Unpacking experimentation in design thinking

Contributions to innovation performance and the moderating role of digital technologies

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Unpacking experimentation in design thinking: Contributions to innovation performance and the moderating role of digital technologies

Stefano Magistretti [a,*], Claudio Dell'Era [a], Marina Candi [b], Scott K. Swan [c], Mattia Bianchi [d], Giulia Calabretta [e], Ileana Stigliani [f], Roberto Verganti [d]

[a] School of Management, Politecnico di Milano, Piazza L. da Vinci, 32, 20133, Milano, Italy
[b] Reykjavik University Center for Research on Innovation and Entrepreneurship, Menntavegur 1, 102, 101, Reykjavík, Iceland
[c] Raymond A. Mason School of Business – College of William & Mary, 101 Ukrop Way, Williamsburg, VA, 23186, United States
[d] Stockholm School of Economics, Sveavägen 65, 113 83, Stockholm, Sweden
[e] TU Delft, Mekelweg 5, 2628 CD, Delft, Netherlands
[f] Imperial College Business School, South Kensington Campus, Exhibition Rd, London, SW7 2AZ, UK

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ABSTRACT

Design thinking is an innovation approach that emphasizes developing and testing hypotheses about the desirability, feasibility, and viability of an idea through iterative experimentation. Although widely used, there is limited empirical evidence to support the effectiveness of experimentation practices in design thinking projects. Similarly, the impact of integrating digital technologies into experimentation processes remains underexplored. This study addresses these gaps by analyzing data from 246 design thinking projects to examine how early and frequent experimentation influences innovation performance, specifically in terms of effectiveness and efficiency. It also examines how the use of digital technologies moderates these relationships. The results show that both early and frequent experimentation positively influence innovation effectiveness, while only early experimentation significantly improves innovation efficiency. Moreover, the use of digital technologies strengthens the positive effects of early experimentation on both effectiveness and efficiency. This research provides valuable theoretical and practical insights by deepening our understanding of how experimentation and digital tools drive innovation performance in design thinking projects.

1. Introduction

Innovation methodologies such as design thinking (Magistretti et al., 2021; Carlgren and Ben Mahmoud-Jouini, 2022), agile development (Bianchi et al., 2020), lean startup (Ries, 2011; Shepherd and Gruber, 2021), and growth hacking (Cavallo et al., 2024), have gained significant traction among both academics and practitioners. Despite their different principles and practices, these approaches share a fundamental reliance on experimentation (Mansoori and Lackeus, 2020). The concept of experimentation has been explored in various disciplines, including strategy (e.g., Nicholls-Nixon et al., 2000) and entrepreneurship (e.g., Lindholm-Dahlstrand et al., 2019). In the context of innovation, experimentation serves to validate the core assumptions behind novel ideas by assessing their desirability, feasibility, and viability (Brown, 2008; Thomke, 1998; Hampel et al., 2020). This process typically involves the use of prototypes – early, imperfect representations of the innovation (Beltagui et al., 2023) – to actively engage with and modify real-world scenarios (Bogers et al., 2010). By testing these prototypes with target users, innovators can create realistic simulations of potential products or services and generate valuable user feedback (Pisano, 2019). This feedback is essential for making informed design and strategic decisions throughout the development process. According to Bogers and Horst (2014), experimentation is characterized by "active engagement, concrete intervention, and selective encounter of reality through prototypes". Active engagement fosters continuous interaction between innovators and end users, which enhances the iterative learning process (Magnusson, 2009). Prototypes can create a vivid experience, a tangible preview of future innovations, and elicit authentic user responses (Pisano, 2019). When conducted early and often, these encounters with simplified models of reality provide critical insights that strengthen

* Corresponding author.
E-mail addresses: stefano.magistretti@polimi.it (S. Magistretti), claudio.dellera@polimi.it (C. Dell'Era), marina@ru.is (M. Candi), ksswan@wm.edu (S.K. Swan), Mattia.Bianchi@hhs.se (M. Bianchi), G.Calabretta@tudelft.nl (G. Calabretta), i.stigliani@imperial.ac.uk (I. Stigliani), Roberto.Verganti@hhs.se (R. Verganti).

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decision-making as innovation projects evolve (Magistretti et al., 2021). In environments characterized by uncertainty and complexity (Howard-Grenville, 2020), experimentation helps organizations interpret their context and set the strategic direction (Furr and Eisenhardt, 2021). For example, system dynamics modeling can simulate the impact of strategic and organizational changes on business models, allowing firms to anticipate potential outcomes (Cosenz and Noto, 2018). By leveraging this dynamic approach, firms gain a deeper understanding of how external factors shape decisions, making experimentation an essential tool for evaluating and refining strategies prior to full implementation.

Experimentation has become central to innovation processes as its adoption and importance continue to grow (Watanabe and Tou, 2019), with an increasing focus on experimentation as a key practice (Hampel et al., 2020; Thomke, 2020; Sanasi et al., 2023). It is now widely implemented across industries (Pisano, 2019), firm functions (Spear and Bowen, 1999; Petersen and Wohlin, 2010), and firm contexts, from startups to large established companies (Felin et al., 2020; Sanasi et al., 2021) and consulting firms (Magistretti et al., 2022a). At companies such as Airbnb and Booking.com, designing and running thousands of experiments is a core, routine process (Verganti et al., 2020).

Unlike traditional innovation management frameworks such as stage-gate and waterfall, which rely on high-fidelity testing at the end of a project to validate results before launch (Paluch et al., 2019), modern approaches such as design thinking, agile development, lean startup, and growth hacking (Mansoori and Lackeus, 2020; Blank and Eckhardt, 2023; Cavallo et al., 2024) integrate experimentation for exploratory learning throughout the innovation process (Shaik et al., 2023; Yi et al., 2022). This continuous experimentation is particularly important for innovation projects characterized by high levels of ambiguity (Liedtka, 2015; Magistretti et al., 2022b).

