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Defining problems worth solving: Design thinking practices in the problem space, data technologies, and radical innovation

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ABSTRACT

In an era of rapid technological advancement and evolving user expectations, the paradox of choice, whereby more options reduce satisfaction, increase anxiety, and trigger decision paralysis, creates distinctive challenges for innovation. This study examines the relationship between problem-space design thinking practices, innovation radicalness, and the moderating role of data technology adoption. Analyzing survey data from Europe and the US, we find that empathy-driven, human-centered approaches significantly contribute to innovation radicalness. Reframe practices are also positively associated with innovation radicalness, whereas frame practices are not. The adoption of data technologies, although not directly related to innovation radicalness, accentuates the impact of observe and notice practices. Our findings contribute to the discourse on problemistic search by highlighting the role of empathy and reframing in challenging cognitive frames and assumptions. While data technologies, such as big data analytics, the internet of things, and artificial intelligence, can complement observe and notice practices by improving the collection of user insights, they prove less effective in supporting reframe practices for achieving innovation radicalness.

1. Introduction

In today's world, characterized by vast access to data, a proliferation of creative professionals, digitally connected communities, and the generative capabilities of artificial intelligence, individuals and organizations increasingly face an abundance of ideas and options (Verganti, 2017; Verganti et al., 2020). Rather than simplifying innovation, this abundance gives rise to a "paradox of choice" (Schwartz, 2005). Contrary to the traditional belief that more choices lead to better decisions, modern society reveals a different reality: an excess of options often produces decision paralysis, heightened anxiety, and a pervasive sense of busyness that complicates daily life (Iyengar & Lepper, 2000). In innovation contexts, the abundance of information and ideas makes the identification of meaningful development pathways exceptionally challenging. To navigate this paradox, organizations increasingly adopt deliberate methods and practices to identify, interpret, and frame problems that cut through the noise (Cornelissen & Werner, 2014). Addressing complex, ill-defined problems requires a deep understanding of the problem before attempting solutions (Ananth et al., 2025; **Magistretti et al., 2025a). Innovation models consistently begin with identifying a problem worth solving (Wilson, 1997; Amabile, 1988; Seidel et al., 2020), underscoring the importance of problem definition and prioritization in driving innovation (Beckman & Barry, 2007; Vaccaro et al., 2011; Lucas & Mai, 2022; King, 1993; Wedell-Wedellsborg, 2017). The concept of problemistic search (Posen et al., 2018; Angus, 2019; Banerjee et al., 2019) has been a foundational theoretical framework in management over the past half century, explaining organizational behaviors and outcomes such as performance feedback, strategic change and reorientation, risk taking, adaptation, knowledge generation, learning, resource creation, and innovation (Karhade & Dong, 2021). However, traditional views of problemistic search have largely emphasized the search for solutions (Posen et al., 2018), often

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overlooking the processes and challenges involved in defining or discovering problems (Nickerson et al., 2012). Bianchi and Verganti (2022) offer an alternative perspective by emphasizing the importance of designing more meaningful problems. Building on earlier scholarship (e.g., Getzels, 1979; Lai & Grønhaug, 1994), they argue that problems can be created or even invented.

The processes guiding problem definition have been studied from multiple perspectives. Social studies of engineering examine the antecedents of problem and solution definition (e.g., Murray et al., 2019), while innovation research emphasizes creative problem solving (e.g., Garbuio & Lin, 2021). Strategy and organization studies examine problem definition through shared cognitive and behavioral dynamics in decision-making (e.g., Baer et al., 2013). Marketing research builds on the concept of market orientation, defined as the "organizational culture that most effectively and efficiently creates the necessary behaviors for the creation of superior value for buyers and, consequently, continuous superior performance for the business" (Narver & Slater, 1990, p. 21). Kohli and Jaworski (1990, p. 6) emphasize its behavioral dimension, describing it as the "organization-wide generation of market intelligence pertaining to current and future customer needs, dissemination of this intelligence across departments, and organization-wide responsiveness to it.".

Design studies offer an alternative perspective, suggesting that problems are not inherently "out there" but are socially constructed (Ananth et al., 2025). Individuals perceive and prioritize things differently, thereby determining what is considered significant or irrelevant, how elements are interconnected, and how the design space is interpreted (Schön, 1982). From this perspective, problems are "constructed" through interpretation, making problem definition and solution design inherently intertwined processes (Verganti et al., 2021). Design thinking, which extends beyond the "form" or aesthetics of products, is recognized as a structured methodology that harnesses creativity to address complex challenges (Brown, 2009; Martin, 2009; Magistretti et al., 2025b). It serves the dual purpose of defining problems worth solving and developing innovative, user-centered solutions (Liedtka et al., 2013; Dell'Era et al., 2020). This approach combines divergent and convergent thinking, fostering empathy, ideation, and iterative experimentation to uncover insights and test solutions (Magistretti et al., 2022a). A key tenet of design thinking is the ability to discover and frame ill-defined problems in novel ways (Magistretti et al., 2022a; Buchanan, 1992; Boland & Collopy, 2004; Dorst, 2011) through the uncovering of unmet needs and their original interpretation (Dorst & Cross, 2001; Liedtka, 2015). Generating alternative frames through which challenges can be viewed and interpreted can lead to more meaningful problems (Dorst, 2011; Bellis et al., 2026), particularly when these frames are drawn from different domains or reflect entirely new perspectives (Cukier et al., 2021).

Effective problem definition is essential for navigating the ambiguity and complexity inherent in the innovation process (Wang et al., 2019), providing direction, and establishing a foundation for developing novel and meaningful solutions (Mumford et al., 1994; Harvey & Kou, 2013). The discovery-oriented nature of problem definition has also been shown to increase the originality of outcomes (Csikszentmihalyi & Getzels, 1971). However, empirical evidence suggests that organizations often bypass this critical stage and move prematurely into problem-solving mode when faced with challenges (Binder & Watkins, 2024). Although problem definition is widely recognized as a cornerstone of innovation through creativity (Abdulla et al., 2020; Unsworth, 2001; Pham et al., 2023), research has focused primarily on two other aspects: the generation of solutions (Amabile, 1988; Kaplan & Vakili, 2015) and their subsequent evaluation (Berg, 2019; Mueller et al., 2014). As a result, the equally important role of problem definition remains relatively underexplored, despite its significant influence on the direction and outcome of innovative efforts.

Innovation radicalness, defined as the extent to which an innovation is novel or significantly different from existing solutions, is pivotal in driving technological progress and economic growth. It often leads to breakthroughs that redefine industries, create new markets, and establish competitive advantages. Emphasizing its role in sustaining long-term growth and competitiveness, Damanpour et al. (2009) show that radical innovation improves firm performance and productivity by introducing fundamentally new products or processes. Similarly, Bessant and Tidd (2015) argue that radical innovations are critical for addressing grand challenges, such as climate change and healthcare, by offering transformative solutions beyond incremental improvements. Innovation radicalness can stem from developing a radically new solution to an existing problem or from identifying a completely new problem to address. Consequently, understanding the relationship between design thinking in the problem space and innovation radicalness is essential.

