly embedded in activities such as idea generation, prototyping, and market implementation, offering considerable potential to build and reinforce these innovation capabilities over time (e.g., Bouschery et al., 2023; Cooper, 2024b; Marion et al., 2024). Yet, despite the broadening application of AI, little is known about how the intensity of AI usage at different NPD stages contributes to strengthening organizational innovation capability.

We propose that the usage of AI tools can contribute to all three stages of NPD. In the concept development stage, AI leverages its ability to rapidly and flexibly process ill-structured data and to learn and improve over time, enabling organizations to extract insights from vast datasets (e.g., reports from sales representatives) (Babina et al., 2024; Marion et al., 2025; Pescher & Tellis, 2025). By analyzing, organizing, and identifying patterns in complex market and organizational data, AI reduces informational redundancy, enhances early-stage insight generation, and helps firms uncover novel business opportunities grounded in data-driven evidence (Bouschery et al., 2023; Marion et al., 2025). For instance, Bouschery et al. (2023) demonstrate that transformer-based language models can significantly enhance innovation team performance by uncovering patterns and insights in extensive market data that would be impossible for humans to analyze manually.

Beyond data processing and analysis, AI systems increasingly exhibit generative capabilities, enabling the creation of novel product concepts during the ideation phase. As shown by Marion et al. (2025), AI-augmented platforms such as LUCID can synthesize large-scale customer input to generate and evaluate thousands of product ideas in real time, thereby identifying design opportunities and unmet customer needs that would likely remain undetected through conventional methods. These use cases underscore AI's dual role in enhancing data-driven decision-making and fostering creativity, particularly by enabling the early recognition of emerging customer demands and innovation potentials. Taken together, these capabilities position AI tools as especially valuable in the concept development stage, where early insights and creative exploration are critical for downstream innovation success. Given these findings and AI tools' ability to process ill-structured inputs, generate creative outputs, and learn over time, their use in concept development can substantially enhance innovation capability by enabling early detection of customer needs and improving market responsiveness (Cooper, 2024b; Marion et al., 2025).

In the product development stage, AI tools play a pivotal role in design creation, evaluation, and testing (Cooper, 2024b; Marion et al., 2024; Nieto-Rodriguez & Vargas, 2023). Generative design tools can create prototypes from initial specifications, while predictive modeling simulates consumer responses to product designs based on aesthetic and functional elements (Bilgram & Laarmann, 2023; Eastwood, 2024; Marion et al., 2024). These capabilities help organizations reduce redundant development paths and concentrate resources on the most promising concepts. For instance, General Motors leverages predictive models to identify and eliminate designs unlikely to resonate with customers, achieving cost savings of up to $100,000 per design and improving responsiveness to shifting customer expectations (Eastwood, 2024).

Beyond design, AI accelerates testing through virtual prototyping, enabling rapid iterative improvements before physical production (Bilgram & Laarmann, 2023; Cooper, 2024b; Nieto-Rodriguez & Vargas, 2023). In biotechnology, AI-driven rapid testing has proven particularly valuable; for example, Moderna used this approach to expedite the development of its mRNA COVID-19 vaccine (Euchner & Iansiti, 2020). AI tools also enhance physical product evaluation by detecting weaknesses in prototypes, shortening development cycles, and ensuring alignment with consumer preferences (Cooper, 2024b). Collectively, these features suggest that AI tools—by integrating complex design inputs, simulating customer reactions from extensive training data, and collaborating with development teams—can streamline product development, improve alignment between technical feasibility and market expectations, enhance coordination, and reduce redundant efforts (e.g., Baumgartner et al., 2024; Marion et al., 2025).

During the implementation stage, AI supports tasks such as market analysis, customer engagement management, supply chain coordination, and sales optimization (Cooper, 2024b; Cooper & McCausland, 2024; Marion et al., 2024). AI tools are particularly promising in tailoring marketing strategies to specific target segments and prevailing market conditions. For example, Google's targeted advertising algorithms enhance firms' responsiveness to shifting market demands (Cooper, 2024b). Similarly, generative AI tools can create images, videos, and textual content, enabling more efficient innovation marketing (Deeb, 2023).

In sales and distribution, AI tools facilitate advanced demand forecasting, helping organizations optimize inventory levels and pricing strategies to reduce response times to market fluctuations (Cooper, 2024b). Procter & Gamble, for instance, uses AI to predict sales volumes and streamline stock management—an approach especially valuable for new product launches (Cooper, 2024b). AI also plays a crucial role in post-launch activities, analyzing customer feedback and competitor data to anticipate emerging opportunities and guide product adjustments that strengthen market position (Cooper & McCausland, 2024; Marion et al., 2024). Collectively, these capabilities suggest that AI tools—through predictive analytics, adaptive learning from real-time data, and rapid responsiveness to market changes—can enhance implementation and launch activities by anticipating market needs, improving market fit, and decreasing response times to post-launch dynamics.

Taken together, these stage-specific insights suggest that greater overall AI usage intensity is likely to enhance organizational innovation capability across all three NPD stages. Accordingly, we hypothesize:

Hypothesis 1. AI usage intensity throughout all stages of NPD increases organizational innovation capability.

Hypothesis 1a. AI usage intensity in the conceptual development stage of NPD increases organizational innovation capability.

Hypothesis 1b. AI usage intensity in the product development stage of NPD increases organizational innovation capability.

Hypothesis 1c. AI usage intensity in the implementation stage of NPD increases organizational innovation capability.

3.2. *Varying effects of AI usage across the stages of the new product development process*

While we propose that AI tool usage across all stages of the NPD process enhances an organization's innovation capability, we argue that these benefits are asymmetrical—with the greatest effects occurring in the early stages and diminishing marginal effects in the later stages. This argument rests on the specific functions that AI tools provide and the differing requirements of each NPD stage.

AI functions can be broadly categorized into two roles: originators, which autonomously generate novel ideas or artifacts, and facilitators, which accelerate processes or enhance the accuracy of tasks that humans would otherwise perform more slowly or less precisely (Cooper, 2024b; Cooper & McCausland, 2024). We argue that these functions play distinct roles across the NPD stages, critically determining the extent to which the use of AI tools at different stages contributes to an organization's innovation capability.

The concept development stage—often referred to as the “fuzzy front end”—is highly digital and knowledge-intensive, involving creative ideation, exploration of market gaps, and rapid iteration (Marion et al., 2025; Takey & Carvalho, 2016). In this stage, organizations face a broad set of possibilities that must be narrowed into promising concepts amid considerable uncertainty and ambiguity. AI originator functions are well suited to this challenge, leveraging vast datasets to generate a wide variety of novel ideas. Recent studies demonstrate that large language models can even outperform seasoned professionals in creative ideation tasks (Eisenreich et al., 2024; Li et al., 2024; Marion et al., 2024). These originator functions are particularly powerful when combined with human input, as such collaboration can create unique synergies that surpass the capabilities of either humans or AI alone under the right conditions (Vaccaro et al., 2024).