Design thinking has gained widespread adoption and prominence in organizations ranging from consulting firms, such as Deloitte Digital, PwC, and Accenture (Dell'Era et al., 2020), to established corporations such as PepsiCo and 3M (Gemser et al., 2023). Recognized as an effective approach to product and service innovation (Magistretti et al., 2023), design thinking is widely accepted as a formal method for creative problem solving that is particularly well suited to addressing ill-defined problems (Brown, 2008). Central to design thinking is the ability to navigate ambiguity, making it particularly useful for tackling "wicked problems" (Buchanan, 1992; Rittel and Webber, 1973). Verganti et al. (2021) highlight iterative prototyping as a defining characteristic of design thinking. This approach involves learning through trial and error, frequent user involvement, and the use of visual and material representations to explore potential solutions. Rooted in experimentation (Bogers et al., 2010), design thinking fundamentally relies on iterative testing (Elsbach and Stigliani, 2018; Klenner et al., 2022). For example, the development of "quick and dirty" prototypes allows teams to explore the solution space and identify the most promising innovation opportunities (Stigliani and Ravasi, 2012; Ben Mahmoud-Jouini and Midler, 2020). In addition, experimentation in design thinking is critical during the definition phase, where it helps reframe problems (Pham et al., 2023). Crafting problem statements and transforming them into "how might we" questions allow design thinkers to better understand and address complex problems through continuous, iterative exploration (Durante et al., 2024). Indeed, the initial problem statement in design thinking serves as a preliminary hypothesis that is subsequently tested to assess its robustness and value. This process naturally leads to reframing the problem similar to experimenting with artifacts (i.e., problem formulation) in real-world interactions (Bogers et al., 2010). Furthermore, experimentation is widely recognized as essential during the prototyping phase to test ideas (Liedtka, 2015). This aligns with designers' iterative approach to identifying and testing assumptions about problems and developing tangible solutions (Micheli et al., 2019). As such, experimentation is integral to every stage of the design thinking process, both early (Durante et al., 2024) and late (Liedtka, 2015). Despite the growing adoption of experimentation within design thinking and its recognized importance in driving innovation (Hampel et al., 2020; Thomke, 2020), there is still a lack of systematic evidence detailing how experimentation specifically contributes to innovation performance in design thinking contexts. While qualitative studies have highlighted the importance of rapid prototyping and user engagement (e.g., Liedtka et al., 2024), quantitative research examining the direct impact of design thinking practices – and experimentation in particular – on innovation outcomes remains scarce (Nagaraj et al., 2020; Nakata and Hwang, 2020; Magistretti et al., 2022a; Robbins and Fu, 2022). Recent literature reviews have highlighted the need for empirical validation of the impact of design thinking on measurable innovation outcomes (Micheli et al., 2019; Magistretti et al., 2021), yet this gap remains. Given the widespread use of design thinking in practice, its potential impact on innovation performance, and the central role of experimentation in both innovation and design thinking, understanding this relationship is critical. Such insights are valuable not only for scholars seeking to advance innovation theories, but also for practitioners seeking to make informed decisions about investing in experimentation practices. Hence, we pose the following research question.

RQ1: How do experimentation practices contribute to innovation performance in design thinking projects?

In parallel, the rapid advancement and widespread adoption of digital technologies – such as artificial intelligence (AI), big data analytics, and 3D printing – have created new opportunities for early-stage, low-cost prototyping and accelerated user feedback cycles (Bianchi et al., 2020; Candi and Beltagui, 2019; Mariani and Nambisan, 2021). Recent studies examining the impact of AI on innovation processes show how these technologies enable faster, more affordable experimentation while generating richer consumer insights (Roberts and Candi, 2024). As a result, there is growing scholarly interest in exploring how digital technologies are transforming innovation practices. Research has increasingly focused on the role of AI, big data (Mariani et al., 2023), 3D printing, the Internet of Things (IoT), and other next-generation digital tools in shaping innovation outcomes (Cho et al., 2023). These studies aim to deepen our understanding of not only how these technologies are used in innovation processes (Mariani et al., 2023; Roberts and Candi, 2024), but also how they can be effectively integrated and leveraged together to improve experimentation and overall innovation performance (Cho et al., 2023). Liedtka (2020) envisions a synergistic relationship between design thinking and digital technologies, suggesting that design thinking practices can be enhanced by digital tools, while these technologies can simultaneously support and streamline design thinking processes. Extending this perspective, recent research has highlighted the role of AI, particularly generative AI, in expanding the scope of problem solving and solution generation, thereby accelerating the innovation process (Bouschery et al., 2023). Conversely, empirical studies have shown that big data, while providing valuable insights, may be insufficient to fully support design thinking. Instead, thick data – rich, qualitative insights – remain essential for effective creative problem solving, requiring a balance of both data types (Mortati et al., 2023). Despite these advances, however, there is still a lack of quantitative evidence on how digital technologies influence the relationship between experimentation and innovation performance in design thinking contexts. To address this gap, we propose the following research question.

RQ2: How does the use of digital technologies moderate the relationship between experimentation practices and innovation performance in design thinking projects?

To answer these questions, we analyze quantitative data from 246 innovation projects conducted by consulting firms that use design thinking to solve their clients' problems. Our results show that early experimentation in design thinking projects is positively associated with both innovation effectiveness and efficiency. Furthermore, the use of digital technologies significantly strengthens these relationships. In contrast, while frequent experimentation is positively associated with innovation effectiveness, it does not enhance innovation efficiency, and the use of digital technologies does not moderate this relationship.

The contributions of this research are threefold. First, it provides important empirical evidence on the effectiveness of experimentation practices in the context of design thinking, directly addressing recent calls for more quantitative research in this area (Micheli et al., 2019; Magistretti et al., 2021). This paper also advances our understanding of design thinking as an evidence-based, iterative approach rooted in various forms of experimentation (Bogers and Horst, 2014; Thomke, 2020), rather than a rigid, prescriptive process. By emphasizing the dynamic and exploratory nature of design thinking, this research reinforces the central role of experimentation in driving problem solving and innovation (Carlgren et al., 2016; Liedtka, 2020). Second, it advances the discourse on experimentation (Thomke, 2020) by demonstrating that this is not a singular concept (Verganti et al., 2021), but includes distinct practices, especially early and frequent experimentation, each of which uniquely influences innovation performance. Recognizing this distinction allows for a more nuanced understanding of how different experimentation strategies contribute to innovation outcomes and provides a refined framework for managing experimentation in design thinking processes. Third, this study contributes to the growing discussion on the role of digital technologies in creative processes (i.e., design thinking) (Liedtka, 2020) by revealing how digital technologies moderate the relationship between experimentation and innovation performance. This finding highlights the critical role that digital technologies play in enhancing the effectiveness of experimentation and the need for granular, quantitative testing to validate relationships that are often merely hypothesized or assumed. Moreover, by providing actionable insights into how specific experimentation practices affect innovation outcomes, this research offers valuable implications for scholars seeking to deepen theoretical models and practitioners seeking to optimize innovation strategies.

2. Literature review and hypotheses

2.1. Experimentation practices in design thinking projects

Design thinking goes beyond a focus on aesthetics and product form to provide a comprehensive creative problem-solving approach that fosters innovation (Brown, 2008; Liedtka et al., 2013; Dell'Era et al., 2020). It is particularly effective in addressing "wicked" and ill-defined problems by expanding both the scope of the problem and the potential solutions (Dorst and Cross, 2001; Foss and Saebi, 2018), while encouraging creativity among those involved in solving the problem (Tripp, 2013). Although design thinking can be interpreted in many ways, it is generally recognized for three core characteristics: a human-centered perspective (Buchanan, 2001; Brown, 2008), the use of creativity to reframe problems (Beckman and Barry, 2007; Dorst, 2011; Beckman, 2020), and a strong emphasis on prototyping or experimentation (Fraser, 2009; Holloway, 2009; Magistretti et al., 2022b).