Data technologies, including Big Data Analytics (BDA), the Internet of Things (IoT), and Artificial Intelligence (AI), are changing how new products and services are created (Cooper & McCausland, 2024). A notable example is Netflix, which uses data to analyze consumer behaviors and needs, leveraging past and current patterns to predict future trends and create new entertainment content (Smith & Telang, 2018; Verganti et al., 2020). This highlights the growing role of data technologies in understanding problems and supporting creative processes such as design thinking. Recent research has further shown how data, whether big or thick, can enhance design thinking processes (Mortati et al., 2023). In particular, AI adds value to problem exploration and exploitation by generating novel associations (Bouschery et al., 2023; Roberts & Candi, 2024). As these capabilities make data technologies powerful tools for identifying new problems to address, understanding their role in navigating the problem space is vital.

Therefore, this study examines the relationship between design thinking practices used to explore the problem space and innovation radicalness, as well as the moderating role of data technology adoption. Prior studies have examined a wide range of innovation-related outcomes, including product utility and novelty (Nagaraj et al., 2020), new product development (NPD) performance (Nakata & Hwang, 2020), innovation capability (Robbins & Fu, 2022), dynamic and knowledge capabilities (Kaur, 2025), effectuation and causation (Kamble et al., 2023), innovation quality (Balzano & Bortoluzzi, 2025), and agility in NPD decision-making (Kyriakopoulos et al., 2025). However, radical innovation has received limited attention in quantitative research (e.g., Cai et al., 2025), and to the best of our knowledge, no study has examined the effect of design thinking practices on radical innovation. Furthermore, although research has addressed a variety of external and project-level contingencies influencing the adoption of design thinking (e.g., Dell'Era et al., 2025; Magistretti et al., 2022a; Nakata & Hwang, 2020), the moderating role of data technology adoption on the outcomes of these practices remains underexplored.

Following Beckman's (2020) framework, the analysis focuses on two sets of problem-space practices: observe and notice, and frame and reframe. Using survey data from Europe and the US, the findings reveal a positive relationship between observe and notice practices and innovation radicalness, underscoring the importance of empathy and human-centered approaches in uncovering hidden and latent needs. Reframe practices are also associated with innovation radicalness, whereas frame practices are not. The ability to reinterpret and reorganize an initial problem construct emerges as particularly beneficial for radical innovation. In addition, the findings indicate that although data technology adoption alone does not directly contribute to innovation radicalness, it amplifies the impact of observe and notice practices in the problem space, enhancing their role in fostering radical innovation.

This research offers significant contributions to both innovation management theory and practice. First, by elucidating the relationships between design thinking practices (Magistretti et al., 2021) for exploring the problem space and innovation radicalness, we move beyond traditional paradigms focused on problem-solving practices (Berg, 2019). Specifically, our empirical investigation highlights how observe and

notice, frame and reframe practices relate to the development of radical innovations. Second, we advance the discourse on problemistic search theory (Posen et al., 2018) by emphasizing the nuanced roles of empathy, human-centered design, and the critical but underexplored process of problem reframing. This approach builds on the reflective practice and critical framing discussions initiated by Schön (1984, 1987, 1995). Finally, we shed light on the role of data technologies in enhancing design thinking practices (Mortati et al., 2023), providing a contemporary perspective on how digital tools intersect with human creativity and intuition in fostering innovation.

Our findings also provide actionable insights for managers and innovation practitioners. The demonstrated link between human-centered observation and radical innovation underscores the value of engaging deeply with users to uncover unarticulated needs, fostering novel problem ideation and breakthrough solutions. This impact can be amplified through the adoption of data technologies. We further highlight the importance of reframe practices that challenge existing assumptions and open up diverse perspectives on problems and their solutions, thereby expanding the scope for radical innovation.

2. Theoretical background and hypotheses development

Schwartz (2005) highlights the psychological costs of the paradox of choice, arguing that beyond a certain point, an increase in choices reduces satisfaction, heightens anxiety, and can lead to decision paralysis. This phenomenon is explained by decision fatigue, whereby the cognitive effort required to evaluate numerous options depletes mental resources and results in poorer decisions (Iyengar & Lepper, 2000). The implications for organizations are significant. Efforts to optimize consumer choice may inadvertently exacerbate this paradox, underscoring the need for a nuanced approach to choice architecture. Organizations must therefore identify which problems are truly worth solving, a process that goes beyond prioritization to ensure that solutions drive meaningful progress (Verganti, 2017). Christensen et al. (2016) propose a "work to be done" framework that focuses on understanding consumer behavior by identifying the underlying problems consumers seek to solve, rather than relying solely on demographics or product categories. This perspective shifts the narrative from a plethora of solutions in search of problems to a more targeted approach focused on the most impactful issues. McGrath (2013) further emphasizes that in an era of rapid change and uncertainty, the ability to reframe problems rather than rush to solutions is a critical competitive advantage. This requires fostering an environment in which questioning and exploration precede decision-making, enabling innovation that is both relevant and meaningful. By prioritizing problems worth solving, organizations can mitigate the challenges posed by the paradox of choice while increasing strategic agility and responsiveness to evolving market needs.

2.1. Design thinking practices and innovation radicalness

Over the past two decades, design thinking has gained widespread recognition as a structured methodology that harnesses creativity to define problems worth solving and develop innovative, user-centered solutions (Magistretti et al., 2021; Robbins & Fu, 2022). One of the most prominent frameworks for describing design thinking is the double diamond model proposed by the Design Council.[1] This model alternates between divergent phases, which explore a wide range of possibilities, and convergent phases, which narrow these possibilities to identify the most viable option. The double diamond consists of two interconnected spaces: the first centers on broad exploration to develop a deep understanding of the problem (problem space), the second emphasizes focused and actionable steps toward a solution (solution space) (Pham et al., 2021). Although typically presented in four sequential phases, in practice the framework is dynamic and iterative, reflecting the complexity of real-world challenges (Dell'Era et al., 2020).

Addressing open-ended, complex problems has spurred interest in creative approaches to problem framing (Stacey et al., 2000; Dorst, 2011). In line with the double diamond, Gruber et al. (2015) propose a framework with four activities: observe and learn, synthesize and frame, vision and opportunity, and solve and realize. Similarly, Beckman (2020) identifies four core design thinking practices: observe and notice, frame and reframe, imagine and design, and make and experiment. The first two practices align with the problem space, and the latter two with the solution space. Beckman (2020) locates observe and notice at the intersection of concrete experience and reflective observation, while frame and reframe occur at the intersection of reflective observation and abstract conceptualization.

Observe and notice practices are powerful tools for uncovering and understanding both basic usability needs (Thomke & Von Hippel, 2002; Norman, 2005; Brown, 2009) and deeper, meaning-based needs (Mariampolski, 1999, 2005; Squires & Byrne, 2002; Elliot & Jankel-Elliott, 2003). These practices go beyond superficial observations to explore the motivations, emotions, and values that drive user behavior. Liedtka et al. (2013) define design thinking as a creative problem-solving methodology characterized by a focus on empathetic, human-centered research. This approach prioritizes a deep understanding of user needs, behaviors, and experiences to produce innovative outcomes. Beckman and Barry (2007) identify observation and ethnography as essential methods for building empathy with users. In this context, empathy is more than understanding; it requires stepping into users' shoes, adopting their perspectives, and validating their experiences as truth (Carlgren et al., 2016). This process calls for openness to diverse inputs, suspension of judgment, intuitive sensing of emotions, and meaningful communication through reflection of user thoughts and feelings. Underscoring the centrality of empathy, Lockwood (2009) asserts that placing the user at the center of the process is the foundational principle of a design-oriented mindset.

