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The impact of design thinking and artificial intelligence capabilities on performance: The role of new product development decision-making agility

Nikolaos Kyriakopoulos [*] , Euiyoung Kim , Erik Jan Hultink , Sicco Santema

Department of Design, Organization, and Strategy, Delft University of Technology, the Netherlands

ARTICLE INFO

ABSTRACT

Design thinking and artificial intelligence (AI) capabilities are gaining prominence in today's dynamic markets. However, research gaps remain regarding their influence on the outcomes of new product development (NPD), such as decision-making agility, and the structural conditions facilitating or impeding their effective implementation. Considering design thinking as a dynamic capability and AI capabilities as technology-driven innovation enablers, this study examines their impact on NPD performance via NPD decision-making agility. An empirical investigation using data collected from 230 U.S. firms shows that design thinking and AI capabilities positively influence agility, which in turn drives NPD performance. This study also uncovers that the moderating role of organizational formalization attenuates the impact of design thinking on NPD decision-making agility but strengthens the impact of AI capabilities on NPD decision-making agility. These findings provide NPD managers with insights into using these capabilities to enhance agility and improve NPD performance in the organizational context.

1. Introduction

In today's dynamic markets, firms are facing challenges in their new product development (NPD) efforts due to the accelerating pace of change and the short-lived nature of competitive advantages (D'Aveni et al., 2010). In such a business context, firms have embraced two widely adopted but different forms of capabilities: design thinking and artificial intelligence (AI) capabilities. Given the transience of competitive advantages, capabilities that drive change and responsiveness are gaining prominence. With design thinking, Procter & Gamble revived a declining product pipeline (Yu, 2016) and Infosys developed new products that are proximate to customers' needs (Infosys Limited, 2016). Firms also did not shy away from embracing AI capabilities to boost their NPD efforts. Recent reports indicate that the adoption of AI in business processes has surged at an unprecedented rate, with its regular use in business practice doubling from 2023 to 2024 (Singla et al., 2024). For example, Unilever leverages AI to analyze trends and generate new ideas to develop new products (Cooper, 2024). Similarly, the firm-wide implementation of AI capabilities within BMW Group enables employees across departments to make faster and more informed decisions using AI, even without any coding expertise

(Neumann et al., 2024).

Notwithstanding their growing relevance, there are noteworthy gaps in the research streams of both design thinking and AI capabilities. Design thinking has been theorized as a dynamic capability for innovation because it is closely linked to sensing, transforming, and reconfiguring resources and competencies (Magistretti et al., 2021). It enables firms to tackle complex, multi-faceted problems and comprises the dimensions of human-centeredness, diversity of perspectives, visualization, experimentation, and (re)framing during innovation activities (Klenner et al., 2022). From a quantitative perspective, design thinking research remains limited and has important gaps that merit attention despite the recent surge in empirical studies. Prior research has examined innovation outcomes such as new product utility and novelty (Nagaraj et al., 2020), innovation capability (Robbins & Fu, 2022), and NPD performance (Nakata & Hwang, 2020). However, to the best of our knowledge, no other study has investigated the impact of design thinking on the speed and adaptability of decision-making in NPD. Although scholars have addressed external and project-level contingencies (e.g., Dell'Era et al., 2025; Magistretti et al., 2022; Nakata & Hwang, 2020), scant attention has been paid to organizational-level structural factors that facilitate or impede the implementation of

design thinking.

Similarly, AI capabilities represent one of the most transformative technological advancements for businesses, but their link to innovation outcomes, especially in NPD, is still understudied. AI capabilities are defined as the organization's integration of cognitive computing technologies, custom data analytics, machine learning algorithms, and interactive dashboards within organizational processes and routines to undergird organizational decision-making (Sahoo et al., 2024). These capabilities act as levers, reinforcing and streamlining organizational processes and enhancing decision-making (Gama & Magistretti, 2025). Notwithstanding the exponential integration of AI capabilities into firms' processes and their importance in accelerating innovation, only a limited number of studies examine the impact of AI capabilities on NPD outcomes, primarily focusing on aspects such as exploration or exploitation orientation and new product creativity (e.g., Ameen et al., 2024; Kumar et al., 2024). Research has also addressed external and internal factors influencing AI deployment (e.g., Abou-Foul et al., 2023; Arias-Pérez & Huynh, 2023; Sahoo et al., 2024), yet little is known about the role of organizational structure in either enhancing or impeding the effective deployment of AI for NPD decision-making.

This study examines the influence of design thinking and AI capabilities on NPD performance through NPD decision-making (DM) agility, which refers to the firm's ability to swiftly adapt its NPD DM to shifts in customer preferences, technological advancements, competitive moves, resource availability, and evolving strategic priorities. Prior research has identified a limited number of drivers, such as cultural factors (e.g., Kock & Gemünden, 2016), leadership styles, and different types of DM processes (e.g., Kester et al., 2011). However, research focused on the role of firm-level capabilities, particularly those entrenched in relatively novel human-centered capabilities (i.e., design thinking) and cutting-edge technological advancements (i.e., AI capabilities) is scant.

This study addresses these knowledge gaps through the following research questions: (a) how and through what mechanisms do design thinking and AI capabilities influence NPD performance? and (b) under what organizational structural conditions are design thinking and AI capabilities beneficial for NPD DM agility? In the first research question, we focus on these two capabilities due to their conceptual alignment with agility and their growing relevance in business practice. Design thinking reflects a socially embedded dynamic capability shaping how routines and processes are governed within organizations (Liedtka, 2020), whereas AI capabilities represent technology-driven innovation enablers that enhance DM and efficiency. Despite their theoretical differences, both capabilities enable firms to reduce decision latency and pivot more swiftly and effectively in response to internal or external changes. This study aims to understand the mediating role of agility, which funnels the effects of design thinking and AI capabilities on NPD performance. Unveiling such a mechanism is critical to explain how firms can translate capabilities into superior performance, as they are becoming increasingly important in the current dynamic markets, where competitive advantages are transient.

To answer the second research question, this study aims to uncover potential tensions in the capability-structure fit of two inherently different types of capabilities (human-centered vs. technology-driven). In doing so, we examine the moderating role of organizational formalization on the relationships between (a) design thinking and NPD DM agility and (b) AI capabilities and NPD DM agility through the lens of structural alignment logic (e.g., Day, 2006). Organizational formalization reflects the extent to which an organization's standardized rules, procedures, and responsibilities are documented and specified in detail (Jansen et al., 2006). Understanding its role in how firms leverage design thinking to accelerate their NPD and enhance adaptability is intriguing because design thinking is often characterized by tolerance for ambiguity and low levels of structure (e.g., Carlgren et al., 2016), but it rarely operates in a vacuum. For example, in many organizations, design thinking coexists with formal structures and procedures (Liedtka, 2020). With our focus on organizational formalization, we also aim to

contribute to research on organizational adoption of AI capabilities (e. g., Makarius et al., 2020), investigating when (i.e., extent of organizational formalization) they are most effective in driving agility.