Experimentation is a central practice in design thinking (Carlgren et al., 2016; Micheli et al., 2019; Magistretti et al., 2021). Beverland et al. (2015, p. 593) emphasize that "design thinking is characterized by trial-and-error learning through iterative forms, prototyping, and trials that test a range of possible solutions with end-users and other project stakeholders." Experimentation in design thinking helps designers generate and process information, ultimately supporting decision-making throughout the creative problem-solving process. These experiments explore the potential of innovative ideas in terms of desirability, feasibility, and viability (Brown, 2008). In the context of innovation, experimentation involves the development of prototypes, which are considered incomplete representations of new solutions designed to actively engage with and manipulate reality (Bogers et al., 2010; Beltagui et al., 2023). Testing prototypes with target users creates a realistic experience of the innovation and allows users to provide valuable feedback (Pisano, 2019). In design thinking, experimentation aims at exploration rather than validation (Magistretti et al., 2022b), focusing on the discovery of innovative solutions. Multiple, partial, and "fast and frugal" prototypes are used to "see what would happen if" (Garvin, 2003, p. 142) and help designers explore the solution space to uncover promising new concepts (Carlgren et al., 2016). Scholars have identified several experimental activities in design thinking, including prototyping Micheli et al. (2019), running tests (Carlgren et al., 2016), using early rough versions of prototypes (Beltagui et al., 2023; Elsbach and Stigliani, 2018), and iteration (Thomke and Manzi, 2014). However, despite the recognition of these experimentation practices, their impact on innovation performance in design thinking projects remains underexplored. As a result, further research is needed to better understand the relationship between experimentation practices and innovation outcomes in design thinking contexts.

2.2. Experimentation practices and innovation performance in design thinking projects

Experimentation, which involves the creation and testing of hypotheses, is gaining increasing attention in academic discussions in fields ranging from design management (Micheli et al., 2019) and software engineering (Wohlin et al., 2012) to business model design (Andries et al., 2013; Cosenz and Noto, 2018) and entrepreneurship (Patel et al., 2015; Hampel et al., 2020). Evidence on the emerging practices used to implement experimentation (Thomke, 2020), the types of project outcomes that can be achieved (Gans et al., 2019), and their reliance on digital technologies (Candi and Beltagui, 2019; Roberts and Candi, 2024) calls for further exploration of this phenomenon. Previous empirical studies on the performance effects of experimentation have yielded mixed results. For example, MacCormack et al. (2001) find a positive relationship between early experimentation and the quality of innovation output. In contrast, in their cross-industry experimental study, Camuffo et al. (2019) identify disciplined experimentation-based decision making as important in the innovation process. However, Contigiani (2018) highlights the risk of replication in experimentation, especially when adopting lean startup approaches. The literature on project performance and its link to experimentation reveals several trade-offs (Bianchi et al., 2020). Different experimentation approaches may lead to different innovation performance outcomes (Koning et al., 2022), and innovators may focus on scope and thus adopt experimentation processes to ensure that specific goals are achieved (Gans et al., 2019). In addition, research shows that project quality increases with experimentation (Nightingale, 2000). The ability to learn from the market allows innovators to improve solutions, thereby increasing market fit and quality (Thomke, 1998). The effectiveness of the experimentation process in influencing innovation performance has been debated, with some studies questioning whether the focus should be on time or budget (Unterhitzenberger and Bryde, 2019). While experimentation requires time, it must also meet market demands for timely innovation (Thomke et al., 1998). Efficiently managing the timing of experimentation is critical, making efficiency an important project performance outcome when considering experimentation (Bianchi et al., 2020). Despite a large body of research on experimentation and innovation performance in management, few studies have examined the impact of design thinking practices on innovation performance. Specifically, Nagaraj et al. (2020) and Nakata and Hwang (2020) are among the few that examine the role of experimentation in design thinking practices. Nakata and Hwang (2020) conceptualize design thinking as consisting of three mindsets: human-centeredness, abductive reasoning, and learning by failing. These mindsets correspond to three key actions: discovery, ideation, and experimentation. Using data from 312 innovation professionals, Nakata and Hwang (2020) show that each mindset drives its respective action, with human-centeredness leading to discovery. Their findings also suggest that design thinking positively impacts new product performance, particularly through experimentation. Nagaraj et al. (2020) examine the impact of design thinking on project-level performance. By applying structural equation modeling to survey data from 247 new product development projects, they show that using four design thinking practices – user empathy, collaborative abduction, iteration, and collaborative representation – results in more effective new products. However, both studies focus on product performance rather than broader innovation performance. To capture innovation performance more comprehensively, we follow Bianchi et al. (2020) in distinguishing between innovation effectiveness (related to the quality and scope of the project) and innovation efficiency (related to the use of resources, including time and budget).

The literature identifies various experimentation practices, such as build-measure-learn loops in lean startup (Ries, 2011) and A/B testing in late stage development (Bianchi et al., 2020). In line with the literature on experimentation (MacCormack and Verganti, 2003; Carlgren et al., 2016; Thomke, 2020; Liedtka et al., 2024), we distinguish two widely used forms of experimentation during the innovation process. First, *early experimentation* is used to reduce uncertainty, understand problems, and address ambiguity in the early stages of innovation. It focuses on broad exploration rather than specific outcomes (Carlgren et al., 2016; Liedtka et al., 2024). Second, *frequent experimentation* occurs both in early and in the later stages of innovation, with the goal of continuous improvement of ideas and iterative testing of assumptions. This form of experimentation keeps open the possibility of aligning the innovation with market expectations (MacCormack and Verganti, 2003; Thomke, 2020).

Early experimentation has been shown to reduce the risk of failure, particularly in software development (Boudreau, 2012). By providing alternative solutions and reducing investment through techniques such as low-resolution prototyping (Thomke, 1998; MacCormack, 2001; Beltagui et al., 2023; Ries, 2011), early experimentation fosters alignment among stakeholders. Liedtka (2015) argues that early prototypes, such as journey mapping and storyboarding, help immerse users in their experiences, spark creativity, and generate numerous new ideas in design thinking projects. Stigliani and Ravasi (2012) advocate for the early expression of new ideas through material artifacts to promote their generation and testing, especially in design-intensive industries. Beltagui et al. (2023) highlight the role of artifacts in facilitating ongoing product development discussions. Early-stage experimentation can promote reasoning and creativity by exploring a wide range of potential possibilities (Fischer, 2001). This is particularly important in highly uncertain projects where stakeholders may have limited or no understanding of the solution. In such contexts, experimentation practices can help make sense of the complex choices facing stakeholders (Liedtka et al., 2024). Early experimentation is designed to make innovation projects more flexible and responsive to external turbulence (Candi et al., 2013), while providing feedback on the quality and effectiveness of the proposed solutions. Prototypes are used to generate new knowledge, stimulate potential developments in the early stages of innovation (Buganza et al., 2009), and improve project effectiveness. Hence, our first hypothesis.