Observe and notice practices are particularly valuable for uncovering latent, unrecognized needs that users may not be aware of or may struggle to articulate. These insights are critical to fostering radical innovation, which thrives on addressing unmet or overlooked opportunities and reimagining future possibilities. By challenging established assumptions and drawing on rich, nuanced user data, observe and notice practices pave the way for innovations that break away from conventional norms and redefine markets (O'Connor & DeMartino, 2006). This process enables designers to move from empathy-driven insights to transformative innovation. Martin (2009) and Verganti (2017) emphasize that combining deep user understanding with strategic, visionary design thinking creates fertile ground for radical innovation. This fusion enables design thinkers to move beyond solving existing problems to envision entirely new categories of value and meaning. In doing so, observe and notice practices become a cornerstone of design-driven innovation, allowing solutions to resonate deeply with users while challenging the boundaries of what is possible. Hence, we posit:

> ***H1:*** *Observe and notice practices are positively related to innovation radicalness.*

Frame and reframe practices aim to create new perspectives on the problem at hand. Foundational studies on problem framing (e.g., Schön, 1984, 1987, 1995; Cross, 2006; Lawson, 2006) underscore its importance in innovation processes. Scholars widely recognize problem framing as the first creative step in the innovation journey, grounded in creativity and preceding problem solving and solution implementation (Basadur, 1995). Framing serves as a foundational step by establishing the criteria that guide both problem-solving efforts and idea implementation (Harvey & Kou, 2013). By activating knowledge schemas that influence how individuals perceive, reason, and act in specific contexts (Cornelissen & Werner, 2014), people, teams, and organizations form a coherent understanding of the problem. This process enables the

[1] https://www.designcouncil.org.uk/our-resources/the-double-diamond/.

construction of a mental representation of the innovation challenge (Mumford et al., 1994; Cornelissen & Werner, 2014). Reynolds et al. (2025) define reframing as "the process of framing innovations in an alternative way to existing framings by introducing new frames or redirecting audience attention to alternative frames" (p. 199). As Reynolds et al. (2025) emphasize, reframing is pivotal in influencing how an innovation is perceived, determining whether it is regarded as socially desirable or legitimate, and, in turn, substantially affecting its success. The design discipline offers a rich body of literature on problem reframing (Bellis et al., 2026). For example, Bianchi and Verganti (2022) highlight the importance of reframing in uncovering new opportunities and insights. Dorst (2011) emphasizes that the ability to reframe a problematic situation in novel and engaging ways is a defining characteristic of design. Reflective practice, as proposed by Schön (1984, 1987, 1995), has strongly influenced the concept of framing in design theory by combining problem perception with a specific mode of reasoning that enables the framer to develop a range of possible actions. In turn, design thinking practices support the creative framing of ill-defined problems (Buchanan, 1992; Boland & Collopy, 2004; Dorst, 2011) that organizations frequently encounter and cannot effectively address through purely analytical methods.

According to Paton and Dorst (2011), reframing refers to the adoption of new frames that interpret the design context and the problems under investigation in original ways. Problem reframing describes the process through which individuals, teams, and organizations make sense of ambiguity in the innovation environment to find new ways to frame a problem (Beckman, 2020; Dzombak & Beckman, 2020). Frame and reframe practices require a deep understanding of current mental models and the development of alternative models (Senge, 1991), engaging participants in dialogue involving inquiry, divergence, and convergence. Inquiry encourages individuals to discuss assumptions and recognize the limitations of their perspectives (Schein, 1999). According to Paul and Elder (2013), critical thinking provides the foundation for frame and reframe practices. Developing new frames is based on several activities: identifying facts (what is real), inferences (what follows), assumptions (what is taken for granted), and viewpoints (what is the filter) (Page, 2007; Mayfield, 2007).

Frame and reframe practices enable a shift from conventional perspectives, allowing designers and innovators to reconceptualize problems beyond existing solutions or paradigms. This reimagining is central to radical innovation because it helps identify novel challenges that differ substantially from the status quo. The cognitive flexibility fostered by frame and reframe practices is essential for radical innovation, enabling innovators to move beyond current market and technological limitations to envision entirely new possibilities (Verganti, 2009). By challenging and reconstructing the mental models that influence problem perception, innovators can uncover pathways to radical innovation that may not be apparent within existing frameworks (Dorst, 2011). Bianchi and Verganti (2022) outline specific methods for reframing problems and categorize them according to key factors that facilitate reframing. Martin (2009) underscores that the ability to reframe problems in unexpected ways is characteristic of organizations that consistently produce radical innovations, suggesting a direct link between effective problem reframing and innovation radicalness. Through reframing, design thinkers transcend traditional boundaries and explore the innovation landscape with creativity and openness conducive to radical outcomes. The ability to deconstruct and reconstruct problem spaces is therefore a critical driver of innovation radicalness, leading to the following hypothesis:

H2: *Frame and reframe practices are positively related to innovation radicalness.*

2.2. The moderating effect of data technologies

For the purposes of this study, we define data technologies as encompassing Big Data Analytics (BDA), the Internet of Things (IoT), and Artificial Intelligence (AI). BDA involves the use of data to identify patterns and predict future trends (Mortati et al., 2023) by analyzing multiple data sources available to the innovation team. IoT mainly consists of devices that communicate and transmit data related to various factors based on their functions (Santoro et al., 2018), thereby generating big data. AI refers to computer systems capable of performing tasks that typically require human intelligence (Gama & Magistretti, 2025). These systems learn and make decisions autonomously through data interpretation without human intervention (von Krogh, 2018).

The growing interest in data technologies aligns with the ongoing shift toward the fourth industrial revolution and the emerging machine economy (Rabah, 2018). Specifically, BDA, IoT, and AI enable transformative interactions between different types of information, such as big data (quantitative), thick data (qualitative), and innovation practices (Ghasemaghaei & Calic, 2020). In many cases, these technologies are not used in isolation but in combination to achieve optimal results. For example, traditional data analytics, IoT solutions, and networking technologies alone are insufficient to support highly autonomous vehicles; instead, these technologies must be integrated to achieve the desired goals. The ability to triangulate qualitative (thick data) and quantitative (big data) sources is becoming a critical organizational asset (Hartmann & Henkel, 2020). Competitive advantage increasingly depends on the ability to access vast amounts of information and quickly extract valuable insights, with data technologies playing a central role in this process.

Technological breakthroughs can be realized through the integration of BDA, IoT, and AI (Rabah, 2018). Data technologies are instrumental in supporting innovation processes (Groves et al., 2013; Wamba et al., 2017; Roberts & Candi, 2024) and improving innovation performance (Bughin et al., 2017; von Krogh, 2018). As Urbinati et al. (2020) observe, digital transformation, defined as the adoption of data technologies in internal processes, has become a crucial enabler of radical innovation. This is evidenced by the large number of firms leveraging data technologies to drive innovation efforts (Verganti et al., 2020). Verganti et al. (2021) detail how these technologies not only expand innovators' knowledge bases but also accelerate iterative cycles of experimentation, revealing unexpected opportunities for radically new value creation. Despite this qualitative exploration of the impact of data technologies on innovation, knowledge of how these technologies influence design and innovation processes remains limited.