This paper is organized as follows. We first discuss the theoretical underpinnings of dynamic capabilities and organizational structural alignment, we present the proposed conceptual model, and develop the research hypotheses. We then outline the research methodology and perform the data analysis. Finally, we discuss the theoretical and managerial implications, followed by the limitations and future research directions.

2. Theoretical background and research hypotheses

2.1. Theoretical foundations and overview of the conceptual model

The theory of dynamic capabilities provides the theoretical lens for conceptualizing design thinking. Dynamic capabilities reflect firms' strategic stance toward adapting, integrating, and reconfiguring internal and external competencies (Teece, 2007). Although it has been scarcely theorized as such, design thinking is considered a dynamic capability because it encompasses sensing, seizing, and reconfiguring (Magistretti et al., 2021). In design thinking, *sensing* connotes empathy, understanding user needs, and embracing diverse viewpoints (Beverland et al., 2016; Kim et al., 2016). It also involves visualization and experimentation, enabling firms to *seize* opportunities by moving quickly from ideation to product launch (Nakata & Hwang, 2020). Design thinking also contributes to *reconfiguring* by reframing challenges or contingencies to align with emerging patterns in the external environment (Dorst, 2011).

Of primary interest for our conceptualization are AI capabilities, which have infiltrated business processes and provided competitive advantages such as improved efficiency and enhanced organizational DM (Shrestha et al., 2021). Given their immense ability to analyze large volumes of data and leverage machine learning applications, AI capabilities enable firms to improve their responsiveness to change (Mikalef et al., 2023). We consider AI capabilities *technology-driven innovation enablers*, as they can reinforce existing internal processes and DM and accelerate analysis of the external environment (Gama & Magistretti, 2025).

As a key NPD outcome, we focus on NPD DM agility and propose that it filters the impact of design thinking and AI capabilities on NPD performance. In the rapidly evolving business environment, the transience of competitive advantages requires firms to adapt their product development decisions to succeed. As stated in the seminal work of Teece et al. (1997), firms that succeed in global markets demonstrate "timely responsiveness and rapid and flexible product innovation, coupled with the management capability to effectively coordinate and redeploy internal and external competencies." In this study, design thinking and AI capabilities are conceptually relevant because they provide firm-level means to swiftly sense and respond to change to succeed in an era of short-lived competitive advantages.

We also apply the structural alignment perspective (e.g., Day, 2006), which theorizes that firms adapt their organizational structure to leverage their capabilities and resources and enjoy superior performance. The structural dimension of the research model is represented by the moderating role of organizational formalization, which is a key element of organizational design. Fig. 1 illustrates our aim to understand how firms adapt formalization by aligning it with design thinking and AI capabilities to enjoy superior agility in NPD DM.

2.2. Design thinking and NPD DM agility

Design thinking enables firms to adapt to changing internal or external conditions by including human-centeredness, diversity of perspectives, visualization, experimentation, and re(framing) (Dell'Era et al., 2020). Human-centeredness focuses on understanding consumers'
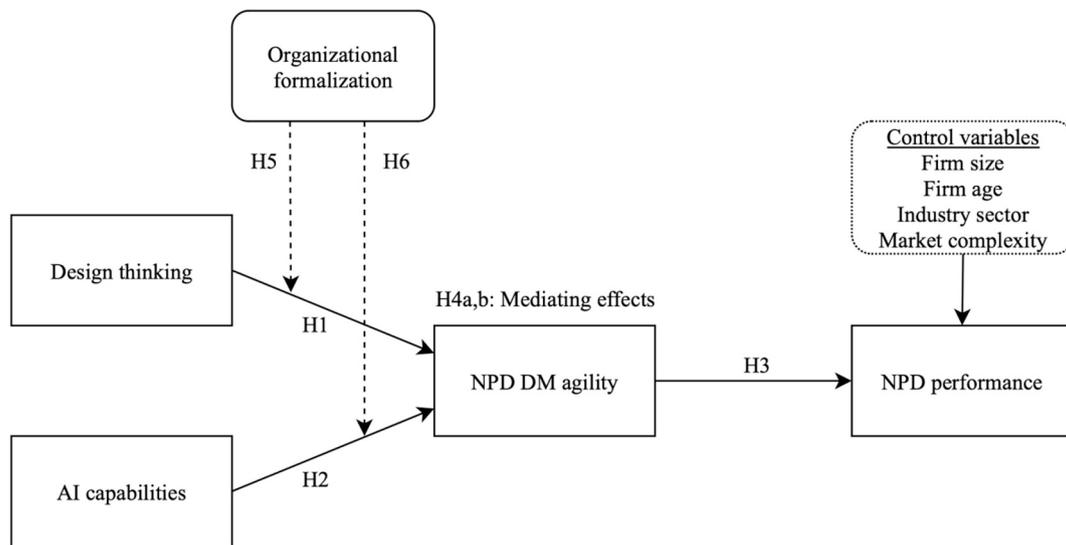
Fig. 1. Conceptual model.

(latent) needs and behaviors to gain valuable insights (Michlewski, 2008) and inform innovation processes. Centering innovation efforts on the human side facilitates the use of existing knowledge to acknowledge potential opportunities (Klenner et al., 2022). Prior research shows that evidence-based approaches are critical to enhancing NPD agility (Kester et al., 2011). The evidence-based element of design thinking via user-centeredness empowers firms to anticipate rather than react, thus creating first-mover competitive advantages that are central to swiftly acting to change. Furthermore, a deeper understanding of users mitigates cognitive biases in DM (Liedtka, 2015), a practice that may enable firms to overcome inertia and focus on accelerating DM. Diversity is another dimension of design thinking that includes multiple stakeholders, both internal and external to the organization (Beverland et al., 2016). Specifically, NPD teams comprising individuals from various backgrounds view problems from multiple angles and rapidly integrate different insights into the development process (Meier & Kock, 2024). Kock and Gemünden (2016) suggest that the firm's ability to align innovation projects with changing strategic goals enhances agility in NPD. This alignment can be strengthened by the design thinking dimensions of visualization through various artifacts and rapid prototyping (Magistretti et al., 2023). A culture of early failure through experimentation can empower NPD DM with rapid learning and greater flexibility (Carlgren et al., 2016; Kalaignanam et al., 2021). Reframing can also impact how swiftly firms make NPD decisions. The ability to (re)frame problems may allow NPD teams to remain adaptable and open to novel solutions by challenging existing ideas and established norms (Drews, 2009). This may further reduce inertial forces that usually slow down the NPD DM process. Therefore, we suggest that design thinking encourages NPD DM agility through its core dimensions. Formally:

H1: Design thinking is positively associated with NPD DM agility.