H1. Early experimentation practices are positively related to innovation effectiveness in design thinking projects.

By challenging a problem through early prototypes, designers gain a deep understanding of the problem at hand (Magistretti et al., 2021). Innovators using design thinking can turn insights into prototypes, which reveal new opportunities to share with stakeholders and gather feedback. This process helps avoid potential costs, mitigate misunderstandings, and prevent project delays, ultimately improving the efficiency of innovation projects (Dell'Era et al., 2020). The experimentation approach based on framing and reframing – core elements of design thinking (Carlgren et al., 2016) – can accelerate time to market and reduce project costs through rapid prototyping (Dell'Era et al., 2020). Thus, we propose.

H2. Early experimentation practices are positively related to innovation efficiency in design thinking projects.

Frequent experimentation and continuous iteration allow for ongoing hypothesis testing and real-world feedback (Becker et al., 2005), consistent with the view that hypothesis testing is an ongoing process throughout innovation (Thomke, 2020; Verganti et al., 2021). Frequent experimentation allows innovators to remain flexible and accept changes also at later stages (MacCormack and Verganti, 2003). It fosters a learning-by-doing mindset, which is recognized as a key driver of success in startup creation (Ries, 2011) and innovation more broadly (Candi et al., 2013; Hatch and Mowery, 1998). Through continuous iteration and refinement, innovators generate new knowledge that increases the effectiveness of the entire innovation process (Buganza et al., 2009). Rapid testing of concepts and prototypes with end-users, whether analytical or physical, helps reduce uncertainty and validate assumptions (MacCormack et al., 2001; Cosenz and Bionva, 2021). Frequent experimentation also reflects a culture focused on continuous hypothesis testing and validation (Nakata and Hwang, 2020). As Eisenhardt and Tabrizi (1995) suggest, frequent milestones involving testing accelerate knowledge generation. Moreover, experimentation supports the divergent and convergent dynamics central to design thinking (Rylander, 2009; Carlgren et al., 2016), helping to reconcile competing views among team members and accelerate the creative process, ultimately improving the effectiveness of design thinking projects (McCullagh, 2013; Micheli et al., 2019). Therefore, we propose.

H3. Frequent experimentation practices are positively related to innovation effectiveness in design thinking projects.

Frequent experimentation, especially in uncertain and complex environments, supports both product and process innovation (Wriegly and Straker, 2016). In innovation projects characterized by uncertainty, frequent experimentation can reduce project duration, manage budgets efficiently (Ellis and Brown, 2017), and increase the likelihood of project success (Klenner et al., 2022) in terms of project efficiency. Hence, we posit.

H4. Frequent experimentation practices are positively related to innovation efficiency in design thinking projects.

2.3. *Digital technologies, experimentation practices, and innovation performance in design thinking projects*

As society becomes increasingly digitally connected, digital technologies profoundly shape how we experience products and services (Nambisan et al., 2017). Scholars have debated the role of digital technologies in innovation, with different perspectives on their effectiveness (Beltagui et al., 2023). Technologies such as 3D printing and additive manufacturing are recognized as central to supporting physical prototyping and experimentation (Rayan and Striukova, 2016; Geissdoerfer et al., 2022) and even play a role in creating new ecosystems (Beltagui et al., 2020). Moreover, AI is highly valued for its ability to explore the problem space in design thinking, significantly reducing the time needed to propose potential solutions (Bouschery et al., 2023). Virtual reality, on the other hand, offers an innovative way to represent proposed solutions, accelerating experimentation by enabling early testing and faster learning (Thomke et al., 1998). In addition, new digital technologies can lower the cost of experimentation, allowing organizations to conduct experiments more frequently (Gruber et al., 2015; Cai et al., 2023). Recent studies have primarily examined the role of these digital technologies in design thinking qualitatively, exploring how they enhance the process (Bouschery et al., 2023; Mortati et al., 2023; Wang, 2022; Chouki et al., 2021). By incorporating digital technologies, companies can reduce costs and, in turn, significantly increase the frequency of experimentation with new solutions (Lee and Trimi, 2021). As a result, the use of digital technologies is expected to positively moderate the relationship between experimentation practices (both early and frequent) and innovation performance outcomes (effectiveness and efficiency) in design thinking projects, as illustrated in Fig. 1. Therefore, we propose.

H1a. The use of digital technologies positively moderates the relationship between early experimentation practices and innovation effectiveness in design thinking projects.

H2a. The use of digital technologies positively moderates the relationship between early experimentation practices and innovation efficiency in design thinking projects.

H3a. The use of digital technologies positively moderates the relationship between frequent experimentation and innovation effectiveness in design thinking projects.

H4a. The use of digital technologies positively moderates the relationship between frequent experimentation practices and innovation efficiency in design thinking projects.

The research model presented in Fig. 1 hypothesizes the relationships between early and frequent experimentation practices and innovation effectiveness/efficiency, along with the moderating effects of digital technologies.

3. Research methodology

3.1. Data collection

The empirical context for this study is innovation projects using a design thinking approach conducted by consulting firms for their clients. As mentioned above, experimentation is a core practice of design thinking (Micheli et al., 2019; Beverland et al., 2015), making design thinking projects an ideal context to study the benefits of experimentation. In recent years, consulting firms have increasingly adopted design thinking practices to address the complex innovation challenges faced by their clients (Magistretti et al., 2022a), making this a relevant setting in which to study experimentation and the use of digital technologies. In addition, the consulting industry is characterized by the early adoption of innovative practices, which aligns with the exploratory and adaptive nature of design thinking (Armbrüster, 2006).

Design thinking uses experimentation to test assumptions and address wicked problems –complex, ill-defined challenges that require iterative problem solving (Johansson-Sköldberg et al., 2013; Buchanan, 1992). The innovation projects analyzed were intentionally designed to address specific client needs, ensuring their relevance and grounding in real-world challenges, rather than being ad hoc or conducted solely for the purposes of this study.

The authors contacted consultants they had worked with over the past five to ten years who had used design thinking and invited them to participate in an online survey conducted through Qualtrics in 2020. The survey yielded 246 valid responses from consultants working at firms in North America and Europe. To ensure that each response represented a unique project, only one response was collected from each consulting firm. The response rate of just over 10% is considered acceptable for an online survey (Wilson, 1999), especially when participants are well informed about the survey topic (Pollard, 2002; Skinner, 2009). This was ensured by targeting design thinking practitioners who had recently completed consulting projects. In particular, the unit of analysis was "a specific, recently completed consulting innovation project managed through design thinking," which respondents identified and used as the context for answering the survey questions.