In the context of design thinking, both the problem and solution spaces can be significantly enhanced by data technologies such as BDA, IoT, and AI (Fuller & Matzler, 2007; O'Leary, 2013; Lee et al., 2015; Nambisan et al., 2017; Roberts & Candi, 2024). In particular, BDA can support user empathy practices (Magistretti et al., 2022b; Mortati et al., 2023) by enabling the systematic analysis of interview, observational, and other user-generated data aggregated into a big data pool. A combination of big and thick data is essential in design thinking to fully understand user needs (Mortati et al., 2023). Therefore, BDA is expected to help identify relevant patterns that guide teams toward radical innovations. IoT enables new data collection strategies (Narang & Chowdhery, 2022). Given the importance of exploring all facets of a problem (Dell'Era et al., 2020), technologies that automatically collect and make data available can significantly support innovation outcomes. Finally, AI tools are increasingly applied to tasks requiring abstract reasoning and creativity (Amabile, 2020). AI can help explore options (Roberts & Candi, 2024) and support decision-making throughout the innovation process (Bouschery et al., 2023). As several scholars highlight (e.g., Cross, 1999; Dorst, 2011; Dorst & Cross, 2001), data technologies are often used in design processes such as problem framing to foster creativity and provide "raw" or "semi-finished" materials, typically generated through ethnographic observation of users in their contexts and/or supplemented by videos, newspapers, sketches, etc. (Eckert & Stacey, 2000; Cillo & Verona, 2008; Beltagui et al., 2023).

Data technologies can facilitate both the collection and

interpretation of user insights (Verganti et al., 2021). For example, Netflix analyzes customer interactions to guide writers in creating more engaging content (Smith & Telang, 2018). This example illustrates how data technologies are instrumental not only in observing users and collecting data but also in identifying patterns that inform solution development within the design process. As a result, data technologies enhance the effectiveness of design thinking practices within the problem space, providing insights into user behavior, mitigating mental model biases, and challenging entrenched perspectives on user problems (Liedtka, 2015; Carlgren et al., 2016; Micheli et al., 2019). Moreover, data technologies, especially AI, have been shown to uncover new and unexpected patterns that can drive radical innovation (Gama & Magistretti, 2025) and facilitate problem exploration and reframing (Bouschery et al., 2023). Previous studies (e.g., Pham et al., 2021) have highlighted that the integration of data technologies strengthens design thinking practices by providing richer insights into user needs and informing decisions about which problems to address creatively, thereby supporting both frame and reframe practices in the design process (Ananth et al., 2025). While research acknowledges the role of data technologies in design thinking, it has predominantly explored this topic qualitatively (Pham et al., 2021; Mortati et al., 2023) or conceptually (Bouschery et al., 2023), without empirically testing their moderating effect on design practices. Despite ongoing debates, the evidence suggests that the moderating role of data technologies in enabling radical innovation within design-driven innovation projects is important but remains underexplored. Therefore, we posit:

H3: *The adoption of data technologies positively moderates the relationship between observe and notice practices and innovation radicalness.*
H4: *The adoption of data technologies positively moderates the relationship between frame and reframe practices and innovation radicalness.*

In summary, as Fig. 1 shows, this study examines the relationship between practices aimed at exploring the problem space and innovation radicalness (H1 and H2), and the moderating role of data technologies (H3 and H4).

3. Research methodology

3.1. Data collection

The empirical data for this study were collected using an online survey of design practitioners involved in client innovation projects undertaken by their firms using design thinking practices. This empirical setting was selected for several reasons. Consistent with the nature of their activities, consulting firms tend to be early adopters of new management approaches, which they incorporate into services and methodologies developed to support clients' growth (Armbrüster, 2006). In recent years, consulting firms have increasingly embraced design thinking to address the complex innovation problems faced by clients (Magistretti et al., 2022a), making them a particularly suitable context for examining both design thinking practices and the application of data technologies. Most major consulting firms have acquired design agencies to expand their capabilities and toolkits, especially in response to widespread digital transformation and the growing need for advanced skills to create superior user experiences (Dell'Era et al., 2020). Moreover, the consulting industry is known for its rapid adoption of innovative practices, a characteristic closely aligned with the experimental and flexible logic of design thinking (Micheli et al., 2019). Design thinking addresses wicked problems through practices that support the exploration and investigation of the problem space (Buchanan, 1992; Carlgren et al., 2016). The innovation projects examined were deliberately structured to address ill-defined problems, ensuring their relevance and grounding in real-world challenges rather than being ad hoc initiatives or projects undertaken solely for the purposes of this study. Finally, this empirical strategy offers a sufficiently large population for quantitative analysis while ensuring substantial variation, given the diversity of clients, suppliers, and services involved.

Through purposive sampling, we identified potential participants within our professional networks, specifically targeting individuals directly involved in client design thinking projects. We then contacted design practitioners with five to ten years of experience in applying design thinking. To minimize selection bias, only one respondent was recruited per consulting firm, and we diversified the sample by including firms serving a broad range of industries while ensuring a balanced distribution across demographic variables, such as firm size and practitioner role. This resulted in a sample that is reasonably representative of the target population. In addition, we compared the mean responses of individuals who completed the survey within one week of the initial request with those who responded later. As the means were consistent across both groups, we cautiously infer that non-respondents would not have differed systematically from respondents, thereby reducing non-response bias concerns. Participants were invited via email to complete our online survey, which captured detailed information about a specific, recently completed innovation project grounded in design thinking. The unit of analysis was a single innovation project, defined as one that delivered novel solutions, processes, or approaches to address a client problem or opportunity. These projects were intended to create new value in the form of products, services, business models, or operational improvements. Respondents were instructed to select a project completed within the past 12 months to ensure accurate recall and relevance. Confidentiality and anonymity were assured, and questions were designed to avoid violating client privacy or company policy.

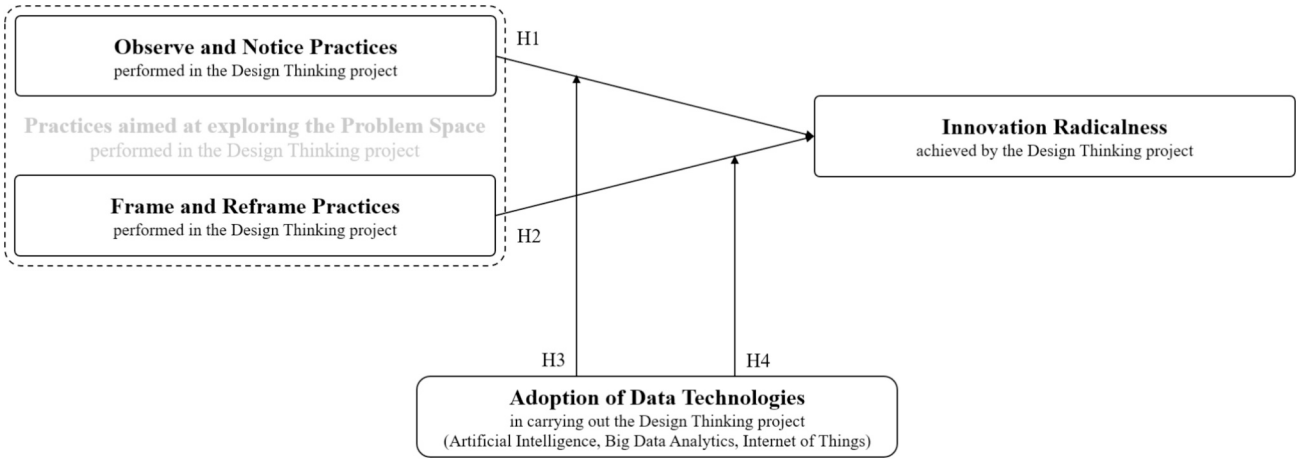


Fig. 1. Research model.