2.3. AI capabilities and NPD DM agility

In this study, we examine AI capabilities that play an increasingly important role in boosting business processes (Mikalef et al., 2023). One such area is the NPD process wherein AI capabilities empower firms to analyze large volumes of data and quickly understand complex circumstances (Sjödin et al., 2021). For example, using AI-generated insights, NPD teams gain access to information related to competitors' products, pricing, and market positioning. Decision makers can seamlessly share such insights via AI tools (Sahoo et al., 2024) to streamline complex data into a user-friendly format to assist NPD DM. Machine learning algorithms can quickly diagnose process interruptions and

resource bottlenecks, ensuring that unforeseen delays do not disrupt innovation processes (Roberts & Candi, 2024). AI technology using cognitive computing can also accelerate innovation cycles, from ideation to prototyping and iteration (Füller et al., 2022). Illustrative of such efficiency improvements and reduction in innovation cycle times is the example of General Electric, which used AI-enabled technologies to effectively test millions of iterations of a product design in just 15 minutes (Bogaisky, 2019; Cooper, 2024). Such automation of procedures can save time for employees and free up resources, allowing NPD teams to shift focus to other areas, especially during concept development, refinement, and testing stages (Booth et al., 2024). Based on this discussion, we suggest that AI capabilities enable firms to respond quickly and adapt their NPD DM to changing conditions and can be critical for realizing transient competitive advantages. Formally:

H2: AI capabilities are positively associated with NPD DM agility.

2.4. NPD DM agility and NPD performance

Extant research has emphasized the importance of continuous change for firms' survival and success (e.g., Brown & Eisenhardt, 1997). In the context of NPD, agility reflects a firm's flexibility and speed in DM when responding to rapidly evolving market and operational demands (Kock & Gemünden, 2016) . Such agility enables firms to achieve success by quickly adopting a customer-centric attitude, which is crucial for increasing customer satisfaction and market share (Meier and Kock, 2024). Furthermore, agility enhances firms' adaptability to new technological advancements and enables them to incorporate novel technologies into their new products (Kester et al., 2014). By doing so, firms can offer superior product features and increase product functionality and quality. Agile DM allows project teams to swiftly adjust and balance product portfolios, ensuring efficient resource allocation and thereby enhancing the financial performance of NPD projects (Kester et al., 2014). For example, firms may balance their portfolios by quickly discontinuing unprofitable products or trimming product lines to boost performance (Argouslidis et al., 2015). At a strategic level, alignment of the NPD DM with the overarching firm strategy may improve market positioning, market share, profitability, and revenue (Baum & Wally, 2003). Against this backdrop, we postulate that NPD DM agility is critical for firms aiming to achieve iterative temporal competitive advantages characterized by short-lived but renewable performance gains. Therefore, we hypothesize:

H3: NPD DM agility is positively associated with NPD performance.

2.5. NPD DM agility as a mediating mechanism

As hypothesized in H1 and H2, both design thinking and AI capabilities are beneficial for NPD DM agility. Design thinking, as a dynamic capability comprising human-centeredness, diversity, visualization, experimentation, and (re)framing, enables organizations to swiftly respond to change. Similarly, AI capabilities facilitate analysis of complex external and internal data, reinforce managerial DM, and accelerate innovation cycles to boost NPD DM. However, to be beneficial for NPD performance, these capabilities must be channeled through the firm's ability to swiftly adapt NPD DM in response to changing customer preferences, technological advancements, competitive moves, resource availability, and evolving strategic priorities. Stated differently, without agility, the potential benefits of design thinking and AI capabilities may remain unrealized. Therefore, we postulate that NPD DM agility mediates the relationships between (a) design thinking and NPD performance and (b) AI capabilities and NPD performance. Formally:

H4a: NPD DM agility mediates the positive association between design thinking and NPD performance.

H4b: NPD DM agility mediates the positive association between AI capabilities and NPD performance.

2.6. Moderating role of organizational formalization

While organizational formalization may enhance efficiency and process control, prior research shows that a firm's ingrained structural elements may conflict with design thinking (Carlgren et al., 2016). Highly formalized organizations can be detrimental to communication and collaboration for knowledge creation (Lee & Choi, 2003) and could impede variation-seeking behaviors that drive innovation (Jansen et al., 2006). This could increase cognitive inertia and reinforce existing schemas instead of reducing them through design thinking. Furthermore, formalization of organizational structure emphasizes standardized processes and predefined rules that limit adaptability and constrain creative problem-solving beyond the firm's boundaries (Wei et al., 2022). This rigidity may restrict the transformational capacity and outside-in perspective that design thinking fosters. Formalization also aims at reducing ambiguity (Carson et al., 2006), which conflicts with design thinking's emphasis on embracing ambiguity in tackling complex problems and addressing stakeholder needs (Micheli et al., 2019). Conversely, when formalization is low, the impact of design thinking on NPD DM agility is amplified because a context that encourages flexibility, creativity, and iterative processes for problem-solving is critical to facilitate design thinking (Dorst, 2011). Dimensions of design thinking, such as human-centeredness, (re)framing, prototyping, and early experimentation, may prove more critical for agility in an organizational context where organic DM is encouraged. To summarize, although formalized organizational structures may provide a certain level of stability, they could hamper firms from reaping the benefits of design thinking on NPD DM agility. Therefore, we hypothesize:

H5: Organizational formalization attenuates the positive effect of design thinking on NPD DM agility.