AI facilitators, in turn, play a crucial role by systematically analyzing and synthesizing unstructured data sources—such as patent abstracts, user reviews, or social media posts—within minutes. This enables the identification of opportunities and latent trends far beyond the reach of manual analysis (Kakatkar et al., 2020; Schemmann et al., 2016). Such capabilities accelerate the discovery of promising domains and help teams align initial concepts with emerging customer needs. Moreover, AI facilitators support convergence by rapidly evaluating and prioritizing concepts based on criteria such as technical feasibility, market potential, and strategic alignment. This accelerates the transition from a broad idea pool to a focused set of viable concepts, enabling teams to enter subsequent development stages with greater clarity and confidence.

Some AI systems even combine originator and facilitator functions, creating synergies that deliver greater value than either function alone. A prominent example is the LUCID platform described by Marion et al. (2025), which integrates large-scale customer analytics (facilitator) with generative algorithms (originator) to draft and iteratively refine thousands of product design variants. In one instance, LUCID distilled insights from more than one million customer reviews into novel, data-validated concepts in under a minute—compressing what had previously been a multi-month front-end cycle into seconds (Marion et al., 2025).

In sum, AI tools are particularly valuable in the concept development stage because they combine creative generation with systematic analysis, accelerating the transition from broad exploration to focused concept selection and providing organizations with a decisive advantage in navigating the uncertainty and complexity of the early innovation process.

As projects move into product development, the nature of tasks changes fundamentally. Abstract concepts must now be translated into manufacturable prototypes, requiring both design feasibility and alignment with technical constraints (Lu et al., 2024). At this stage, the originative role of AI diminishes markedly (Brem et al., 2023). While generative models can still produce rich design spaces, many outputs are “completely unmanufacturable” without expert re-engineering (Booth et al., 2024). Creativity reaches its peak only when human designers iteratively refine AI-generated proposals through tangible prototypes that reveal quality and usability issues invisible in virtual form (Zhang et al., 2024).

Likewise, recent research in smart manufacturing suggests that full factory automation remains unlikely in the near term, as human involvement is still essential for managing complexity, ensuring operational flexibility, and resolving last-mile issues on the shop floor

(Sidorenko et al., 2023). Moreover, the wide variety of conventional IT tools already firmly established in many organizations to support product development limits the additional value that AI tools can provide.

Overall, we propose that AI continues to offer facilitative support—for example, by identifying redundancies in concurrent workflows or optimizing parameter ranges (Cooper, 2024b; Zhang et al., 2024)—but its contribution to overall innovation capability is lower than in the concept development stage.

In the implementation stage, the strategic contribution of AI tools further diminishes, as success depends less on creative ideation or analytics and more on human-centered execution. Tasks such as sales enablement, customer onboarding, service training, and partner coordination require empathy, improvisation, and interpersonal communication—areas where the abilities of AI systems remain limited (Luo et al., 2021; Munck et al., 2020; Song & Parry, 1997; Stone et al., 2020). Likewise, many implementation-stage activities, particularly in sales and distribution, rely on relationship capital, including trust-based ties with key accounts, distributors, and partners—relational dynamics that AI cannot effectively navigate. These soft-skill-intensive tasks demand emotional nuance and situational judgment, especially in high-stakes or trust-sensitive settings. Reflecting these limitations, studies show that customers consistently prefer human interaction over AI in emotionally charged or complex situations, particularly when credibility, contextual adaptation, or lived experience is required (Castelo et al., 2023; Jeyapriya & Suganthi, 2025; Jin & Zhang, 2025; Markovitch et al., 2024).

While AI may still support tasks such as monitoring market signals, surfacing real-time feedback, or tracking competitor activity (Cooper & McCausland, 2024; Marion et al., 2024), its role in this stage remains largely facilitative rather than strategic. Compounding this limitation is the strong presence of well-established implementation-stage systems—such as ERP, CRM, and SCM platforms—that already govern many executional routines. Accordingly, we argue that in the implementation stage, AI tools contribute comparatively little to the enhancement of higher-order innovation capabilities.

Synthesizing this stage-contingent argumentation, we propose a diminishing dual-mode advantage of AI: its steepest returns materialize when both originator and facilitator functions can be exploited in parallel, as in the conceptual stage. As the process advances, however, the originator function becomes less relevant, and AI contributes only as a facilitator, while human expertise, tacit knowledge, and interpersonal trust dominate decision processes. This progressive mismatch between AI capability and task requirements results in a declining marginal effect of AI usage intensity on organizational innovation capability. Accordingly, we hypothesize:

Hypothesis 2. The effect of AI usage intensity on organizational innovation capability decreases across the NPD process stages.

Hypothesis 2a. The effect of AI usage intensity on organizational innovation capability is strongest during the conceptual development stage.

Hypothesis 2b. The effect of AI usage intensity on organizational innovation capability decreases during the product development stage.

Hypothesis 2c. The effect of AI usage intensity on organizational innovation capability is weakest during the implementation stage.

3.3. The moderating role of AI competence

While prior research increasingly emphasizes the potential of AI tools to enhance innovation activities such as ideation, development, and commercialization (e.g., Cooper, 2024b; Marion et al., 2025; Pescher & Tellis, 2025), these tools do not create value in isolation. Their effective application depends heavily on the skills, knowledge, and experience of the employees who use them (e.g., Baumgartner et al., 2024; Chen & Tajdini, 2025; Horvat & Heimberger, 2023; Keegan et al., 2022; Tekic & Füller, 2023). Supporting this notion, the recent Artificial Intelligence Index Report 2025 identifies skill shortages in AI competence as a key barrier to effective AI adoption (Maslej et al., 2025). Relevant competencies go beyond technical proficiency to include the ability to understand task characteristics, judge when and how to apply AI, and interpret its outputs meaningfully in light of domain-specific goals (Piller et al., 2024).

To conceptualize this human-centric enabler, we build on well-established literature on IT competence, which frames the technological capabilities of employees as critical to the effective use of information systems (e.g., Chakravarty et al., 2013; Ravichandran, 2018; Tippins & Sohi, 2003). Extending this logic to the context of AI, we adopt recent conceptualizations of AI competence, defining it as the aggregated knowledge, skills, and experience of a firm's workforce in using AI tools (Baumgartner et al., 2024; Mikalef et al., 2023).

Although conclusive empirical research explicitly linking AI competence to NPD—particularly its stage-specific influence—remains limited, recent exploratory and conceptual work provides indications that such competence is crucial for the effective use of AI in NPD (Baumgartner et al., 2024; Bilgram & Laarmann, 2023; Marion et al., 2025). Building on these insights, we posit that AI competence enhances the extent to which AI usage intensity translates into an organization's innovation capabilities.

This moderating effect likely unfolds differently across the stages of NPD. In the concept development stage, AI competence may facilitate high-quality usage by helping employees structure unrefined inputs, craft effective prompts, and critically evaluate outputs. These capabilities support iterative concept refinement and alignment with latent customer needs and emerging demands. While AI has shown strong performance in idea screening, recent research emphasizes that human expertise remains essential for final selection decisions, underscoring the importance of user competence in balancing automation with judgment (Bell et al., 2024; Pescher & Tellis, 2025). For example, Bilgram and Laarmann (2023) illustrate how users with contextual and technical understanding can leverage large language models (LLMs) to support activities such as idea generation, need exploration, and early-stage prototyping.