Respondents were asked to identify the focal project to ensure attention remained on that specific case, although they were encouraged to use pseudonyms to avoid sharing sensitive or proprietary information. Respondents included practitioners from consulting firms in Italy (55%), Sweden (21%), the Netherlands (11%), the UK (8%), and the US (5%), capturing regional diversity in innovation practices. A total of 246 usable responses were obtained, reflecting a response rate of just over 10%, consistent with established benchmarks for online surveys (Forza, 2016).

3.2. Variables

The survey items were adapted from prior studies, with additional items developed where necessary. The variables related to design thinking practices based on Micheli et al. (2019), Seidel and Fixson (2013), and Nakata and Hwang (2020). The survey instrument was refined through several rounds of testing. First, 11 academics and 12 design practitioners serving on advisory boards of design-related organizations, including collaborative research centers, university research centers, and international master's programs, reviewed the items for specificity, domain representativeness, and clarity. The survey was then pilot tested in the field (N = 146). The pilot data were analyzed using exploratory factor analysis followed by confirmatory factor analysis. Poorly loading items were dropped or reworded to improve clarity, relevance, and comprehensibility. The measures of innovation radicalness were based on Gatignon et al. (2002) and Garcia and Calantone (2002). The moderating variable capturing data technology adoption was measured by asking respondents whether specific technologies had been used in the execution of the design thinking-based innovation project. Responses for each technology were recorded as either yes or no. To construct this measure, the binary responses across the three technology types were summed, resulting in an index ranging from 0 to 3.

We analyzed the data using Stata version 17. Factor analysis revealed that the items for observe and notice practices loaded onto a single factor, while the items for frame and reframe practices loaded onto two distinct factors (see Table 1). All Cronbach's alphas exceeded 0.7, and confirmatory factor analysis indicated good model fit, with a chi-squared value of 50 (31 degrees of freedom), an RMSEA of 0.047, and a CFI of 0.98.

The pairwise correlations are shown in Table 2. Notably, the highest correlations are observed between pairs of practices, which is expected given that all three measures capture the use of practices in exploring the problem space.

Given the high correlations, multicollinearity could be a concern. To assess this, we examined variance inflation factors (VIFs). In Step 3 of the hierarchical regression models, which included all interaction terms, the highest VIF was 2.46 for the interaction between frame practices and the adoption of data technologies. As this value is well below the conservative threshold of 5 (Marquardt, 1970), multicollinearity does not appear to be a problem, supporting our decision to distinguish among the three design thinking practice variables. All VIFs are reported in Table 3.

4. Findings

To examine how the adoption of data technologies moderates the effects of observe and notice, frame and reframe practices on innovation radicalness, interaction analysis was called for (Aiken & West, 1991). Hierarchical regression was used to examine moderating effects because it enables an explicit comparison between models with and without interaction terms, thereby assessing the incremental variance explained by moderators. This approach is widely used in moderation analyses relying on ordinary least squares estimation and aligns with the study's theoretical emphasis on conditional effects. It also enabled us to test all four hypotheses within a single model (see Table 4). In hierarchical regression (in Stata, the *hireg* function is used), predictors are entered in steps to assess whether they explain a statistically significant amount of variance in the dependent variable after accounting for the variance explained by variables entered in previous steps. In our analysis, H1 and

Table 1
Variables and items.

Variables	Survey items
Innovation Radicalness (IR) [based on Gatignon et al. (2002), Garcia and Calantone (2002)]	[X] represented a breakthrough in the eyes of your client [X] was new to your client's industry [X] was new to the world[X] proposed radically new experiences to users
Observe and Notice Practices (ONP) [based on Micheli et al. (2019), Nakata and Hwang (2020), Seidel and Fixson (2013)]	We applied user research techniques that discover hidden and unexpressed user needs. We applied ethnography to collect data about user behaviors in their "real habitat". We applied empathic design techniques to tune into the feelings of users.We applied ethnography to immerse ourselves in the context of use.
Frame Practices (FP) [based on Micheli et al. (2019), Nakata and Hwang (2020), Seidel and Fixson (2013)]	We used analogical thinking to see the problem from multiple perspectives. We worked with a broader and more general formulation of the problem.We applied framing techniques to understand the deep essence of the problem.
Reframe Practices (RP) [based on Micheli et al. (2019), Nakata and Hwang (2020), Seidel and Fixson (2013)]	We probed and criticized ideas regardless of where they came from. We pushed team members to rethink their ideas.We repeatedly asked questions to challenge assumptions.
Adoption of Data Technologies (ADT)	Please indicate which of the following were adopted in carrying out [X]: Big data analytics Internet of ThingsArtificial intelligence, machine learning, and deep learning

Notes: [X] refers to a specific innovation project based on design thinking undertaken for a client. Measurement model fit statistics: CMIN/DF = 1.41, RMSEA = 0.047, CFI = 0.98, TLI = 0.96, SRMR = 0.048. All survey items refer to project [X]. All items, except those related to the adoption of data technologies, were presented as statements with response options ranging from 1 (disagree) to 7 (agree). Responses for each data technology were recorded as yes or no. The data technologies variable was constructed by summing the binary responses across the three technology types, resulting in a range from 0 to 3.

Table 2
Pairwise correlations between variables.

		1	2	3	4
1	Innovation Radicalness (IR)				
2	Observe and Notice Practices (ONP)	0.37			
3	Frame Practices (FP)	0.24	0.51		
4	Reframe Practices (RP)	0.37	0.47	0.51	
5	Adoption of Data Technologies (ADT)	0.16	0.16	0.04	0.16

Table 3
Variance inflation factors (VIFs) for Step 3 of the hierarchical regression.

Variable	VIF
ADT × FP	2.46
ADT × ONP	2.24
Observe and Notice Practices (ONP)	1.58
Frame Practices (FP)	1.56
ADT × RP	1.51
Reframe Practices (RP)	1.46
Adoption of Data Technologies (ADT)	1.13

Table 4
Hierarchical moderated regression results (dependent variable: innovation radicalness).