In contrast, organizational formalization provides the necessary structure to integrate AI into organizational processes, ensuring the consistent implementation of data-driven insights and AI-enabled tools in NPD activities. In formal organizational structures, we expect AI-enabled processes such as data analysis, resource allocation, and predictive modeling to become more streamlined, and the resulting NPD DM to be responsive and faster. For example, predictive modeling that is incorporated into standardized NPD frameworks allows firms to make quick adjustments to changing customer needs or technological opportunities (Cooper, 2024). AI applications can also generate a significant volume of data and insights; however, in the absence of formalized standards or clear responsibilities, they could overwhelm decision-makers and pose several challenges to organizations (Richey Jr et al., 2023). To address this, clear organizational guidelines and a structured integration of external and internal data are critical. This formalized approach enables firms to enjoy the benefits of AI implementation (Mikalef & Gupta, 2021) and ensures the smooth and swift flow of information into DM processes. In addition to managing data complexity, formalization can also improve coordination among diverse NPD project teams (Pesch et al., 2021). It may foster a structural homogeneity of procedures across different departments so that all project participants use AI tools, such as AI-enabled communication channels in the same manner, reducing potential friction and facilitating seamless teamwork and faster NPD DM. Even though AI provides several benefits for NPD processes, it also comes with certain strategic limitations, such as contextual myopia (Kemp, 2024). This refers to the inherent inability of AI routines to extend their analytical scope beyond a narrowly defined context or task, thereby overlooking potential interdependencies among related tasks or processes. Given that NPD DM involves highly interdependent tasks (Kester et al., 2011), a myopic approach to such tasks may impede the effectiveness of NPD DM processes. To tackle such challenges and enhance NPD DM agility, well-defined rules, responsibilities, and standards may offer decision-makers a clear pathway for deploying AI, aligning AI capabilities with organizational goals and processes. Based on this line of reasoning, we hypothesize:

H6: Organizational formalization strengthens the positive effect of AI capabilities on NPD DM agility.

3. Research methodology

3.1. Sample and data collection procedures

The study data were collected using an online survey administered via a leading market research firm, consistent with the data collection approach of other studies on design thinking (e.g., Nakata & Hwang, 2020) and NPD (e.g., Chen et al., 2021). The sampling frame comprised firms based in the United States (U.S.) that have developed new products over the past three years. We chose the U.S. as our sampling frame location as it leads in firms' adoption of design thinking and AI technologies (Caccamo & Beckman, 2022).

For data collection, we instructed the market research firm to recruit senior-level key informants within U.S. firms with job roles related to NPD and innovation. We implemented a series of eligibility and screening criteria and other procedures to ensure the quality of the selected respondents, all of which had to be met before a respondent could proceed with the main questionnaire. First, respondents were required to demonstrate a very high level of involvement and knowledge of NPD and innovation activities within their firms (mean involvement = 4.68, SD = 0.47; mean knowledge = 4.62, SD = 0.49 on a 5-point Likert scale). Those who scored 3 or below were eliminated, ensuring high competence of the key informants of our dataset. Second, respondents needed to hold a sufficiently senior position, ranging from middle management to owner or C-level executive levels. In addition to the screening questions, we also included two attention checks to reduce the likelihood of inattentive respondents and to increase response quality.

A total of 1,485 respondents were initially recruited to participate in the survey. Of these, 1,255 were excluded because they (a) did not comply with our screening criteria, (b) failed attention checks, (c) responded very quickly or selected the same option throughout, or (d) provided incomplete responses. Consequently, the final sample comprised 230 usable responses, yielding a response rate of 15.55 % of those initially contacted. Respondents had a substantially long tenure in their role (mean tenure = 9.53 years), which, together with their high level of job seniority, ensured the reliability of the responses (Homburg et al., 2012). Table 1 presents the sample characteristics.

3.2. Measures

A structured questionnaire was used to examine the main study

Table 1

Descriptive statistics of the sample.

Firm industry	%	Firm size (No employees)	%	Firm age (No of years)	%	Respondent position	%
Construction	13.5	0–250	32.6	0–10	15.7	Product manager	15.2
Manufacturing	20.9	250–1000	48.7	11–20	41.7	UI/UX designer	9.6
Retail trade	10.4	> 1000	18.7	21–50	36.1	R&D manager	7.8
Transportation	4.8			51–100	4.8	Project manager	21.3
Information	10.9			>100	1.7	Marketing manager	6.5
Finance	9.1					Chief executive officer	28.3
Healthcare	5.2					Other	11.3
Other	25.2						

variables. All constructs were adopted or adapted with minor adjustments from prior research. We measured design thinking by adapting the five-item construct from Kamble et al. (2023) and Cui and Wu (2017) to capture the extent to which the firm implements distinct design elements such as human-centeredness, diversity, visualization, experimentation, and (re)framing (1: not at all, 7: to a very great extent). Drawing on Diamantopoulos and Winklhofer (2001), we adopted a formative specification of the focal construct because (a) the direction of causality is from the items to the construct, (b) the items capture different dimensions of the construct, and (c) the items are not interchangeable. To operationalize AI capabilities, we used the four-item reflective scale from Sahoo et al. (2024) (1: strongly disagree, 7: strongly agree), measuring the use of cognitive computing technologies, data analytics, machine learning, and dashboards to enhance access to information and support DM. For NPD DM agility, we adapted the four-item reflective scale from Kock and Gemünden (2016) to capture the speed with which each firm adapts its NPD decisions to changing customer needs, resource situations, new technologies, and strategic goals (1: strongly disagree, 7: strongly agree). We assessed NPD performance using the six-item reflective scale from Kroh et al. (2018) and Griffin and Page (1993), denoting the influence of NPD activities on profitability, revenue, market share, product/service quality, product/service functionality, and customer satisfaction. As an organizational formalization measure, we adopted the five-item reflective scale from Wei et al. (2022) to capture the extent to which management standards, job objectives, responsibilities, and procedures within the firm are clear, specified, and formally documented (1: not at all, 7: to a very great extent). We also included four control variables that may influence NPD performance. We adapted Low and Mohr's (2001) four-item measure of complexity to assess how ambiguous, complicated, ill-structured, and difficult the business environment is. Additionally, we controlled for (a) firm size by the number of employees, (b) firm age by the number of years that the firm has been in operation, and (c) industry sector.

3.3. Common method variance

We undertook several measures, both procedural and statistical, to minimize and control for potential informant bias (Hulland et al., 2018; Podsakoff et al., 2003). Regarding procedural steps, we pretested the constructs with four academics and five executives whose job roles were related to NPD and innovation management. This process ensured the clarity and logical flow of the questions. The respondents were assured that their responses would remain confidential, anonymous, and would be used only for research purposes. We separated the constructs within the questionnaire physically and varied the construct anchoring to minimize the likelihood of undesirable response patterns (MacKenzie & Podsakoff, 2012). We also controlled for potential common method variance statistically (Chin et al., 2013; Kock, 2015). First, we performed a full multi-collinearity test, which indicated that all inner variance inflation factor (VIF) values were well below the conservative threshold of 3.3 (maximum VIF value = 1.691). Second, we employed the latent marker variable procedure using the social desirability scale (Hays et al., 1989) as a theoretically unrelated marker variable. This procedure did

not change the path significance of the structural model tested in this study and had only a minor impact on R^2 values and the model's β parameters. Overall, the procedural and statistical approaches show that common method variance is not a major issue in this study.

4. Analysis and results

4.1. Measurement model assessment

We tested our hypotheses using SmartPLS v.4.1.0.6. The use of partial least squares structural equation modeling is justified for the following reasons: (a) the aim of this analysis is the prediction of dependent variables, (b) the research model is relatively complex, and (c) a formative construct is included in the analysis (Hair et al., 2019).