During the product development stage, AI competence is critical for concrete design tasks such as generating usable code, creating clickable prototypes, and iterating design variants. These practices can accelerate build–test cycles, increase design precision, and reduce redundant rework caused by early-stage misalignments. Bilgram and Laarmann (2023) provide practical examples of how technically literate staff use generative AI to translate natural language into HTML code and UI structures, thereby lowering barriers to prototyping and shortening iteration timeframes.

In the implementation stage, effective AI usage requires employees to interpret outputs, adjust strategies in near real time, and sustain AI-supported operations. These tasks depend on key AI competences, including the ability to make data-driven decisions and adapt AI-generated insights to dynamic customer feedback. For instance, extant research suggests that with strong foundational, development, and utilization competences, AI-generated insights can be used to optimize product–market fit and enhance responsiveness to shifting customer expectations during later stages (Baumgartner et al., 2024; Marion et al., 2025).

Taken together, these insights suggest that across all NPD stages, AI competence plays an important enabling role in the relationship between AI usage and an organization's capability to innovate successfully. Accordingly, we hypothesize:

Hypothesis 3. AI competence moderates the effect of AI usage intensity on organizational innovation capability throughout all NPD stages.

Hypothesis 3a. AI competence strengthens the effect of AI usage intensity on organizational innovation capability in the conceptual development stage.

Hypothesis 3b. AI competence strengthens the effect of AI usage intensity on organizational innovation capability in the product development stage.

Hypothesis 3c. AI competence strengthens the effect of AI usage intensity on organizational innovation capability in the implementation stage.

Fig. 1 summarizes our research model and the corresponding hypotheses.

4. Empirical study

4.1. Sample description

To test our hypotheses, we conducted a cross-sectional online survey in early 2024 and engaged a German market research provider to recruit suitable respondents. The key criterion was that participants possess deep, first-hand knowledge of their firm's NPD activities. To ensure this, the provider pre-selected only full-time employees in middle or upper management who, according to panel records, held responsibility for innovation, R&D, technology, digital transformation, or AI projects in companies with 50 or more employees. In addition to this pre-screening, screening questions were used to confirm compliance with the selection criteria. Participants who did not meet these criteria or failed an attention check within the survey were excluded. Following this procedure, 400 participants who held managerial authority in an innovation-relevant function and could credibly assess AI usage within the NPD process constituted the final sample.

The respondents had an average age of 43 years, with a gender distribution of 56% men and 44% women. Educational attainment in the sample is high: 217 respondents (54.25%) hold a university degree, 96 (24.00%) report a high-school diploma, 55 (13.75%) completed vocational training, 27 (6.75%) report secondary school, 3 (0.75%) elementary school, 2 (0.50%) selected “other,” and none reported “no degree.” We use “university degree” to denote tertiary education in the German context, comprising Bachelor's, Master's, the traditional German Diplom, and PhD degrees (i.e., not only postgraduate degrees in the Anglo-American sense). The participants reported an average of 20 years of professional experience and 13 years with their current employer. They all held management positions, with 79% in middle management and 21% in upper management.

As mentioned, all respondents were screened, by the panel provider and via an internal filter, to ensure managerial responsibility and first-hand knowledge of NPD and digital/AI tool usage; cases indicating “no management position” were screened out. Consistent with German practice, particularly in small and medium-sized enterprises (SMEs), some managers follow non-tertiary vocational tracks (e.g., master craftspersons, state-certified technicians, foremen) yet hold decision-relevant roles in NPD and AI adoption; their inclusion reflects the managerial reality of the target population. Regarding their functional roles, the majority of respondents were department heads (67%), followed by management assistants (15%) and executive managers (11%). Respondents' activities were spread across corporate divisions, with marketing and sales (22%), research and development (20%), strategy and planning (30%), and human resources (28%) well represented.

The sample included companies of various sizes. Medium-sized companies (30%) with 50 to 250 employees and large companies (26%) with 1000 to 10,000 employees accounted for the majority of firms. Sector representation was diverse, with IT (16%), wholesale and retail (14%), and financial services (12%) being the most prominent. On average, the companies had been in operation for 45 years and had engaged in digital transformation for eight years. Comprehensive demographic and organizational details are provided in Appendix Table A-

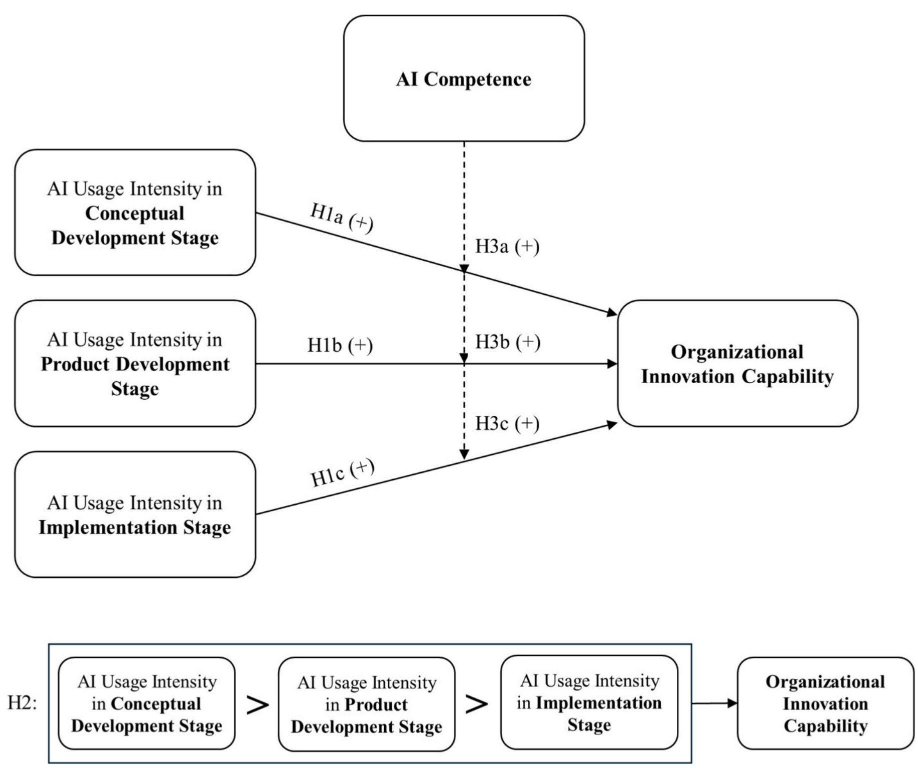

Fig. 1. Research model.
Notes: The ‘+’ in parentheses indicates that the hypothesis postulates a positive effect.
The dotted line indicates a moderating influence.
The ‘>‘indicates that the hypothesis postulates a stronger effect.

1.

4.2. Measures

To measure the variables in our research model, we relied on validated measurement models, which were adapted or modified as needed to suit the study's context. Respondents answered all items using seven-point Likert scales.