3.2. Variables

The survey items were adapted from existing research (see Table 1), with additional items developed as needed. The two variables for experimentation practices were based on the definitions of Carlgren et al. (2016), Micheli et al. (2019), and Bianchi et al. (2020), while the variables for innovation performance were based on Unterhitzenberger and Bryde (2019) and Bianchi et al. (2020). The moderating variable for the use of digital technologies was measured by asking respondents whether specific digital technologies were used in the design thinking project. The variable was dichotomously coded 0 if no digital technologies were used, and 1 if one or more digital technologies were used.

The survey underwent several rounds of testing with consultants carefully selected from the authors' networks who hold advisory board positions in design-related associations (e.g., collaborative research centers, university research centers, and international master's programs). Adjustments were made to ensure the clarity of the questions. During testing, some items, particularly those identified as unclear, were dropped, optimizing the survey length and improving the response rate. Exploratory factor analysis was used to identify items that measured each variable. Items that loaded poorly or had high cross-loadings were removed. This was followed by confirmatory factor analysis, which yielded good fit statistics for the measurement model: a root mean squared error of approximation (RMSEA) of 0.046, X2 of 127 (83 degrees of freedom), comparative fit index (CFI) of 0.97, and a standardized root mean squared residual (SRMR) of 0.053. All composite

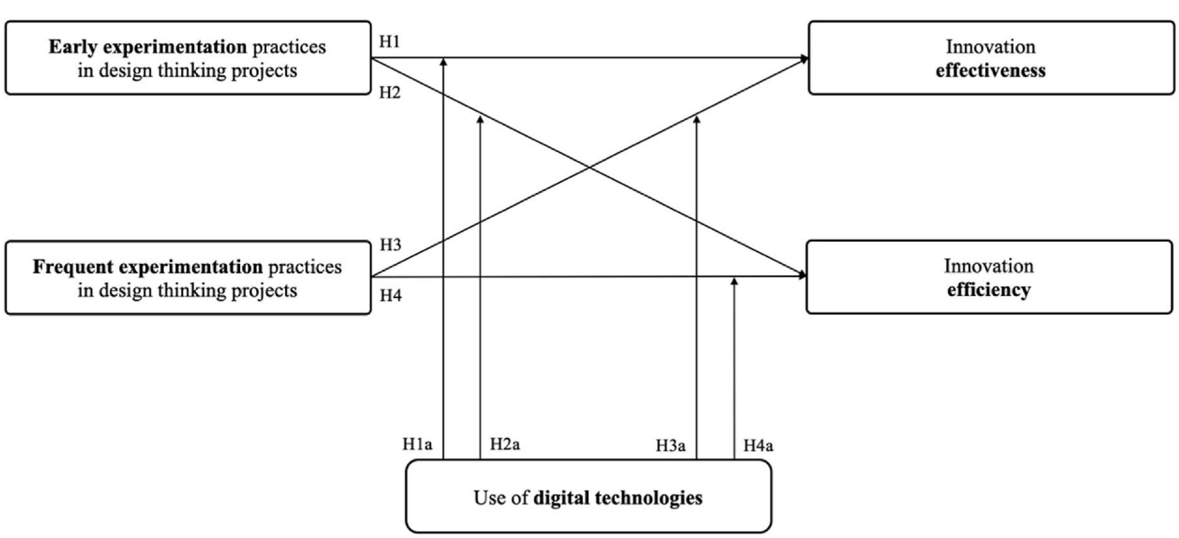

Fig. 1. Research model.

Table 1
Variables and survey items.

Variables	Items	Mean	Std. dev.	References
Early experimentation	*To what extent were the following practices used in THE PROJECT:*			Adapted from Carlgren et al. (2016); Micheli et al. (2019); Bianchi et al. (2020)
	Executing tasks even if they are not clearly defined and their contents might change as the project unfolds.	4.53	1.82	
	Trying out early, rough versions of the solution to see what happens.	4.82	1.82	
	Looking for feedback from the client on ideas as early as possible, even if the ideas are very rough.	5.45	1.60	
Frequent experimentation	*To what extent were the following practices used in THE PROJECT:*			Adapted from Carlgren et al. (2016); Micheli et al. (2019); Bianchi et al. (2020)
	Creating multiple prototypes of the concept as it evolves throughout the project.	5.00	1.88	
	Rapid prototyping technologies.	4.75	2.07	
	Frequently creating and releasing mock-ups and beta versions of the solution to real users.	4.55	2.09	
Use of digital technologies	*Were the following digital technologies used in THE PROJECT:* Extended reality (e.g., augmented reality), additive manufacturing (e.g., 3d printing), Internet of Things (IoT), big data analytics, artificial intelligence	0.51	0.50	Candi and Beltagui (2019); Rayna and Striukova (2016)
Innovation effectiveness	Client satisfaction with THE PROJECT outcome was very high.	5.90	1.17	Unterhitzenberger and Bryde (2019); Bianchi et al. (2020)
	THE PROJECT met the requirements of the client.	5.96	1.18	
	We are likely to work in the future with the same client.	5.83	1.43	
	THE PROJECT outcome exceeded quality expectations.	5.42	1.30	
Innovation efficiency	THE PROJECT was finished on time.	5.22	1.71	Unterhitzenberger and Bryde (2019); Bianchi et al. (2020)
	THE PROJECT requirements were met by the completion date initially agreed with the client.	5.05	1.73	
	The cost estimates made at the beginning of THE PROJECT were accurate.	4.66	1.71	
	THE PROJECT did not require extra resources beyond those budgeted.	4.27	1.96	

Notes: Response options for all items ranged from 1 (not at all) to 7 (to a great degree). THE PROJECT was replaced with the name of the project as provided by the respondent.

reliabilities exceeded the accepted cutoff of 0.7, and the average variances extracted were greater than 0.5 (Hair et al., 2014). Table 1 provides a list of the retained survey items.

Pairwise correlations and summary statistics are shown in Table 2. The highest pairwise correlation is observed between early and frequent experimentation. While this is an intuitive result, it raises the potential concern of multicollinearity. Following the guidelines of Grewal et al. (2004), we note that multicollinearity is unlikely to be an issue, as the composite reliabilities are greater than 0.7, the R2 values range from 16% to 34%, and the sample size is sufficiently large. To further examine multicollinearity, variance inflation factors (VIF) were calculated. The highest VIF in the hierarchical regression models, including all interactions, is 4.12, which is below the conservative threshold of 5 (Marquaridt, 1970). Therefore, we are reasonably confident that multicollinearity is not a problem.

Several control variables were included in the survey and analysis. First, firm size, which relates to the resources available for experimentation and innovation strategy (Kahn and Candi, 2021), was operationalized as the number of employees in both the consulting firm and the client firm. Second, given the focus on design thinking innovation projects, and recognizing that a higher level of design thinking expertise is likely to be associated with a greater propensity to experiment, the number of years of design thinking experience within the consulting firm was included (Magistretti et al., 2022a). Third, the duration of the innovation project, measured in months, was included as a control

Table 2
Pairwise correlations and descriptive statistics.