First, we focused on the reflective measures of our research model (i. e., AI capabilities, NPD DM agility, NPD performance, organizational formalization, and market complexity), examining their loadings, internal consistency, and composite reliability. Owing to low factor loadings, we eliminated one item from the NPD performance measure and one item from the market complexity control variable. Regarding internal consistency reliability, all reflective variables showed satisfactory Cronbach's alphas and composite reliability (CR) values (Table 2). We then assessed convergent validity by examining the average variance extracted (AVE) values. After eliminating the above two items, the AVE values for NPD performance and market complexity improved considerably, and all AVE values were above the required threshold of 0.5 (Table 2). To assess discriminant validity, we used the heterotrait-monotrait (HTMT) ratio. The results showed that all HTMT values were below the conservative cut-off value of 0.85 (Table 3), indicating that the model constructs were empirically distinct, and hence valid and reliable.

Next, we assessed design thinking, specified as a formative construct in our model. Given that multicollinearity is an important consideration for formative measures, we examined the VIF values. All VIF values for design thinking were lower than the conservative threshold of 3.3 (Table 4). Finally, we found all indicators' outer weights statistically significant ($p < 0.05$) and loadings greater than the 0.5 cut-off value.

4.2. Structural model assessment

We first evaluated the in-sample predictive capability of our research model (Guenther et al., 2023). The R^2 values for NPD DM agility ($R^2_{\text{NPD DM agility}} = 0.49$) and NPD performance ($R^2_{\text{NPD performance}} = 0.44$) indicate moderate predictive power. Next, we examined the out-of-sample predictive capability of our model using Stone-Geisser's Q^2 criterion. The Q^2 value was 0.44 for NPD DM agility and 0.29 for NPD performance, indicating that our model had satisfactory out-of-sample predictive accuracy. We then estimated the structural model with 5,000 bootstrap samples. Table 5 summarizes the results.

4.3. Hypotheses testing

We first examined the direct effects of our research model. The results show a significant positive impact of design thinking on NPD DM

Table 2
Reflective measurement model results.

Reflective constructs and items	Loadings
AI capabilities (Cronbach's α = 0.75, CR = 0.84; AVE = 0.57)	
Our organization has invested in artificial intelligence, cognitive computing technologies and relevant infrastructure, which has assisted us in improving our strategic decisions across all functional domains.	0.74
Our organization has its own proprietary data analytics and machine learning algorithms for extracting information and making cognitive interpretations of the collected data (from multiple sources) in the event of a process interruption.	0.72
Our organization has developed a dashboard that helps process administrators in understanding the cognitive computing outputs of multifaceted information in order to make informed decisions.	0.75
Our organization has provisions for installing dashboard applications on our managers' communication devices to ease access to critical information.	0.81
NPD DM agility (Cronbach's α = 0.72, CR = 0.83, AVE = 0.55)	
We quickly adapt our new product development decisions to changing customer needs and competitive conditions.	0.76
We quickly adapt our new product development decisions to changing resource situations.	0.69
We quickly adapt our new product development decisions to new technologies.	0.72
We quickly adapt our new product development decisions to changing strategic goals.	0.79
NPD performance (Cronbach's α = 0.76, CR = 0.84, AVE = 0.51)	
Our NPD activities have contributed to the success of our firm within the last three years with respect to:	
Profitability	0.73
Revenue	0.61
Market share*	–
Product/service quality	0.71
Product/service functionality	0.75
Customer satisfaction	0.75
Organizational formalization (Cronbach's α = 0.76; CR = 0.84; AVE = 0.51)	
The management system of our firm is described detailly and accurately.	0.74
The responsibilities of the positions in our firm are clear and without overlap.	0.78
The job objectives and standards in our firm are very specific.	0.73
The assessment standards for job performance in our firm are clear.	0.70
The logic of the management system is exact and without contradictions.	0.59
Market complexity (*control variable*) (Cronbach's α = 0.87; CR = 0.91; AVE = 0.78)	
The environment in which our organization operates is ambiguous. *	–
The environment in which our organization operates is complicated.	0.82
The environment in which our organization operates is ill-structured.	0.93
The environment in which our organization operates is difficult.	0.89

* Item was deleted.

Table 3
HTMT criterion for validity assessment.

	1	2	3	4
1. AI capabilities	–			
2. NPD DM agility	0.70			
3. NPD performance	0.58	0.75		
4. Organizational formalization	0.71	0.81	0.73	–

Note: HTMT criterion assessment is not applicable to formative constructs.

Table 4
Formative measurement model results.

Formative construct and items	Outer loading	VIF
Design thinking		
We use information about users' needs in the development of a new product or service.	0.70	1.44
Diversity is embraced to integrate and balance the conflicting views of strategic partners that include users, investors, and key stakeholders.	0.82	1.39
Power of visualization is utilized for creating artifacts (such as maps, drawings, and models) to envision desirable futures.	0.71	1.38
Early experimentation helps us to continuously align the goals and limit potential losses.	0.66	1.46
(Re) framing is practiced for developing new perspectives on challenging situations, designing novel solutions effectively turning contingencies into opportunities.	0.59	1.30

Table 5
PLS-SEM results.

Paths	β	t-value	p-value	BCCI
Design thinking → NPD DM agility (H1)	0.17*	2.58	0.010	[0.048, 0.299]
AI capabilities → NPD DM agility (H2)	0.30**	3.71	0.000	[0.151, 0.479]
NPD DM agility → NPD performance (H3)	0.36**	4.15	0.000	[0.196, 0.531]
Design thinking → NPD performance	0.23	1.75	0.079	[0.011, 0.501]
AI capabilities → NPD performance	0.15	1.68	0.093	[−0.013, 0.324]
Design thinking → NPD DM agility → NPD performance (H4a)	0.06*	2.47	0.014	[0.021, 0.116]
AI capabilities → NPD DM agility → NPD performance (H4b)	0.11*	2.56	0.011	[0.045, 0.228]
Organizational formalization → NPD DM agility	0.38**	5.53	0.000	[0.245, 0.513]
Organizational formalization × Design thinking → NPD DM agility (H5)	−0.13*	2.06	0.039	[−0.125, −0.007]
Organizational formalization × AI capabilities → NPD DM agility (H6)	0.16*	3.24	0.001	[0.021, 0.120]
Control variables				
Firm size → NPD performance	0.01	0.19	0.851	[−0.103, 0.124]
Firm age → NPD performance	−0.06	1.01	0.312	[−0.173, 0.060]
Market complexity → NPD performance	−0.14*	2.96	0.003	[−0.225, −0.048]
Construction → NPD performance	0.07	0.38	0.703	[−0.314, 0.427]
Manufacturing → NPD performance	0.05	0.29	0.771	[−0.273, 0.335]
Retail trade → NPD performance	−0.14	0.77	0.443	[−0.508, 0.199]
Transportation → NPD performance	0.16	0.61	0.542	[−0.331, 0.698]
Information → NPD performance	−0.26	1.34	0.179	[−0.668, 0.079]
Finance → NPD performance	−0.05	0.32	0.746	[−0.364, 0.252]
Healthcare → NPD performance	−0.02	0.08	0.940	[−0.543, 0.515]