	Step 1				Step 2				Step 3			
	Coef.	SE	$p > t$		Coef.	SE.	$p > t$		Coef.	SE	$p > t$	
[H1] Observe and Notice Practices (ONP)	0.34	0.09	0.00	***	0.32	0.09	0.00	**	0.38	0.09	0.00	**
[H2] Frame Practices (FP)	−0.04	0.09	0.64		−0.03	0.09	0.72		−0.06	0.09	0.49	
[H2] Reframe Practices (RP)	0.33	0.09	0.00	***	0.32	0.09	0.00	**	0.31	0.09	0.00	**
Adoption of Data Technologies (ADT)					0.10	0.07	0.20		0.05	0.08	0.54	
[H3] ADT × ONP									0.24	0.12	0.04	*
[H4] ADT × FP									−0.20	0.11	0.08	
[H4] ADT × RP									0.13	0.09	0.17	

Notes: N = 246. $^{**}p < 0.01$; $^{*}p < 0.05$.

H2 were tested in the first step, and H3 and H4 in the third step. As recommended by Aiken and West (1991), the independent variables were standardized prior to analysis. The results are shown in Table 4.

In Step 1, H1 is supported by a statistically significant relationship between observe and notice practices and innovation radicalness. H2 is supported for reframe practices but not for frame practices. This suggests that the ability to creatively reorganize the interpretation of a problem fosters radical innovation, whereas simply organizing and interpreting information within existing representations does not. In Step 2, the adoption of data technologies alone is not significantly related to innovation radicalness. Step 3 introduces three interaction terms into the model. Among these, only the interaction between observe and notice practices and data technologies is positive and statistically significant, supporting H3. The interaction plot in Fig. 2 illustrates that the relationship between observe and notice practices and innovation radicalness is stronger when more data technologies are adopted than when fewer are adopted. Neither the interaction between frame practices and data technologies nor the interaction between reframe practices and data technologies is significant, indicating that H4 is not supported.

4.1. Additional analyses

To further explore the relationships and underlying dynamics, we examined the moderating effects of each of the three data technologies separately. The results from the final step of the hierarchical regression analysis for each data technology are presented in Table 5. We find that BDA adoption positively moderates the relationship between observe and notice practices and innovation radicalness, consistent with the findings for H3. In addition, IoT adoption positively moderates the relationship between reframe practices and innovation radicalness, whereas AI adoption does not moderate any of the examined relationships. Because each data technology class was measured dichotomously, the technology-specific moderation tests in Table 5 should be interpreted as adopter versus non-adopter contrasts rather than as comparisons across different levels of intensity or sophistication.

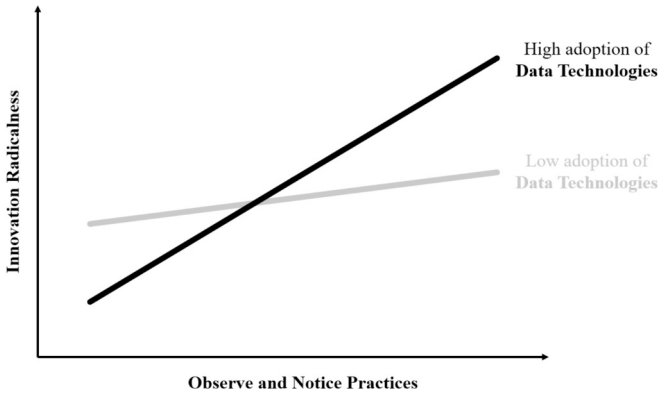


Fig. 2. Interaction plot showing the moderating effect of the adoption of data technologies on the relationship between observe and notice practices and innovation radicalness. The relationship is plotted at one standard deviation above the mean (high adoption) and one standard deviation below the mean (low adoption) of data technology adoption (Aiken & West, 1991).

When interpreting these results, it is important to consider the average adoption levels of the three data technologies in our sample. BDA shows the highest average adoption (0.28 on a 0–1 scale), followed by IoT (0.15), whereas AI has the lowest level (0.09). This distribution helps explain why the moderating effect for BDA is significant in both the combined and separate analyses, whereas IoT and AI yield more nuanced results. Notably, the technology-specific analysis reveals a positive moderating effect of IoT on reframe practices. This finding suggests that the enhanced data collection capabilities enabled by IoT strengthen the contribution of reframe practices to innovation radicalness. Specifically, IoT data can creatively enrich understanding of how users interact with objects. By contrast, the adoption of AI, which was less prevalent in our sample, does not moderate the tested relationships. This suggests that, despite growing attention to AI, its application, particularly in the context of problem framing, remains underdeveloped. Importantly, our data were collected prior to the public release of ChatGPT in November 2022 and the subsequent surge in interest in generative AI, suggesting that data collected after this period could reveal different patterns of AI adoption and moderating effects.

4.2. Robustness testing

Our construction of the data technology adoption variable was consistent with He et al. (2024), who summed nine binary (dummy) variables for various data technologies to create a moderating variable. Since prior studies have also operationalized data technologies as single binary variables (e.g., Rammer et al., 2022; Niebel et al., 2019), we conducted a robustness test using a binary moderator for data technology adoption. The variable was assigned a value 1 if one or more data technologies had been adopted and 0 otherwise. The results of the hierarchical regression analysis using this moderator were consistent with those reported in Table 4. We therefore conclude that our findings are robust across both operationalizations of data technology adoption.

5. Discussion

Discovering or even creating problems worth solving helps mitigate the paradox of choice (Schwartz, 2005). Rather than overwhelming decision-makers with numerous solutions to familiar problems, design thinking emphasizes the depth of the problems themselves. Previous studies have shown that traditional approaches focus on finding solutions (Posen et al., 2018), whereas problemistic search centers on the process of defining or discovering problems (Nickerson et al., 2012). Our findings contribute to this perspective by demonstrating the value of shifting attention from solutions to problems (Ananth et al., 2025), ultimately leading to more innovative outcomes.

Our empirical results indicate that observe and notice practices in design thinking contribute positively to innovation radicalness. This

Table 5
Final-step of hierarchical regression results for each data technology separately.

	Big data analytics				Internet of Things				Artificial intelligence			
	Coef	SE	$p > t$		Coef	SE	$p > t$		Coef	SE	$p > t$	
Observe and Notice Practices (ONP)	0.43	0.10	0.00	**	0.30	0.13	0.03	*	0.40	0.10	0.00	**
Frame Practices (FP)	−0.11	0.09	0.23		−0.10	0.11	0.36		−0.09	0.10	0.35	
Reframe Practices (RFP)	0.32	0.09	0.00	**	0.46	0.13	0.00	**	0.33	0.09	0.00	**
Adoption of one Data Technology (ADT)	−0.09	0.07	0.21		0.26	0.23	0.25		0.04	0.09	0.65	
ADT × ONP	0.26	0.11	0.02	*	−0.15	0.30	0.62		0.23	0.19	0.23	
ADT × FP	−0.16	0.10	0.12		−0.28	0.23	0.24		−0.10	0.17	0.55	
ADT × RFP	0.04	0.10	0.68		0.55	0.28	0.05	*	0.00	0.13	0.98	

Notes: **p < 0.01; *p < 0.05.

highlights the importance of empathy and human-centered approaches in uncovering hidden and latent needs (Magistretti et al., 2021) that can drive radical innovation. Research on ethnographic methods (Kelley, 2001; Lojacono & Zaccai, 2004) similarly shows that observing users in their natural contexts leads to deeper, more accurate interpretations of their actual needs (Patnaik & Becker, 1999; Whitney & Kumar, 2003). Observe and notice practices rely on a human perspective, enabling innovation teams to grasp problem complexity and detect weak signals reflected in user behavior (Liedtka, 2015). Empathy is central to this process, serving as a gateway to uncover insights and latent needs that users may not consciously recognize or articulate. It is indispensable to design thinking because it provides the foundation for problem identification and framing (Brown, 2009; Giacomin, 2014), enabling designers to immerse themselves in users' natural contexts to examine behaviors, uncover hidden patterns, and infer the deeper meanings of user experiences. Techniques such as in-depth contextual interviews and direct observation provide access to intangible dimensions of user needs, revealing insights that might otherwise remain hidden (Sanders, 2006). Through active engagement and listening, designers not only validate assumptions but also uncover radically new ways to address unarticulated or emerging needs (Elsbach & Stigliani, 2018; Seidel & Fixson, 2013; Zhang & Ma, 2026).