The degree of AI usage intensity in the three NPD stages (conceptual development, product development, and implementation) was measured using scales adapted from Munck et al. (2020). The Likert scales ranged from 1 ("very low") to 7 ("very high"). Notably, all items capturing the degree of AI usage intensity relate specifically to NPD functions within the respective stages, deliberately excluding unrelated activities (e.g., branding tasks such as logo or slogan design).

In the scale for the conceptual development stage, respondents rated AI usage intensity in tasks such as idea generation, analyzing market trends and potentials, or preparing product concepts. In the product development stage, participants assessed AI usage intensity in tasks such as developing prototypes, executing prototype test, or evaluating market potential. AI usage intensity in the implementation stage was measured through tasks such as product training for customers, after-sales support, or monitoring competitor reactions.

To measure AI competence, we adapted Chakravarty et al.'s (2013) five-item IT-capabilities scale to the AI context and retained the four items that focus explicitly on human skills. Respondents indicated on a 7-point Likert scale (1 = "Does not apply at all" to 7 = "Fully applies") the extent their organization's employees possess experience, knowledge, and skills in the use of AI tools. Organizational innovation capability was measured using seven items from Gold et al. (2001), which capture key dynamic capabilities considered prerequisites for organizational success (e.g., coordination of development efforts, anticipation of market opportunities, and market response times). The exact item wording for all variables is provided in Appendix Table A-2.

To address potential confounding factors, control variables related to both the individual respondents (age, gender, education, position level) and their organizations (number of employees, organizational age) were collected and incorporated into the analysis. Including these control variables enhances the reliability and validity of the results by reducing the influence of external factors. This, in turn, enables a clearer understanding of the dynamics under investigation and strengthens the overall analysis (Becker et al., 2016).

4.3. Common method bias

Given that both independent and dependent variables were assessed through the same survey using similar response scales, there is a potential risk of common method variance. To minimize potential common method bias, we employed several procedural remedies. Respondents were assured of anonymity and confidentiality, informed that there were no "correct" answers, and encouraged to provide honest responses; in addition, we relied on established, validated measurement instruments and presented items for the independent and dependent variables on separate pages of the survey (Klein et al., 2021; Podsakoff et al., 2003).

Furthermore, we statistically tested for common method bias using the full collinearity assessment approach proposed by Kock (2015), which is designed to detect both vertical and lateral collinearity and thus serves as a proxy for common method bias (CMB). Following Kock's procedure, we conducted the full collinearity test by regressing all latent variables on a dummy variable (Kock & Lynn, 2012). All resulting VIF values were below the recommended threshold of 3.3, indicating that common method bias is unlikely to have substantially distorted the results. We additionally performed Harman's single-factor test, which showed that no single factor accounted for more than half of the total variance. Together with the full collinearity assessment approach, this suggests that common method bias is unlikely to be a major concern in our data (Klein et al., 2021). Beyond these tests, we estimated an unmeasured latent methods construct (ULMC) that loaded on duplicated versions of all reflective indicators in parallel with the substantive constructs (Kock et al., 2021; Podsakoff et al., 2024). *Re*-estimating the model with the ULMC yielded substantively identical results: all structural coefficients retained their signs and significance, changes in coefficient magnitudes were negligible, and the R^2 values were virtually identical to those of the baseline model. Overall, these diagnostics indicate that common method bias is unlikely to drive our findings.

4.4. Analysis and results

Our data analysis employed structural equation modeling (SEM), a robust technique for simultaneously analyzing large datasets and uncovering complex relationships (MacKenzie, 2001; Steenkamp & Baumgartner, 2000). SEM is particularly effective in addressing measurement error and generating reliable validity metrics. For this study, we adopted the component-based partial least squares (PLS) SEM approach, which performs more robustly than covariance-based SEM when dealing with non-normal data and moderately large samples (Chin & Newsted, 1999; Hair et al., 2022).

All calculations were conducted using SmartPLS 4.0 and non-parametric bootstrapping ($n = 5000$). All constructs were specified as conceptually reflective. Following the logic of PLS-SEM, the estimated construct scores represent composite proxies of the underlying conceptual variables; accordingly, structural path coefficients should be interpreted as relationships among these composite proxies rather than factor-consistent latent variables (Hair et al., 2022).

Following established procedures (e.g., Chin, 1998; Hair et al., 2022), we assessed quality criteria at both the measurement and structural model levels. The measurement model evaluation indicated compliance with standard quality benchmarks for reflective models (see Appendix Table A-2, Hair et al., 2022). All indicator loadings exceeded the threshold of 0.70, indicating strong indicator reliability. Composite reliabilities (CR) surpassed the critical value of 0.70, providing evidence of internal consistency (Bagozzi & Yi, 1988). AVE values exceeded 0.50 for all constructs. Importantly, in PLS-SEM, AVE is considered a conservative, factor-oriented indicator rather than a decisive validity criterion (Hair et al., 2022).

To assess discriminant validity, we employed the Heterotrait-Monotrait (HTMT) ratio of correlations (Henseler et al., 2015) and the Fornell-Larcker criterion (Fornell & Larcker, 1981). While the HTMT scores for AI usage intensity across the sequential NPD stages exceeded the conservative 0.85 threshold—reaching a maximum of 0.949 (see Appendix Table A-3)—they remained strictly below the 1.0 criterion. To further validate these results, we conducted a bootstrap analysis (5000 subsamples) to derive 95% bias-corrected and accelerated (BCa) confidence intervals for the HTMT values. The analysis confirms that the upper bound (97.5%) for all construct pairs remains strictly below the 1.0 threshold (maximum $CI_{upper} = 0.979$), providing statistical evidence of discriminant validity. Given that three predictors (i.e., AI usage intensity in the different stages) represent conceptually related phases of a single functional process, this degree of overlap is theoretically expected. Supporting this, the Fornell-Larcker criterion was met, as the AVE of each construct exceeded its squared correlation with all other constructs. Furthermore, inner model Variance Inflation Factors (VIF) remained below the threshold of 5.0 (see Appendix Table A-4), confirming that multicollinearity does not distort the structural model results (Hair et al., 2012).

The structural model demonstrated an acceptable fit, with an R^2 value of 0.532 for organizational innovation capability (Hair et al., 2022). As described, all VIF remained below the threshold of 5. Estimation results (see Fig. 2) indicate that AI usage intensity positively influenced organizational innovation capability across three NPD stages: conceptual development ($\beta = 0.321$, $p < .001$), product development ($\beta = 0.226$, $p < .01$), and implementation ($\beta = 0.195$, $p < .05$), supporting

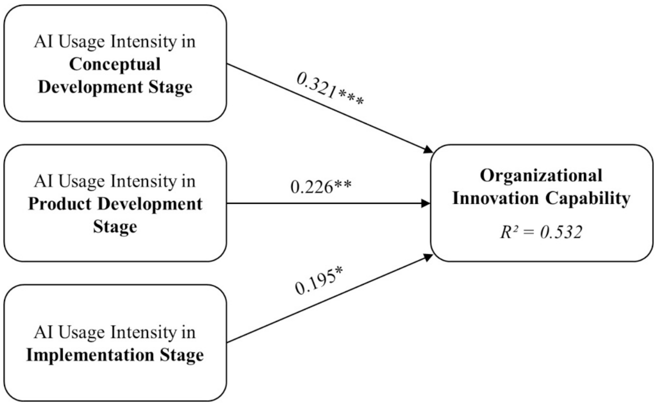

Fig. 2. Structural model results.
Notes: *** significant at $p < .001$, ** significant at $p < .01$, * significant at $p < .05$.
Controls: age, education, gender, number of employees, organization age, position line (Appendix Table A-5).