	Variable	Mean	Std. dev.	1	2	3	4
1	Innovation efficiency	4.80	1.35				
2	Innovation effectiveness	5.78	1.02	0.50			
3	Early experimentation	4.94	1.40	0.20	0.38		
4	Frequent experimentation	4.86	1.63	0.15	0.31	0.63	
5	Use of digital technologies	0.51	0.50	−0.01	0.04	0.17	0.21

variable, as longer projects are more likely to involve more extensive experimentation. Logarithmic transformations of the control variables were applied to ensure normal distributions.

4. Findings

The data were analyzed using Stata (version 17). Hierarchical moderated regression analyses were conducted to test the hypotheses, with the results presented in Table 3 for innovation effectiveness and Table 4 for innovation efficiency. Prior to the analysis, all independent variables were standardized as recommended by Aiken and West (1991). In Table 3, Step 1 shows that two control variables are significantly related to innovation effectiveness. Specifically, the level of design thinking expertise within the consulting firm and the size of the client firm are both positively related to innovation effectiveness. In Step 2, the independent variables for early experimentation and frequent experimentation are introduced, and both coefficients are statistically significant, providing support for H1 and H3. In Step 3, the use of digital technologies is found to be unrelated to innovation effectiveness at a statistically significant level, suggesting that the use of digital technologies in design thinking projects by itself does not directly influence innovation effectiveness. Step 4 introduces the interaction terms. The interaction between early experimentation and the use of digital technologies is positive and statistically significant, with a significant change in R^2 between Steps 3 and 4, supporting H1a. However, the interaction between frequent experimentation and use of digital technologies is not statistically significant, indicating that H3a is not supported. The interaction plot for early experimentation, shown in Fig. 2, illustrates that the relationship between early experimentation and innovation effectiveness is stronger when digital technologies are used than when they are not.

In Table 4, Step 1 shows that three control variables are significantly related to innovation efficiency: consulting firm size and project length are negatively related to innovation efficiency, while client firm size is positively related to innovation efficiency. In Step 2, when the independent variables for early experimentation and frequent experimentation are added, the coefficient for early experimentation is positive

Table 3
Results of hierarchical regression analysis with innovation effectiveness as the dependent variable.

	Step 1			Step 2			Step 3			Step 4		
Innovation effectiveness	Coef.	*p*		Coef.	*p*		Coef.	*p*		Coef.	*p*	
Consulting firm size	−0.05	0.48		−0.04	0.60		−0.03	0.62		−0.04	0.50	
Consulting firm DT experience	0.53	0.00	***	0.42	0.01	***	0.42	0.01	***	0.41	0.01	***
Project length	−0.05	0.77		−0.24	0.16		−0.23	0.20		−0.24	0.18	
Client firm size	0.19	0.01	**	0.20	0.01	***	0.20	0.01	**	0.20	0.00	***
Early experimentation (H1)				0.30	0.00	***	0.31	0.00	***	0.34	0.00	***
Frequent experimentation (H3)				0.15	0.04	**	0.16	0.04	**	0.15	0.05	*
Use of digital technologies							−0.02	0.70		−0.03	0.67	
Early exp. x Use of dig. tech. (H1a)										0.14	0.06	*
Frequent exp. x Use of dig. tech. (H3a)										−0.01	0.94	
R^2	0.06			0.24			0.24				0.27	
F	3.89	0.00	***	11.75	0.00	***	10.09	0.00	***	9.08	0.00	***
Change in R^2				0.17	0.00	***	0.00	0.55		0.03	0.01	**

Notes: Step 1: control variables only; Step 2: independent variables added; Step 3: moderator added; Step 4: interactions added. DT = design thinking; *$p < 0.1$ **$p < 0.05$ ***$p < 0.01$.

Table 4
Results of hierarchical regression analysis with innovation efficiency as the dependent variable.

	Step 1			Step 2			Step 3			Step 4		
Innovation efficiency	Coef.	*p*		Coef.	*p*		Coef.	*p*		Coef.	*p*	
Consulting firm size	−0.25	0.01	**	−0.23	0.01	**	−0.23	0.01	**	−0.25	0.01	**
Consulting firm DT experience	0.21	0.34		0.16	0.45		0.16	0.45		0.17	0.43	
Project length	−0.55	0.03	**	−0.70	0.01	***	−0.69	0.01	***	−0.70	0.01	***
Client firm size	0.17	0.09		0.17	0.09	*	0.17	0.09	*	0.17	0.08	*
Early experimentation (H2)				0.23	0.03	**	0.23	0.03	**	0.28	0.01	**
Frequent experimentation (H4)				0.12	0.27		0.12	0.27		0.10	0.37	
Use of digital technologies							−0.01	0.87		−0.02	0.85	**
Early exp. x Use of dig. tech. (H2a)										0.20	0.06	*
Frequent exp. x Use of dig. tech. (H4a)										−0.12	0.27	
R^2	0.07			0.14			0.14				0.16	
F	4.58	0.00	***	5.91	0.00	***	5.10	0.00	***	4.90	0.00	***
Change in R^2				0.06	0.03	**	0.00	0.56		0.28	0.02	**

Notes: Step 1: control variables only; Step 2: independent variables added; Step 3: moderator added; Step 4: interactions added. DT = design thinking; *$p < 0.1$ **$p < 0.05$ ***$p < 0.01$.

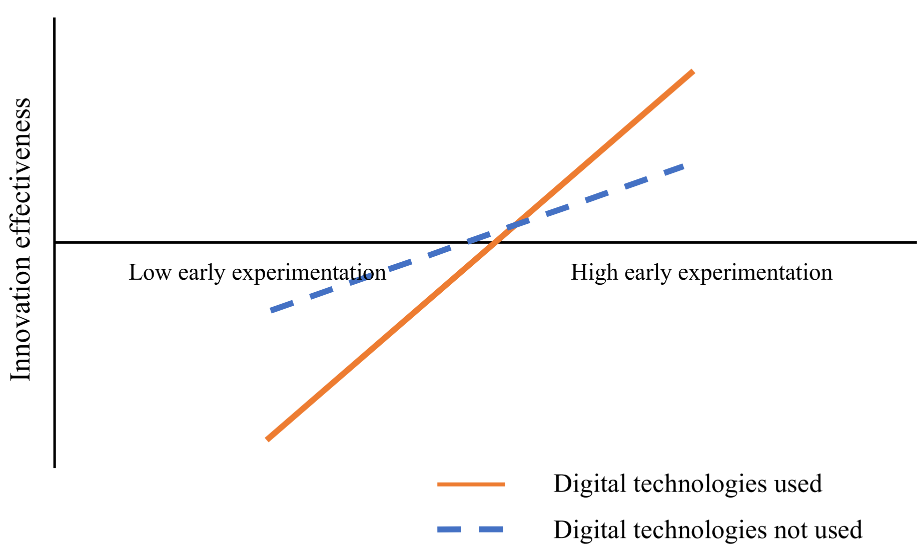

Fig. 2. Interaction plot showing how the use of digital technologies moderates the relationship between early experimentation practices and innovation effectiveness in design thinking projects (H1a).

and statistically significant, while the coefficient for frequent experimentation is not. This provides support for H2, but not H4. In Step 3, the use of digital technologies is found to be unrelated to innovation efficiency, mirroring the results for innovation effectiveness. Step 4 introduces the interaction terms. The interaction between early experimentation and the use of digital technologies is statistically significant, supporting H2a. However, the interaction between frequent experimentation and the use of digital technologies is not statistically significant. Therefore, H4a is not supported.