Interestingly, our findings reveal that reframe practices are positively related to radical innovation, whereas frame practices are not. This suggests that the ability to creatively reorganize the initial interpretation of a problem is critical to achieving radical innovation. Dillon (1982) distinguishes between presented, discovered, and created problems, noting that higher levels of problem creation are better suited to environments characterized by volatility, uncertainty, complexity, and ambiguity (Baer et al., 2013; Troise et al., 2022). Reframe practices are consistent with this view because they involve challenging assumptions, uncovering hidden dimensions, and using abductive reasoning to imagine possibilities beyond conventional knowledge (Dorst, 2011). While creativity is commonly viewed as essential for generating innovative ideas, Dorst and Cross (2001) argue that reframe practices also rely on creativity to radically reinterpret problems worth solving. Reframing requires intense engagement in sensemaking to develop a deep understanding of the problem or challenge at hand (Buchanan, 1992; Boland & Collopy, 2004; Dorst, 2011). Beckman and Barry (2009) emphasize that sensemaking and reframing activities facilitate the creation of collective, emotionally connected narratives that can be easily communicated and heuristically used to guide decision-making. Reframe practices are driven by criticism, which probes more deeply into the interpretation of issues and seeks to uncover what lies beneath the surface by considering multiple perspectives, ultimately fostering a more comprehensive and robust understanding (Verganti, 2016; Verganti & Norman, 2019). Criticism involves challenging cognitive frames and questioning how individuals make sense of their environment. Simply framing a problem based on existing interpretations can limit the potential for radical innovation, whereas reframing opens up alternative perspectives and deeper insights (Bellis et al., 2026). Reframing involves challenging the current frame, generating new viewpoints by questioning the problem space, and integrating novel elements (Dorst, 2015).

The positive relationships of observe and notice, and reframe practices with innovation radicalness, contrasted with the absence of such a relationship for frame practices, underscore the complementary roles these practices play in understanding users' desires, uncovering latent needs, and reinterpreting the core problem. Although design thinking has become a widely embraced approach to stimulating innovation, its different effects on radical versus incremental innovation remain insufficiently explored. Only a limited number of studies explicitly address this distinction, and those that do often focus exclusively on radical innovation (e.g., Bicen & Johnson, 2015; Zheng, 2018; Robbins, 2018; Radnejad et al., 2021).

The literature presents contrasting perspectives on this issue. Some scholars suggest that design thinking facilitates radical innovation by encouraging creative experimentation and challenging established assumptions (e.g., Bicen & Johnson, 2015; Radnejad et al., 2021), others argue that outcomes derived from design thinking are predominantly incremental. For instance, Robbins (2018) and Robbins and Sandberg (2023) contend that the strong emphasis on addressing current customer needs tends to favor incremental improvements, as design thinking may lack the visionary leap necessary for radical innovation. Other contributions view design thinking as an inherently ambidextrous approach, capable of supporting both radical and incremental innovation, depending on how it is applied (Zheng, 2018; Randhawa et al., 2021). Our empirical findings offer a more nuanced perspective on the role of design thinking practices in the pursuit of innovation radicalness. Specifically, they suggest that radical innovation requires not only empathetic engagement with users but also the capacity to reframe problems in unexpected and transformative ways. The findings point to complementary roles of outside-in practices (i.e., observe and notice) and inside-out practices (i.e., reframe). While user empathy helps organizations navigate the problem space and uncover previously unexplored design opportunities, the mere framing of collected insights is insufficient to achieve radical innovation (Cromwell & Harvey, 2025). Instead, avoiding the trap of incrementalism requires the deliberate use of creative logics that enable the reframing of initial interpretations and the questioning of entrenched assumptions (Pham et al., 2023).

Our findings indicate that while the adoption of data technologies (BDA, IoT, AI) does not directly correlate with innovation radicalness, it positively moderates the impact of observe and notice practices. This moderating effect is consistent with research showing that BDA can capture user behavior at the individual level, manage complex analytics, and identify unconventional patterns (Mortati et al., 2023; Verganti et al., 2020). Large volumes of user data, such as demographics, browsing histories, social media interactions, and purchasing behaviors, can substantially enrich observe and notice practices. By leveraging data mining techniques, AI systems can anticipate user needs by uncovering patterns in preferences, interests, and behaviors. Such data are particularly critical for machine learning-based AI systems, as they enable more accurate predictions and decision-making. The adoption of digital technologies (BDA, IoT, AI) in conjunction with observe and notice

practices further enhances the human-centered approach by combining data-driven insights with empathetic understanding. Through large-scale analysis of user data, designers can identify subtle trends and latent preferences that inform design choices (Mortati & Cautela, 2025). Moreover, embedding BDA within design thinking processes can improve designers' decision-making by supporting the validation of assumptions and the refinement of solutions through the systematic incorporation of user feedback (Mortati et al., 2023).

However, our findings suggest that the adoption of data technologies does not moderate the relationships between frame and reframe practices and innovation radicalness. As Mortati and Cautela (2025) highlight, designers tend to rely extensively on big data to support observe and notice practices, as large-scale user data enable the identification of patterns, behaviors, and unmet needs. Conversely, when engaging in reframe practices, designers predominantly draw on intuition, creativity, and interpretation. This shift points to the limitations of purely data-driven approaches in generating meaningfully novel directions, underscoring the continued importance of human sensemaking in design processes. In a similar vein, Verganti et al. (2020) argue that as algorithms increasingly support and automate analytical and creative tasks, the role of human designers evolves from generating solutions toward interpreting insights and determining which problems should be addressed. As a result, data technologies may be more effective for collecting and analyzing user insights, than for fundamentally reframing the problem space.

Moreover, although data technologies can play a valuable role across various stages of the innovation process (Chen et al., 2012; Sivarajah et al., 2017; Urbinati et al., 2020), our findings indicate that their contribution is more limited when it comes to the complex and nuanced practice of problem reframing. Reframing requires more than data-driven insights; it relies on deep sensemaking, imaginative reasoning, and critical reflection, capabilities that remain predominantly human (Verganti et al., 2021). These cognitive processes involve questioning existing assumptions, exploring paradoxes, and constructing entirely new perspectives that often transcend the limitations of current datasets. In this regard, data may serve as a starting point by highlighting inconsistencies, surfacing weak signals, or identifying unexpected correlations, but it is ultimately the creative and interpretive agility of human designers that enables the transformation of these signals into meaningful redefinitions of the problem space. As such, organizations should view data technologies not as substitutes for human creativity but as complementary enablers that can enhance, rather than replace, the abductive and critical thinking essential for radical innovation.