Hypotheses H1a–H1c. Furthermore, in line with Hypotheses H2a–H2c, the effect of AI usage intensity was strongest in the conceptual development stage, followed by the product development stage, and weakest in the implementation stage. Accordingly, the results confirm the proposed diminishing impact of AI usage intensity across the NPD stages. All path coefficients and t-values, including those associated with the control variables, are reported in Appendix Table A-5.[1]

The moderating effect of AI competence on the relationship between AI usage intensity and organizational innovation capability across the three NPD stages (H3) was tested using interaction analysis with the Interaction software package (Soper, 2011). All analyses were computed based on standardized values (z-scores) of the focal variables prior to constructing the interaction terms. The results show that all interaction terms had a significant positive influence on organizational innovation capability (conceptual development: $\beta = 0.097$, $p < .01$; product development: $\beta = 0.090$, $p < .01$; implementation: $\beta = 0.113$, $p < .001$). This indicates that higher (lower) AI competence strengthens (weakens) the positive effect of AI usage intensity on organizational innovation capability across all NPD stages. Consequently, H3 is supported. Fig. 3 presents the stage-specific interaction plots.

5. Conclusion

5.1. Theoretical implications

The influence of AI across industries is rapidly expanding causing profound and enduring changes. Although prior research has demonstrated AI's potential to enhance NPD activities such as idea generation, prototyping, and market implementation (e.g., Bouschery et al., 2023; Marion et al., 2024; Pescher & Tellis, 2025), important gaps remain in understanding how AI usage across the different stages of the NPD process shapes an organization's innovation capability. Furthermore, existing studies offer only limited insights into the contingency factors influencing the benefits of AI tools in NPD. By addressing these gaps, this study provides stage-specific evidence of AI's impact on innovation capability and identifies organizational competencies that amplify its effectiveness, thereby advancing the innovation literature on AI-enabled NPD.

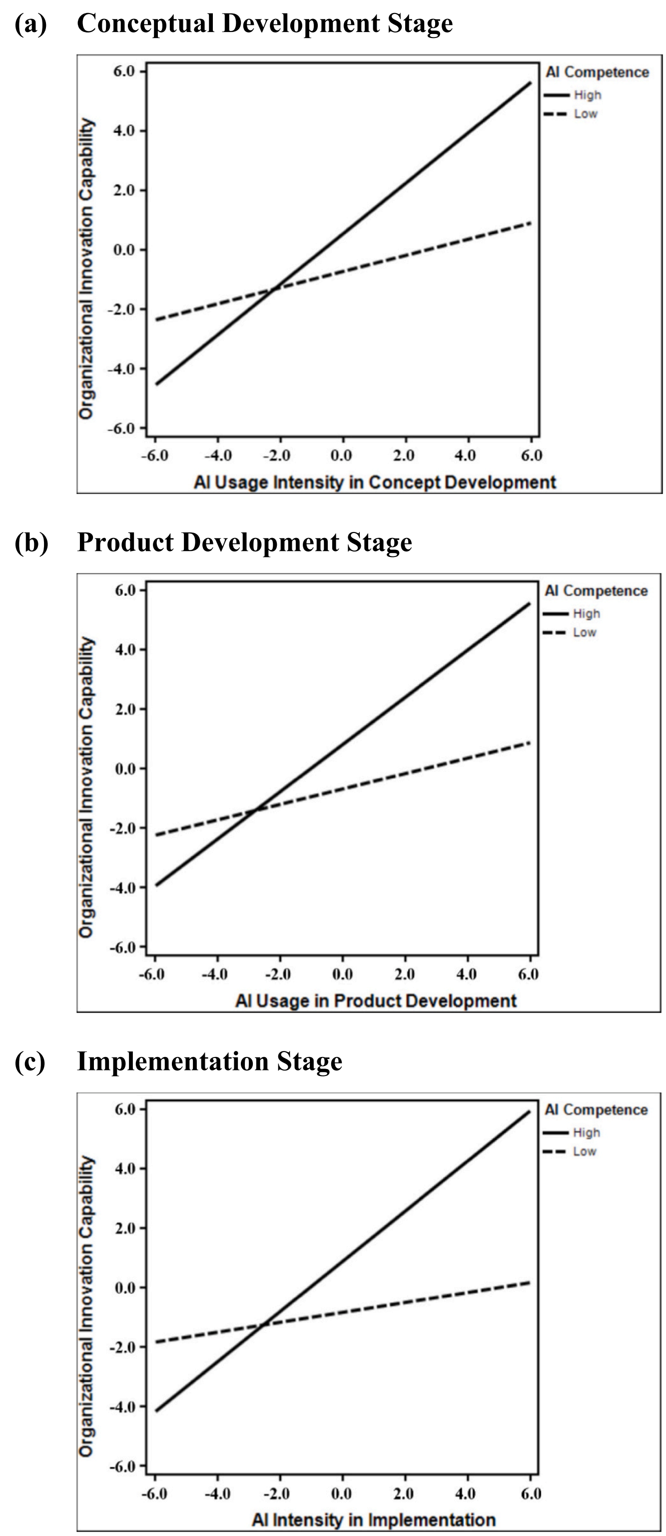

Fig. 3. Interaction effect plots of moderating effects of AI competence and AI usage intensity on organizational innovation capability, in: (a) conceptual development stage, (b) product development stage (c) implementation stage.

[1] It must be noted that some participants provided information that can be viewed implausible or questionable (four reported very short professional experience, three reporting very young firm age, and one reporting an implausible "length of service with digital transformation"). Accordingly, to test the robustness of our results, we re-estimated the measurement and structural models after excluding these eight cases. All structural relationships remained directionally consistent, with comparable magnitudes and significance (differences only at the third decimal). In line with methodological recommendations to avoid excluding observations solely on suspicion when focal measures appear meaningful (Aguinis et al., 2013; Edwards, 2019), and given the robustness of the results, we retained the full sample in our main analysis.