Fig. 3 provides a visual representation of the significant interaction to help interpret the results.

4.1. Robustness tests

To test the robustness of our findings, we included dummy variables for the country in which the surveyed consulting firms were located in both regression models. The only dummy variable that was statistically significant was for the US, which was positive in both models. This indicates that consulting firms in the US reported better performance compared to firms in Europe. Otherwise, the results remained consistent across the countries included in the study.

As an additional robustness test, we introduced a three-way interaction between digital technology use, early experimentation, and frequent experimentation in the hierarchical regression models. For completeness, this also required adding the two-way interaction between early and frequent experimentation. The three-way interaction was not statistically significant in either model.

Although our survey used validated items, there may still be a conceptual overlap between early and frequent experimentation. To address this concern, we ran hierarchical regression models that included only early or frequent experimentation, rather than both as in Tables 3 and 4 This meant that only one of the two variables was added in Step 2 of the hierarchical regression, and only one interaction was introduced in Step 4. The results of these four regressions are consistent with the main analyses reported in Tables 3 and 4 Therefore, we can conclude that our variables successfully discriminate between early and frequent experimentation, a conclusion further supported by our analysis of the variance inflation factors mentioned earlier. Finally, we examined the added-variables plots and the leverage vs. squared residual plots for all independent variables to ensure that there were no cases that exerted undue leverage. While a definitive determination of external validity would require replicating our findings with additional datasets, which was not feasible, we believe that the four robustness tests we conducted provide useful insights and help move us closer to establishing external validity.

5. Discussion

To better understand the contributions of experimentation to innovation performance, we examine both early and frequent experimentation practices in design thinking projects. As noted above, design thinking projects often address “wicked” problems (Buchanan, 2001; Camillus, 2008) and tend to be human-centered and iterative (Verganti et al., 2021). Our data suggest that both early and frequent experimentation practices contribute positively to the effectiveness of innovation projects. As defined by Bianchi et al. (2020), effectiveness is related to the quality and scope of the project, and experimentation practices are instrumental in fostering this expectation, such as through early and frequent iterations with prototypes (Magistretti et al., 2021).

In terms of innovation efficiency (i.e., use of resources, time, and budget) (Bianchi et al., 2020), we find that only early experimentation is associated with innovation efficiency. While these findings are consistent with previous research (Hampel et al., 2020; Paluch et al., 2019; Thomke et al., 2020), the absent relationship between frequent experimentation and innovation efficiency is surprising. Research suggests that frequent iterations reduce uncertainty (Ellis and Brown, 2017), particularly by minimizing errors and delays in the later stages of development. Given the high uncertainty typically present in design and creative projects (Liedtka, 2015), we expected frequent experimentation to contribute to innovation efficiency. It is possible that too much frequent experimentation leads to the exploration of too many options, causing divergence rather than convergence toward solutions and hindering the creative problem-solving process (Dell’Era et al., 2020), which ultimately does not contribute to innovation efficiency.

We did not find statistically significant relationships between the use of digital technologies and innovation performance. This may be due to the complexity and increased costs associated with adopting and using digital technologies, especially given potential gaps in digital literacy (Kinkel et al., 2021). The use of digital technologies requires ongoing investment in training and upskilling (Ciarli et al., 2021), which could impact time and budget, ultimately affecting efficiency. Further research is needed to examine whether these relationships are affected by the level of digital maturity or knowledge.

Regarding the role of digital technologies in moderating the relationship between experimentation practices and innovation performance, the results appear to be dependent on the type of

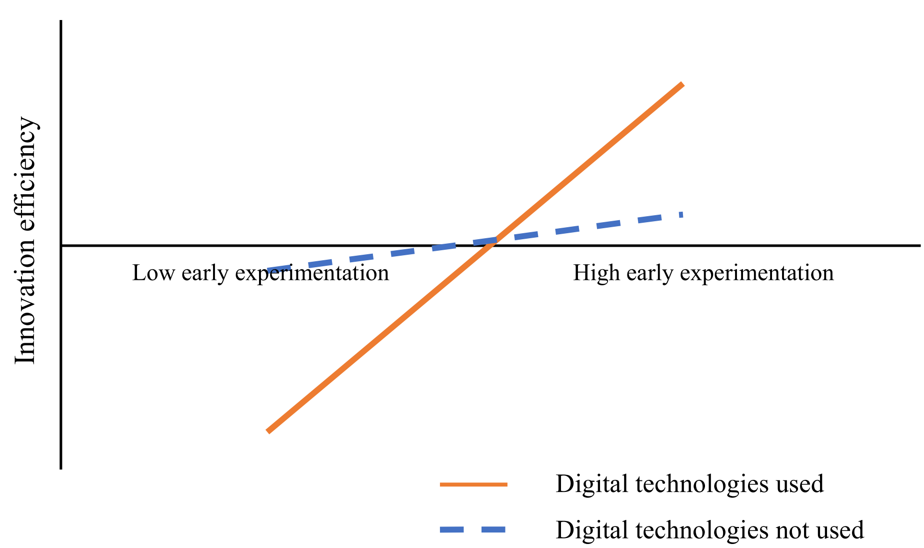

Fig. 3. Interaction plot showing how the use of digital technologies moderates the relationship between early experimentation practices and innovation efficiency in design thinking projects (H2a).

experimentation practice. Statistically significant interactions were found only for early experimentation. This is supported by the literature, as early experimentation typically involves the rough and preliminary embodiment of solutions for further design and sensemaking (Stigliani and Ravasi, 2012; Beltagui et al., 2023). In this context, digital technologies (e.g., AI, big data, 3D printing, IoT) can help to quickly embody and evaluate alternatives with relatively small investments (Bouschery et al., 2023; Roberts and Candi, 2024).