$R^2_{\text{NPD DM agility}} = 0.49$, $R^2_{\text{NPD performance}} = 0.44$.
* $p < 0.05$, ** $p < 0.001$.

agility ($\beta = 0.17$, $p < 0.05$), supporting H1. Consistent with H2, the impact of AI capabilities on NPD DM agility is positive and significant ($\beta = 0.30$, $p < 0.001$). Our findings regarding the influence of NPD DM agility on NPD performance indicate a significant positive effect ($\beta = 0.36$, $p < 0.001$), consistent with H3. The indirect effects of design thinking and AI capabilities on NPD performance through NPD DM agility (H4a and H4b) indicate that NPD DM agility significantly

mediates the associations between design thinking and NPD performance ($\beta = 0.06$, $p < 0.05$) and AI capabilities and NPD performance ($\beta = 0.11$, $p < 0.05$). Both mediating paths are positive and statistically significant, with 95 % bias-corrected confidence intervals (BCCIs) that

do not include zero, confirming H4a and H4b. Despite the non-significant p-value of the direct effect of design thinking on NPD performance ($\beta = 0.23$, $p > 0.05$), the BCCIs do not include zero, indicating a significant direct effect, thus characterizing the indirect effect of design thinking on NPD performance through NPD DM agility as complementary (Zhao et al., 2010). The direct effect of AI capabilities on NPD performance is non-significant ($\beta = 0.15$, $p > 0.05$), and the BCCIs include zero (Table 5). Therefore, the indirect effect of AI capabilities on NPD performance through NPD DM agility can be deemed as indirect-only (Zhao et al., 2010).

Next, we assessed the moderating effects for H5 and H6. The results support H5 as organizational formalization has a significant negative moderating impact on the relationship between design thinking and NPD DM agility ($\beta = -0.13$, $p < 0.05$). Consistent with H6, the moderating effect of organizational formalization on the relationship between AI capabilities and NPD DM agility is positive and significant ($\beta = 0.16$, $p < 0.001$). For H5, simple slope analysis reveals a steeper slope at low (-1 SD) and a flatter slope at high levels ($+1$ SD) of organizational formalization (Fig. 2). In contrast, the opposite pattern is observed for H6. Fig. 3 shows a flatter slope at low (-1 SD) and a steeper slope at high levels of organizational formalization ($+1$ SD).

To decompose these moderating effects, we applied the floodlight procedure, which identifies the Johnson-Neyman points (Spiller et al., 2013). These points determine the regions of organizational formalization wherein the effects are significant for (a) design thinking and (b) AI capabilities on NPD DM agility. This analysis indicates that for formalization (unstandardized) values below 6.24, the effect of design thinking on NPD DM agility is positive and significant ($\beta_{formalization=6.24} = 0.12$). However, for formalization (unstandardized) values above 6.24, design thinking does not have a significant effect on NPD DM agility, indicating that the strength of the relationship diminishes as formalization increases. Additionally, the floodlight analysis reveals that for formalization values greater than 5.02, the impact of AI capabilities on NPD DM agility is positive and significant ($\beta_{AI\ capabilities=5.02} = 0.13$). In contrast, for formalization values lower than the 5.02 level, the effect of AI capabilities on NPD DM agility is non-significant. Therefore, as formalization increases, the impact of AI capabilities on NPD DM agility is amplified.

5. Discussion

Given the transience of competitive advantages and the dynamism of business environments, firms are intensifying their efforts to boost agility in NPD DM and, in turn, attain superior NPD performance. This study has identified two forms of capabilities that firms deploy to respond to change: design thinking as a dynamic capability and AI capabilities as technology-driven innovation enablers. Consistent with our hypotheses, the findings reveal that both design thinking and AI capabilities have a positive impact on NPD DM agility, which in turn positively influences NPD performance. Our findings also show that NPD DM agility funnels the impact of design thinking and AI capabilities on NPD performance. As regards the role of organizational formalization, our study reveals an intriguing contrast that highlights how different types of capabilities (human-centered vs. technology-driven) require fundamentally different structural alignments to enhance agility in NPD DM. Although organizational formalization attenuates the impact of design thinking on NPD DM agility, it strengthens the effect of AI capabilities on NPD DM agility. Stated differently, it encumbers flexibility and creative problem-solving, which are essential for design thinking, but provides the necessary structure to leverage AI capabilities to enhance agility in DM.

5.1. Theoretical implications

This study makes a multifold contribution to extant research by highlighting the important drivers of NPD DM agility and, in turn, NPD performance. First, while most studies frame design thinking as a process, toolbox, or mindset (De Paula et al., 2021), our study contributes to the emerging body of work that theorizes design thinking as a dynamic capability (e.g., Magistretti et al., 2021). We empirically demonstrate its strategic value as an organizational-level dynamic capability that enables firms to sense and seize emerging opportunities and reconfigure decisions in response to change. Our findings also suggest that design thinking encourages the swift adaptation of NPD DM to internal or external changes, contributing to prior empirical investigations on the influence of design thinking on NPD outcomes (e.g., Nagaraj et al., 2020; Nakata & Hwang, 2020; Robbins & Fu, 2022). These investigations lacked insights into the impact of design thinking on an outcome variable that encompasses the element of speed (i.e., the agility of NPD DM).
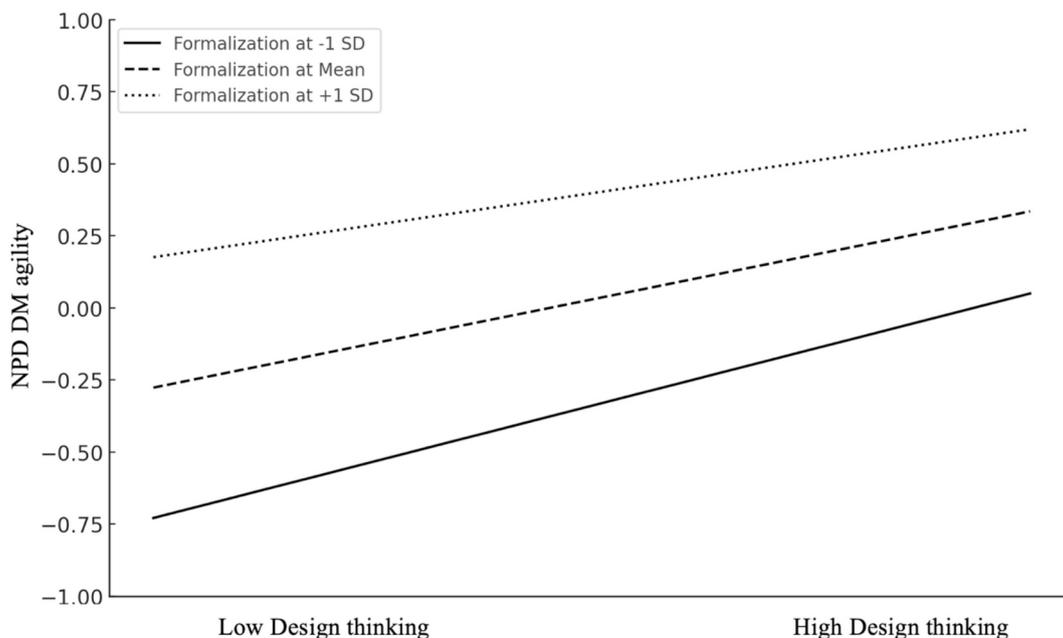