First, our research provides robust empirical evidence that AI usage intensity within the NPD process has a significantly positive impact on organizational innovation capability. Unlike prior studies that predominantly examined either individual AI tools, overall AI adoption, or focused solely on single NPD stages (e.g., Cooper, 2024a, 2024b; Marion et al., 2024, 2025; Pescher & Tellis, 2025), our findings offer a more comprehensive perspective by showing that AI usage at each stage of the NPD process can positively contribute to a firm's innovation capability. Our stage-specific analysis highlights the cumulative benefits of integrating AI across multiple NPD stages, demonstrating that the influence of AI tools extends beyond specific NPD projects, enabling organizations to build capacities to identify and respond to innovation opportunities through effective coordination, responsiveness to market demands, and the reduction of internal inefficiencies. With these insights, we respond to recent calls for more granular investigations into the role of AI in NPD processes (Cooper, 2024a), showing that AI is not merely a supplementary tool but a strategic enabler that, when systematically embedded throughout the NPD process, enhances creativity, decision-making, and overall innovation performance.

Second, while our research confirms the positive impact of AI usage intensity on organizational innovation capability across all NPD stages, it also uncovers a previously underexplored dynamic: the diminishing marginal effect of AI usage as projects progress through the NPD process. Specifically, our findings show that AI use during concept development exerts the strongest influence on innovation capability, with these effects declining progressively in the product development and implementation stages. This pattern challenges prior assumptions that AI maintains uniformly high effectiveness across all NPD stages (Cooper & Brem, 2024; Marion et al., 2024). Moreover, our theoretical development provides initial insight into factors causing stage-specific differences in AI's benefits. In concept development, AI's value lies in its dual role as both originator (e.g., autonomously generating novel ideas) and facilitator (e.g., analyzing unstructured data). Its creative originator function, in particular, distinguishes AI from conventional IT tools and delivers unique advantages at this stage. As projects advance, the need for AI as an originator diminishes, reducing its incremental contribution to innovation capability. In the product development and implementation stages, AI continues to serve as an important facilitator—supporting tasks such as design creation and demand forecasting—but with fewer creativity-intensive demands, its edge over well-established conventional IT tools narrows. Moreover, with additional progress in the NPD process, the importance of human expertise, physical interaction, and emotional intelligence increase limiting the benefits of AI tools (Canuto da Silva & Kaminski, 2016; Luo et al., 2021; Munck et al., 2020; Ricca et al., 2021; Salehi & Burgueño, 2018; Stone et al., 2020). These insights offer a nuanced perspective on the value of AI tools across NPD stages and should guide researchers in developing more stage-contingent theorizing about AI's role in innovation processes. Our findings on the stage-specific effects of AI tools in NPD parallel earlier research on conventional IT usage in NPD, which also indicates that the effectiveness of digital tools varies by stage (Durmuşoğlu & Barczak, 2011; Durmuşoğlu & Kawakami, 2021). However, the pattern of stage effectiveness differs markedly between AI tools and conventional IT tools. Prior studies found that IT tools yielded the greatest benefits during the product development stage (e.g., Durmuşoğlu & Barczak, 2011), whereas our results show AI tools to be most impactful during concept development. These contrasting patterns underscore fundamental differences between AI and conventional IT tools, suggesting that insights on IT use in NPD cannot be directly transferred to the AI era.

Third, our study highlights the moderating role of AI competence in enhancing the positive effects of AI usage intensity. Specifically, employees with advanced AI proficiency represent a critical resource that amplifies the transformative potential of AI across all NPD stages. This finding aligns with and extends theoretical models like the resource-based view (Barney, 1991, 2001; Brock & von Wangenheim, 2019), which emphasize the synergy between technological and human resources in achieving competitive advantages (Dąbrowska et al., 2022; Hwang & Seo, 2025). In comparison to prior studies on IT adoption, such as Gallivan et al. (2005), who demonstrated that coworker training quality and collective IT usage significantly influenced individual adoption behaviors, and Pan et al. (2022), who identified the role of technological competence in enhancing AI adoption, our work advances the discussion by providing one of the first empirical validations of these relationships in the context of NPD. In doing so, our findings respond directly to recent calls for more empirical research on the organizational-level competences required for successful AI-based innovation (Baumgartner et al., 2024; Brem et al., 2023), which remain insufficiently understood despite growing awareness of their strategic importance. By empirically demonstrating that human-AI synergy, particularly through enhanced AI proficiency, is critical to unlocking the full potential of AI-driven innovation, our study contributes to a nuanced understanding of the dynamic interplay between technical and human capabilities (Dąbrowska et al., 2022; Hwang & Seo, 2025; Tekic & Füller, 2023). This includes not only technical know-how, but also the contextual judgment required to understand the nature of tasks, assess when and how to apply AI tools, and interpret their outputs meaningfully in light of domain-specific goals (Piller et al., 2024; Tekic & Füller, 2023). Overall, these findings provide a theoretical foundation for future research on how organizational readiness and workforce development can enhance the adoption and performance of AI tools in innovation processes.

5.2. *Managerial implications*

While AI is widely recognized for its potential to revolutionize the NPD process by enhancing both effectiveness and efficiency (e.g., Cooper, 2024a, 2024b; Cooper & Brem, 2024; Pescher & Tellis, 2025; Piotrowski, 2024), actual adoption in practice remains limited (Singla et al., 2025). Many organizations are still in early experimentation or pilot phases, often constrained by resource shortages, integration challenges, or uncertainty regarding tangible returns. Against this backdrop, our findings underscore that integrating AI technologies into NPD processes is no longer optional but a strategic necessity for firms aiming to maintain competitiveness in the digital age. This is particularly true in B2B markets, where longer innovation cycles, greater complexity, and the need for cross-functional coordination prevail (Ehret et al., 2024; Lievens & Blažević, 2021; Tsai & Hsu, 2014). In such contexts, high investment volumes, multi-stakeholder dependencies, and narrow customer bases mean that product failures carry significant consequences, further highlighting the importance of robust innovation capabilities that AI can help develop (Amankwah-Amoah et al., 2024; Najafi-Tavani et al., 2023). Our findings offer critical insights into the benefits of broader AI adoption in NPD, as well as strategic guidance for effective implementation.

First, the consistent and strategic application of AI across all NPD stages significantly enhances organizational innovation capability. Managers should therefore embed AI throughout the entire process—from concept development to implementation—rather than limiting it to isolated tasks or stages. This requires not only deploying AI technologies but also increasing their usage intensity at each stage. A deliberate and well-orchestrated integration strategy enables organizations to leverage AI's strengths in data analysis, ideation, and decision-making, driving superior innovation outcomes and fostering sustained success. Importantly, AI applications should be tailored to the unique demands of each stage while remaining aligned with overarching innovation goals. Redesigning NPD workflows, communication channels, and data-sharing structures to support seamless AI integration can further amplify these benefits.

Second, the diminishing marginal effectiveness of AI usage as projects progress from concept development to later stages offers critical guidance for resource allocation. Managers should adopt a stage-contingent investment approach, prioritizing AI in concept development—where its capabilities in ideation, market analysis, and trend forecasting deliver the highest returns—especially when resources are limited. Organizations with greater capacity can also enhance AI's value in later stages, such as product development and implementation, by addressing limitations related to nuanced customer interactions, advanced testing, and integration with physical processes. Process optimization, tailored workflows, and robust feedback mechanisms are effective ways to strengthen later-stage performance. A hybrid strategy, adapted to the organization's resources and maturity level, can deliver both immediate gains and long-term adaptability to evolving AI capabilities.