The lack of a moderating effect of digital technology use on the relationship between frequent experimentation and innovation performance – both effectiveness and efficiency – may be because frequent experimentation introduces complexity and cognitive overload (Liedtka, 2015). Digital technologies might exacerbate this by generating large amounts of information, making it more difficult to converge on solutions. In addition, there may be a mismatch between the rapid, iterative nature of frequent experimentation and the time required to set up and interpret data from advanced digital tools, which could slow the process. Frequent experimentation often involves divergent thinking, and digital tools could amplify this by generating more alternatives (Bouschery et al., 2023), potentially delaying the convergence needed for efficiency. Finally, the costs associated with repeated use of digital tools in frequent experimentation may reduce their effectiveness. In contrast, digital technologies appear to be better suited to early experimentation, where they aid in preliminary prototyping (Liedtka et al., 2024) and sensemaking, but their benefits may not be as effective in the frequent iteration process.

5.1. Theoretical contributions

Our findings contribute to theory in three important ways. First, we provide quantitative evidence on the contributions of experimentation practices within design thinking, responding to calls for empirical validation of their impact on innovation performance (Micheli et al., 2019; Magistretti et al., 2021). Second, we provide a more nuanced understanding of experimentation practices by distinguishing between early and frequent experimentation, demonstrating their unique contributions to innovation performance (Paluch et al., 2019; Beltagui et al., 2023). Third, we examine the moderating role of digital technologies in experimentation, uncovering their nuanced effects on innovation outcomes (Verganti et al., 2020; Wang, 2022; Liedtka, 2020). Below, we elaborate on each of these contributions.

First, our study provides empirical evidence on how experimentation practices contribute to innovation performance, responding to recent calls for more quantitative design thinking studies (Micheli et al., 2019; Magistretti et al., 2021). We show that the experimentation practices used in design thinking are valuable and effective in driving innovation, reinforcing the view of design thinking as a valuable approach to innovation (Verganti et al., 2021). Specifically, our study highlights how design thinking, a process rooted in creativity and abductive reasoning (Garbuio et al., 2018; Sahakian and Ben Mahmoud Jouini, 2023), can positively influence innovation performance. This contribution extends previous qualitative findings (Dell'Era et al., 2020) by providing a granular, quantitative perspective that validates the innovation performance outcomes associated with design thinking practices. Furthermore, in a rapidly digitizing world (Mariani et al., 2023), our study complements prior conceptual work on design thinking that theorizes the influence of digital technologies (Bouschery et al., 2023) by examining the moderating role of digital technologies and uncovering their nuanced effects in design thinking projects. For example, while prior research has emphasized the relevance of big data analytics throughout the design thinking process (Mortati et al., 2023) and the role of AI in early-stage ideation (Bouschery et al., 2023; Roberts and Candi, 2024), our findings provide insight into how these claims play out in practice.

Second, our research contributes to the literature on experimentation (Thomke, 2020) by distinguishing between early and frequent experimentation practices, providing a more detailed understanding of their unique contributions. Contrary to traditional approaches, where experimentation is predominantly a late-stage activity focused on market-ready prototypes (Brown, 2008), our findings suggest that experimentation needs to be considered with greater granularity. Early experimentation is essential for fostering divergence in both the problem and solution spaces, addressing ill-defined problems early on (Liedtka et al., 2024), and creating initial minimum viable prototypes in later stages (Knapp et al., 2016). In contrast, frequent experimentation supports iterative refinement and convergence of ideas and solutions in later stages of the design thinking process. This distinction is consistent with previous research (Beltagui et al., 2023), which found that prototypes can either "join conversations" (divergence) or "encapsulate conversations" (convergence). Our findings thus provide a framework for understanding how experimentation practices function differently within design thinking, highlighting their distinct roles in driving innovation performance. In doing so, we provide a more nuanced perspective than earlier work (Magistretti et al., 2021), thereby advancing our understanding of design thinking practices.

Third, we examine the moderating role of digital technologies in experimentation practices, responding to recent calls to explore their impact on innovation processes (Verganti et al., 2020; Wang, 2022; Liedtka, 2020). Our study shows that digital technologies (e.g., big data, 3D printing, AI) can enhance early experimentation by enabling rapid prototyping and sensemaking with lower costs and shorter timelines (Liedtka et al., 2024; Bouschery et al., 2023). However, their moderating effect on the contribution of frequent experimentation is less pronounced, as digital tools may lead to cognitive overload or misalignment with the rapid, iterative nature of these practices. This finding highlights the importance of strategically aligning digital technologies with specific experimentation phases and goals (Warner and Wäger, 2019). Consistent with previous research (Pham et al., 2023; Beltagui et al., 2020), we show that digital technologies can be both enablers and inhibitors, depending on the innovation context and goals. This more detailed understanding underscores the importance of further research into the optimal use of digital technologies in creative-intensive projects (Mariani et al., 2023).

6. Conclusions, limitations, and directions for future research

This research highlights the relationships between experimentation practices in design thinking projects, the use of digital technologies, and innovation performance. In particular, the research shows that experimentation practices in design thinking projects provide benefits. Experimenting with an idea early and often as something tangible, even in low resolution, can provide important benefits such as the ability to test, facilitate alignment and consensus building, and gather feedback. Our study supports this perspective by showing how early and frequent experimentation practices are related to innovation performance, and when digital technology accentuates these relationships. These findings advance both theory and practice about the importance of experimentation in innovation.

Our research provides valuable insights for managers seeking to use digital technologies for experimentation in design thinking projects, highlighting the potential impact on innovation performance. Our findings also inform practitioners that experimentation is not always positively correlated with innovation performance, underscoring the need to carefully consider whether to experiment early or often based on the specific innovation outcomes sought. Thus, our study provides managers with a more nuanced understanding of experimentation in design thinking and the role that the use of digital technologies can play in achieving innovation outcomes.

However, this research has some limitations that are typical of single-respondent survey research. While consultants are a relevant source of information about design thinking projects, as discussed in the methodology section and supported by previous studies, self-reported performance metrics must always be viewed with some skepticism. In addition, our data are drawn from EU and US-based firms, which may introduce a Western bias, limiting the global applicability of the results.

Future research could address these limitations by examining individual projects from the joint perspectives of multiple stakeholders (e.g., consultants, clients, and end-users of the innovation projects) to assess the value created and perceived. Second, expanding the data collection to a global scale would also provide insights from non-Western perspectives on design thinking in innovation. In addition, future research could explore the role of control variables. For example, we found that design thinking experience and client firm size are positively related to innovation effectiveness, while consulting firm size and project length are negatively related to innovation project efficiency. Finally, while our research employs quantitative hypothesis testing, mixed methods research (Morse, 2003) could facilitate the empirical exploration of counterintuitive findings.

CRediT authorship contribution statement

Stefano Magistretti: Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Claudio Dell'Era:** Writing – original draft, Methodology, Data curation, Conceptualization. **Marina Candi:** Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Scott K. Swan:** Writing – original draft, Data curation. **Mattia Bianchi:** Writing – original draft, Methodology, Data curation. **Giulia Calabretta:** Methodology, Data curation. **Ileana Stigliani:** Methodology, Data curation. **Roberto Verganti:** Methodology, Data curation.

Data availability

The data that has been used is confidential.

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