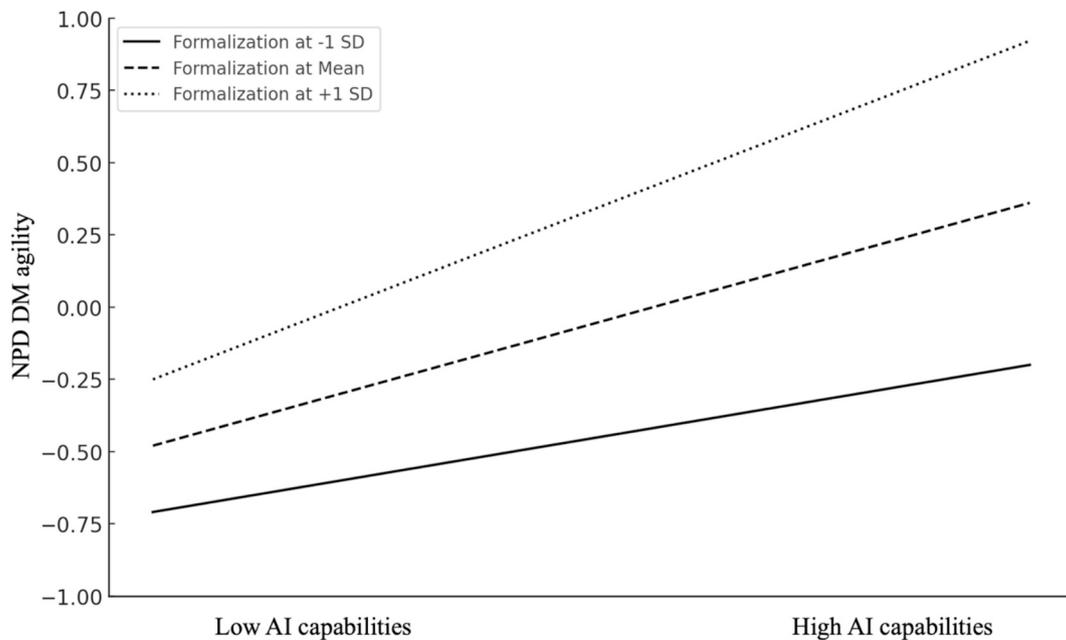**Fig. 2.** Simple slope analysis for H5.

Fig. 3. Simple slope analysis for H6.

Another important contribution pertains to the contingency perspective regarding the effectiveness of design thinking. Prior research has examined internal project-level contingencies such as the goals and uncertainty of the innovation project (e.g., Dell'Era et al., 2025; Magistretti et al., 2022) and external factors such as market turbulence (e.g., Nakata & Hwang, 2020). Our study differs from the aforementioned investigations as it focuses on the contingent role of internal and organizational-level structural characteristics of the firm. Identifying the attenuating role of organizational formalization on the relationship between design thinking and NPD DM agility augments understanding of the conditions that may support the effective implementation of design thinking to accelerate NPD DM. Therefore, a relatively organic structure based on less rigid rules, processes, and responsibilities would better align with the core elements of design thinking.

Our findings also enrich the emerging discourse on the impact of AI capabilities on innovation processes (e.g., Mariani & Dwivedi, 2024). These capabilities provide significant benefits and efficiencies, enabling management and transformation of large amounts of information by applying tools and technological solutions such as dashboards, data analytics, machine learning algorithms, and cognitive computing (Sahoo et al., 2024). We extend the relatively limited evidence on the impact of AI capabilities on NPD outcomes (e.g., Ameen et al., 2024; Kumar et al., 2024), specifically on how firms can enhance and accelerate NPD DM. Thus, our findings provide novel insights into how firms can leverage AI capabilities to achieve faster and more responsive NPD processes.

This study contributes to the contextual perspective on the effectiveness of AI capabilities on NPD outcomes. Prior research examined external factors such as government institutional support (Ameen et al., 2024), environmental dynamism (Kumar et al., 2024; Sahoo et al., 2024), and internal factors such as inter-organizational knowledge hiding (Arias-Pérez & Huynh, 2023). From an internal perspective, our findings enrich understanding of how firms can structure their processes to facilitate AI capabilities. These findings highlight that formalization provides a fertile ground for AI capabilities to enhance NPD DM agility. It enables firms to mitigate potential risks by providing standardized processes, clear guidelines, and responsibilities (Jansen et al., 2006), thus ensuring that information from AI is used effectively throughout the NPD DM process. However, when formalization is low, the effect of AI

capabilities on NPD DM agility becomes non-significant. This implies that firms may not reap the benefits of AI capabilities on agility in the NPD DM without a structured framework to guide AI implementation. Our findings also contribute to Kemp's (2024) propositions about situational AI. We argue that an increased level of structure may help firms overcome the strategic limitations of AI, such as contextual myopia. Well-defined rules, standards, responsibilities, and management systems ensure the structural clarity and boundaries necessary to aid AI capabilities, prevent misalignment with strategic goals, and enable firms' competitive advantage.