Third, building organizational capabilities is pivotal for maximizing AI's impact. Companies should prioritize developing AI proficiency across their workforce, as skilled employees are essential for translating AI's technical potential into innovation outcomes. This can be achieved by recruiting external AI talent for rapid expertise or by investing in internal capacity-building through targeted training programs. While external hiring offers immediate benefits, internally focused training ensures sustainable capability growth and alignment with organizational needs. Training should address stage-specific NPD challenges—from data-driven ideation to AI-supported sales—equipping employees to navigate current and future demands. Crucially, capability development extends beyond technical skills: leadership must actively champion an innovation-oriented culture that encourages cross-functional collaboration, experimentation with AI tools, and openness to change. This includes fostering an environment where employees feel safe to experiment without fear of failure and where leaders model adaptability and a commitment to AI-driven transformation.

By implementing these strategies, managers—regardless of their current level of AI maturity—can progressively unlock AI's full potential within NPD, driving sustained innovation, improving operational efficiency, and securing a leadership position in technology-driven markets. These actions provide a clear roadmap for aligning AI capabilities with organizational goals and achieving significant advancements in innovation performance.

5.3. Limitations and avenues for future research

As with any research effort, this study has its limitations. Addressing these limitations in future research could improve the generalizability and depth of the findings.

First, one key limitation is that the sample for this study was exclusively drawn from Germany, potentially restricting the applicability of the findings to other countries. Cultural and social differences across regions (Berthon et al., 2005) can significantly influence decision-making processes (Dabić et al., 2015) and the adoption of AI technologies (Eitle & Buxmann, 2020; Zöll et al., 2024). Future studies could replicate this research across diverse cultural and national contexts to assess the global applicability of the results. Such cross-cultural investigations would not only enhance the robustness of the findings but also provide valuable insights into how regional differences shape the integration and effectiveness of AI in NPD.

Second, this study utilized a cross-sectional research design, collecting data at a single point in time. While this approach provides valuable insights, it does not account for temporal dynamics or the evolving nature of AI technologies. Given the rapid pace of AI advancements, longitudinal research designs would be instrumental in exploring how the observed effects develop over time. For instance, future studies could examine whether the early-stage advantages of AI adoption in NPD intensify or diminish as AI technologies mature and organizations adapt their innovation processes. Longitudinal analyses could also reveal how the effectiveness of AI evolves with shifting organizational practices, changes in workforce capabilities, and advancements in AI tools, offering a more nuanced understanding of the process and sustained impact of AI in NPD.

Third, the study focused on a single moderator, AI competence, due to its critical role and its proven benefits in prior IT-related research. While this approach provides a strong foundation, exploring additional moderators could yield a more comprehensive understanding of the factors that influence AI's effectiveness in NPD. For example, future research could prioritize examining the impact of organizational resources (e.g., data-related resources such as the availability, quality, and accessibility of NPD-relevant data), regulatory environments (e.g., regulatory stringency in data and AI governance), or technological infrastructure (e.g., IT infrastructure flexibility and modularity) on the relationship between AI usage intensity and organizational innovation capability. Investigating these factors could uncover new insights into how firms optimize AI deployment strategies across different contexts, ultimately contributing to a more refined understanding of the interplay between AI and NPD.

Beyond these limitations, our findings open up several broader and more transformative avenues for future research that go beyond incremental extensions of the present work. A first promising research program concerns the reconfiguration of creativity and agency in AI–human NPD collectives. Our results suggest that AI does not simply automate existing tasks, but changes how ideas are generated, evaluated, and combined. Future studies could explicitly theorize AI as a “non-human agent” in NPD and investigate how the locus of creativity shifts when idea generation, concept refinement, and prototyping are increasingly shared between humans and AI. For example, researchers could use experimental and field designs to examine how different role framings of AI (e.g., “junior team member”, “devil's advocate”, “lead designer”) affect the novelty and feasibility of concepts, the distribution of voice within NPD teams, and professionals' sense of ownership over innovations. Linking these questions to theories of knowledge recombination, cognitive search, and identity could help the field move from viewing AI as a tool to conceptualizing NPD as a hybrid human–AI system.

A second research program relates to AI-enabled NPD ecosystems and platform-based innovation. We study AI within firm boundaries, but many AI-related advantages in NPD may only materialize at the level of inter-organizational networks. Future research could explore how orchestrators of innovation ecosystems leverage AI to curate external ideas, identify promising partners, or dynamically reconfigure value creation architectures. Conversely, complementors and start-ups may use AI to strategically navigate powerful platform owners, for instance by simulating partner reactions to new offerings or by optimizing the timing and positioning of complementary innovations. Multi-actor studies that combine survey data with digital trace data from platforms, developer ecosystems, or open innovation communities could illuminate how AI reshapes power, dependency, and value capture in NPD networks. Such an ecosystem lens would move beyond the firm-centric perspective that dominates current work.

A third research program involves autonomous AI agents that initiate and drive NPD processes. Our study focuses on AI that supports human-defined NPD projects. Emerging autonomous agents, however, can proactively scan markets and technological landscapes, generate opportunity hypotheses, assemble resources, and even launch small-scale experiments with minimal human intervention. Future research could investigate how such agents alter the very definition of an “innovation project”, how firms allocate decision rights between human managers and AI agents, and how responsibility and accountability for AI-initiated innovations are governed—particularly when these innovations fail or generate unintended societal consequences. Methodologically, agent-based simulations and design science approaches that prototype such agents within organizations could complement traditional survey and archival methods, enabling the field to explore scenarios that are only beginning to emerge in practice.

Finally, our findings point to a need for integrating organizational culture and ethics into theories of AI-enabled NPD. Beyond asking whether AI improves innovation performance, future work could examine how different cultural archetypes (e.g., experimentation-driven vs. control-oriented cultures) shape the ways in which AI is used to define “desirable” innovations. This includes the possibility that AI systems encode and reinforce existing biases, thereby narrowing the set of customer segments and problem spaces that NPD teams consider legitimate. Studies that combine cultural diagnostics, ethnographic methods, and audits of AI training data and outputs could shed light on when AI broadens vs. constrains the imagination of NPD teams, and how organizations can build governance mechanisms that align AI-enabled innovation with broader ethical and societal goals. Addressing these questions would position research on AI in NPD at the forefront of debates about responsible and inclusive innovation in the digital age.

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CRediT authorship contribution statement

Henning Meier: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sven Heidenreich:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Slawka Jordanow:** Writing – review & editing, Visualization, Methodology, Conceptualization. **Tobias Kraemer:** Writing – review & editing, Software, Methodology, Formal analysis.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT and DeepL Write in order to improve language and readability. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Appendix A. Appendices

Table A-1
Demographics and sample description.

Category	Average	Low	High
Age	43	18	79
Professional Experience	20	1	50
Length of Service with Organization (years)	13	1	50
Organization Age	45	2	500
Length of Service with Digital Transformation (years)	8	0	75

Category	Characteristic	Frequency	Percentage
Gender	female	176	44.00
	male	223	55.75
	n/a	1	0.25
Education	no degree	0	0.00
	elementary school	3	0.75
	secondary school	27	6.75
	vocational training	55	13.75
	high-school diploma	96	24.00
	university degree (comprises Bachelor's, Master's, Diplom, and PhD degrees)	217	54.25
	other degree	2	0.50
	n/a	0	0.00
Industry	Automotive	17	4.25
	Chemistry / Pharmacy / Cosmetics	33	8.25
	Electronics	19	4.75
	Energy / water supply	14	3.50
	Financial services	48	12.00
	Wholesale and retail	56	14.00
	IT (information technology)	62	15.50
	Aircraft and spacecraft construction	5	1.25
	Mechanical / plant and tool engineering	35	8.75
	Food	12	3.00
	Telecommunications	13	3.25
	Transport / Traffic / Logistics	30	7.50
	Other	56	14.00
Position Line	Department manager	267	66.75
	Management assistant	59	14.75
	Executive management	44	11.00
	Other (e.g.: Group leader/Team leader, Deputy head of division, Operations manager, IT manager)	30	7.50
Organization Size	50 employees	18	4.50
	51–250 employees	121	30.25
	251–500 employees	62	15.50
	501–1000 employees	61	15.25
	1001–10,000 employees	103	25.75
	More than 10,000 employees	35	8.75
Hierarchy	No management position	0	0.00
	Middle management	317	79.25
	Upper management position	83	20.75

(continued on next page)

Table A-1 (*continued*)

Category	Average	Low	High
Position Area	Marketing and sales	89	22.25
	Research and development / Innovation	78	19.50
	Strategy / Controlling / Corporate Planning / Business-Development	122	30.50
	Personnel	111	27.75
	Other	0	0.00

Table A-2
Constructs, sources, and item loadings.

		Loadings (λ_i)	Significance (*t-value*)
AI Usage Intensity in Concept Development Stage (adapted from Munck et al., 2020)			
Mean = 4.532	Please indicate the degree to which artificial intelligence is used in the following process steps in new product development at your company *(1 = Very low to 7 = Very high)*		
SD = 1.545	Planning and formulating of the new product goal and strategy	0.880	55.276***
CR (ρA) = 0.913	Idea generation	0.911	84.595***
CR (ρc) = 0.938	Analysis of trends, market changes, and potentials	0.880	57.983***
AVE = 0.792	Preparation of the written product concept	0.888	72.191***
AI Usage Intensity in Product Development Stage (adapted from Munck et al., 2020)			
Mean = 4.309	Please indicate the degree to which artificial intelligence is used in the following process steps in new product development at your company *(1 = Very low to 7 = Very high)*		
SD = 1.644	Actual development of the prototype	0.890	62.411***
CR (ρA) = 0.943	Execution of prototype tests with customers	0.893	62.291***
CR (ρc) = 0.956	Selection of customers for test-marketing reasons	0.897	65.599***
AVE = 0.813	Execution of test-marketing measures before market introduction of the new product	0.921	95.364***
	Final evaluation of market acceptance before market introduction of the new product	0.907	85.489***
AI Usage Intensity in Implementation Stage (adapted from Munck et al., 2020)			
Mean = 4.352	Please indicate the degree to which artificial intelligence is used in the following process steps in new product development at your company *(1 = Very low to 7 = Very high)*		
SD = 1.654	Product training for customers	0.876	52.665***
CR (ρA) = 0.879	Customer enquiries/after-sales support	0.925	99.916***
CR (ρc) = 0.923 AVE = 0.800	Monitoring competitors' reactions and their strategies	0.881	54.808***
AI Competence (adapted from Chakravarty et al., 2013)			
Mean = 4.194	To what extent do the following statements apply to your company's AI abilities? *(1 = Does not apply at all to 7 = Fully applies)*		
SD = 1.637	The employees in our company are very experienced in dealing with AI.	0.916	84.758***
CR (ρA) = 0.937	The employees in our company have extensive knowledge of AI.	0.933	116.178***
CR (ρc) = 0.955	The skills of the employees in our company in dealing with AI are comparable to the best in the industry.	0.908	76.562***
AVE = 0.840	Our company invests heavily in developing employee competencies related to AI.	0.910	84.927***
Organizational Innovation Capability (adapted from Gold et al., 2001)			
Mean = 4.807	Over the past two years, my company has improved its ability to … *(1 = Does not apply at all to 7 = Fully applies)*		
SD = 1.264	Identify new business opportunities.	0.813	36.921***
CR (ρA) = 0.923	Coordinate the development efforts of different units.	0.840	41.203***
CR (ρc) = 0.937	Anticipate potential market opportunities for new products/services.	0.803	30.999***
AVE = 0.680	Decrease market response times.	0.833	41.499***
	Be responsive to new market demands.	0.836	41.038***
	Avoid overlapping development of corporate initiatives.	0.831	41.432***
	Reduce redundancy of information and knowledge.	0.817	38.005***

Note: *** significant at $p < .001$.

Table A-3
Heterotrait-Monotrait-Matrix (95% bias-corrected and accelerated confidence intervals).

	1. AIU in CD	2. AIU in PD	3. AIU in I	4. OIC
1. AIU in CD				
2. AIU in PD	0.903 [0.862; 0.938]			
3. AIU in I	0.922 [0.884; 0.958]	0.949 [0.914; 0.979]		
4. OIC	0.742 [0.671; 0.809]	0.720 [0.650; 0.785]	0.744 [0.664; 0.817]	

Notes: AIU: AI Usage Intensity; CD: Conceptual Development; PD: Product Development; I: Implementation; OIC: Organizational Innovation Capability.

Table A-4
Inner model variance inflation factors.

Variable	Variance inflation factor
AI Usage Intensity in Concept Development Stage	3.977
AI Usage Intensity in Product Development Stage	4.952
AI Usage Intensity in Implementation Stage	4.529
Age	1.013
Education	1.007
Gender	1.024
Number of Employees	1.014
Organization Age	1.028
Position Line	1.031

Notes: All variance inflation factors refer to organizational innovation capability as single endogenous variable.

Table A-5
Path coefficients.

Independent variable		Dependent variable	Path coefficient (β)	Significance (*t-value*)
Hypothesized Paths				
AI Usage Intensity in Concept Development Stage	→	Organizational Innovation Capability	0.321	3.958***
AI Usage Intensity in Product Development Stage	→	Organizational Innovation Capability	0.226	2.636**
AI Usage Intensity in Implementation Stage	→	Organizational Innovation Capability	0.195	2.139*
Control Paths				
Age	→	Organizational Innovation Capability	0.013	0.331
Education	→	Organizational Innovation Capability	0.032	0.866
Gender	→	Organizational Innovation Capability	−0.010	0.270
Number of Employees	→	Organizational Innovation Capability	−0.095	1.213
Organization Age	→	Organizational Innovation Capability	−0.084	1.851
Position Line	→	Organizational Innovation Capability	−0.059	1.568

Notes: *** significant at $p < .001$, ** significant at $p < .01$, * significant at p < .05.

Data availability

Data available on request from the authors.

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