Our study provides important theoretical implications for understanding NPD DM agility as a mechanism that links organizational capabilities and innovation performance. Prior research has identified various facets of agility (Pinho et al., 2022). Broadly, studies have focused on organizational agility (e.g., Felipe et al., 2016) while highlighting specific types of agility related to business processes, such as supply chain (e.g., Riquelme-Medina et al., 2022), manufacturing (e.g., Awan et al., 2022), and marketing agility (e.g., Kalaignanam et al., 2021). However, there is a significant gap regarding drivers of agility in the NPD process and the resulting performance outcomes. Although prior NPD research has focused on agility as an outcome of cultural (e.g., Kock & Gemünden, 2016), organizational, and leadership-related factors (e.g., Kester et al., 2011), the role of two inherently different types of capabilities (i.e., design thinking and AI capabilities) that enable change is relatively unexplored. Our findings advance this stream of research by positioning NPD DM agility not only as an outcome influenced by internal and external contextual factors but also as a mediator channeling firm capabilities into superior NPD performance. These mediation effects emphasize that NPD DM agility enables organizations to swiftly act on the insights generated by design thinking and AI capabilities and, in turn, enhance NPD performance. Based on this finding, we propose that agility has high theoretical value as a central part of a firm's efforts to attain transient but renewable competitive advantages.

5.2. Managerial implications

Our study offers guidance for managers who are involved with NPD processes and intend to enhance the agility of their unit's DM. Embracing design thinking at an organizational level will enable practitioners to respond quickly and adapt their decisions to changes in the

firm's internal and external environments. To gain deeper insights into customer pain points and anticipate latent needs, managers can adopt customer immersion activities, empathy maps, or user-centered roadmaps while developing new products (Kim et al., 2020). Managers should also use visualization techniques to communicate complex ideas regarding their new products. Creating artifacts such as maps, drawings, or prototypes and fostering a culture of experimentation using rapid feedback loops will enable NPD teams to iterate rapidly and make more informed NPD decisions. Furthermore, managers should challenge current assumptions by assessing problems through different stakeholder lenses. Such externally focused practices are critical for firms to avoid rigidity and overcome institutionalized routines that may be ingrained in NPD processes, hampering speed and adaptability. In fact, NPD executives should also recognize the beneficial role of AI implementation as an organizational capability to increase agility in NPD DM. AI-enabled insights, trend prediction, and cognitive interpretations enable firms to process and act upon vast and complex datasets efficiently. Without these efficiencies, DM in today's data-intensive environment would be considerably slower. Managers should also realize that the benefits of design thinking and AI capabilities are streamlined through DM agility. Significant efforts should be made to ensure that agility is nurtured as a core aspect of the NPD DM process.

Our findings on the role of formalization in moderating the effects of design thinking and AI capabilities on NPD DM agility answer an important dilemma: what is the balanced approach to incorporate discipline and rules into design thinking and AI capabilities within an organization? The results suggest that managers must align their organizational structure with these capabilities. Firms must be cognizant of the eroding effect of formalization on how design thinking can foster agility. Hence, if the emphasis is on fostering design thinking, a less formalized structure should be adopted. However, a higher level of formalization may maximize the impact of AI capabilities on agility. This contrasting finding emphasizes that firms should adjust their organizational structure to the capabilities they intend to focus on to achieve superior agility and performance.

5.3. Limitations and future research

This study's limitations offer promising research avenues. First, cross-sectional data from a single key informant were used for the analysis. Although we did not identify common method bias issues, a longitudinal design could further alleviate potential method biases. Second, our study relies on a U.S. sample, which may limit the generalizability of the findings. Cultural aspects and contexts in other countries may provide rich insights into inter-country differences in the implementation of design thinking and AI capabilities. For example, in cultures with hierarchical distinctions, DM tends to be more tiered (Daniels & Greguras, 2014), which could be detrimental to the collaborative and participatory nature of design thinking. Third, design-thinking and AI-capabilities constructs rely on recently developed scales. Although they demonstrated satisfactory reliability and validity in this study, they are still at the nascent stage of empirical validation. Future studies could refine these measures using additional indicators to capture a broader picture and strengthen their generalizability across organizational contexts. Fourth, to maintain model parsimony, this study only examines two capabilities influencing NPD DM agility. Future research could examine additional business outcomes as mediators. For instance, product/technology roadmapping (Kim et al., 2018) and future planning may become more flexible with design thinking and AI tools. Avenues for future research also originate from AI capabilities, given the current level of development and adoption of AI within organizations. Recent business reports predict the development of agentic AI (Marr, 2024), which may possess a greater level of autonomy and disrupt the way it is implemented within firms. Therefore, future research may extend the findings of this study while considering AI capabilities at a later stage of their development.

CRediT authorship contribution statement

Nikolaos Kyriakopoulos: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Euiyoung Kim:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Erik Jan Hultink:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Sicco Santema:** Writing – review & editing, Supervision, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

Data availability

Data will be made available on request.

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Nikolaos Kyriakopoulos is a postdoctoral researcher in the Department of Design, Organisation, and Strategy at Delft University of Technology. His research focuses on product rollovers, new product development, strategic marketing, and design thinking. He has published in the *Journal of Brand Management* and the *Journal of Consumer Behavior*, and has presented his work at conferences, such as the American Marketing Association, the European Marketing Academy, and the Innovation and Product Development Management Conference.

Dr. Euiyoung Kim is an Assistant Professor in the Faculty of Industrial Design Engineering at TU Delft, specializing in system design for mobility with a focus on dynamic stability and strategic innovation. He co-directs the Automated Mobility Lab. His research, published in leading journals such as *California Management Review, IEEE Transactions on Engineering Management, Journal of Mechanical Design*, and *Cities*, explores sustainable mobility, automation, and design methodologies for complex systems. With extensive academic and industry experience, Dr. Kim engages globally through interdisciplinary collaborations and invited talks, advancing design-driven solutions that address organizational and societal challenges and foster inclusive innovation.

Erik-Jan Hultink is a Professor of New Product Marketing and the Head of the Department of Design, Organization, and Strategy at the Faculty of Industrial Design Engineering, Delft University of Technology. He founded the Master Program in Strategic Product Design at the Delft University of Technology and is also a Co-Founder of the Dutch Product Development and Management Association (PDMA) chapter. His research focuses on new product marketing and sustainable innovation management. His work has appeared in journals such as the Journal of the Academy of Marketing Science and the Journal of Product Innovation Management, among others.

Prof. Dr. Sicco Santema is a Professor in the Faculty of Industrial Design Engineering at TU Delft, specializing in Network Design and Innovation and is the coordinator for the mobility research in the design school. His research is focused on collaboration between network partners and stakeholders. His research includes sustainability (EGS and CSRD), business models, design methodologies, and simplification of systems. With his extensive academic and industry experience, Prof Sicco Santema engages in global scientific partnerships, invited talks, and societal advisory, fostering inclusivity and equality.