This study contributes to the design thinking literature (Carlgren et al., 2016; Micheli et al., 2019) by providing quantitative evidence of how different design thinking practices influence radical innovation. It also highlights the ongoing need for research on how data technologies intersect with creative problem-solving methodologies. By shedding light on the specific contributions of observe and notice, and reframe practices, our findings provide a strong empirical foundation for understanding the pathways to radical innovation in design-centric processes (Gruber et al., 2015).

5.1. Theoretical implications

Our findings advance the theoretical understanding of design thinking practices, specifically observe and notice, frame and reframe, in fostering radical innovation. First, the findings underscore the critical importance of empathy and human-centered observation in uncovering latent needs and generating innovative ideas. By validating the importance of these practices, this study extends the literature on applied ethnographic methods and human-centered problem exploration, highlighting their relevance in dynamic and complex environments (Liedtka, 2015; Seidel & Fixson, 2013). In particular, our findings underscore the central role of reframing in driving radical innovation by creatively challenging existing cognitive frames and questioning assumptions. This insight aligns with alternative perspectives on problem reframing (Bianchi & Verganti, 2022), as well as with sensemaking and criticism theories, which emphasize the importance of engaging deeply with the problem space (Beckman & Barry, 2009). Second, by identifying the problem-space design thinking practices that contribute to innovation radicalness, particularly observe and notice, and reframe practices, this study deepens our understanding of problemistic search. Although the relevance of problemistic search has been acknowledged, it has rarely been examined through the design thinking lens at this level of depth (Posen et al., 2018). Third, in an increasingly digital world, our findings show that problem-space exploration remains predominantly a human-driven activity (Verganti et al., 2020). While data technologies can enhance observe and notice practices by improving the collection of user insights, their contribution to reframe practices is more limited, reinforcing the idea that significant problem reinterpretation depends largely on human intuition and creativity. Overall, this study addresses gaps in the literature by providing empirical evidence on the interplay between design thinking practices and data technologies, offering a nuanced understanding of their complementary roles in driving innovation.

5.2. Managerial implications

This study offers several critical insights for managers seeking to foster radical innovation in their organizations by leveraging design thinking practices and data technologies. First, observe and notice practices should be recognized as key activities. These practices, rooted in empathy, ethnographic inquiry, and immersive observation, can be instrumental in surfacing latent, unarticulated, or emerging needs that often escape traditional market analysis. Allocating dedicated time and resources to in-context user research should be viewed not as ancillary but as a strategic investment in identifying high-potential innovation opportunities. In practice, this may involve contextual interviews with potential customers, ethnographic observation, customer journey mapping, or short immersion sessions in which project teams observe users interacting with products or services in real-life contexts. Second, reframe practices should be actively encouraged. The study confirms that reframing, rather than merely framing, is essential for generating radical innovations through design thinking. Therefore, reframing should not be treated as an ad hoc creative technique but institutionalized as a core competency across innovation teams. Managers can support this by promoting constructive criticism and cognitive diversity in project teams, encouraging them to regularly revisit and rethink the problem-definition phase throughout the project lifecycle. Workshops and collaborative tools that encourage abductive reasoning and sensemaking can further strengthen these practices. For example, this may involve routines that prompt teams to continuously question initial assumptions, such as revisiting the problem definition during project reviews, incorporating perspectives from different functional backgrounds, or documenting and comparing alternative interpretations of the problem as the project evolves. Third, while big data analytics, AI, and IoT provide valuable ways to enrich observation practices, such as real-time behavioral insights, predictive usage trends, and anomaly detection, their enhancement of frame or reframe practices is limited. Innovation leaders should therefore use data technologies to inform, but not replace, empathic understanding, while remaining cautious of data determinism, that is, an overreliance on algorithmic outputs in problem definition that can narrow the solution space and reduce radical potential. In practice, a more effective use of digital technologies is to combine data generated through usage analytics, sensor data, or digital interaction logs with insights from field observations or user interviews. Reviewing these sources together enables innovation teams to validate emerging patterns and better interpret user needs before finalizing the problem definition.

5.3. Limitations and future research

Our study points to several avenues for future research that can deepen understanding of design thinking and problemistic search. First, the evolving role of AI, particularly in light of recent developments in generative AI, may not be fully captured by our study. Future research should explore how these newer tools influence the contribution of frame and reframe practices to innovation radicalness. Second, our measure of data technology is limited in that it distinguishes between adoption and non-adoption but does not assess its effectiveness or intensity. Our operationalization focuses on the early stages of technology adoption, consistent with Rogers' (2003) diffusion of innovations theory, which emphasizes the initial decision to adopt or reject an innovation. The binary formulation also aligns with the technology acceptance model (TAM) (Davis, 1989) and its subsequent extensions, where initial adoption represents a critical threshold prior to assessing usage intensity or long-term engagement. Recent studies have used similar approaches to measure the adoption of data technologies (e.g., He et al., 2024). Nevertheless, further research examining the moderating effects of data technology usage intensity and effectiveness is warranted. Third, the cross-sectional nature of our data limits the ability to draw causal inferences over time. Longitudinal research could provide valuable insights into how the interaction between design thinking practices and data technologies evolves and influences innovation performance. Fourth, while we focused on specific design thinking practices, we did not examine how these practices interact with other organizational factors, such as leadership, culture, or cross-functional collaboration. Examining these interactions could provide a more comprehensive understanding of the innovation ecosystem. Fifth, our study was conducted within a specific temporal and technological context. As data technologies continue to evolve and proliferate, future research should reevaluate their role in driving radical innovation, particularly in strengthening the effect of reframe practices, to ensure the continued relevance of these findings in dynamic environments. Finally, although our purposive sampling strategy ensured the inclusion of experienced practitioners directly involved in design thinking projects, it also limits generalizability. Because the sample reflects consulting firms already engaged in design thinking, the findings may not be representative of organizations using different innovation practices or industries less familiar with design thinking. The consulting context may also influence the observed relationships, as such firms typically operate across multiple client industries and are often early adopters of innovation practices and advanced data technologies. As a result, the interaction effects observed in our study between design thinking practices and data technologies may be more pronounced than in organizations where these practices are less mature or institutionalized. Accordingly, the generalizability of our findings to innovation management more broadly remains constrained. In addition, the emphasis on firms from Europe and the US may limit the applicability of the results to other geographical or cultural contexts in which the adoption of data technologies or design thinking differs. Future research should therefore validate these findings across industries and regions.

CRediT authorship contribution statement

Claudio Dell'Era: Writing – review & editing, Writing – original draft, Project administration, Investigation, Data curation, Conceptualization. **Marina Candi:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Stefano Magistretti:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Roberto Verganti:** Supervision, Conceptualization. **Ileana Stigliani:** Writing – review & editing.

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Data availability

Data will be made available on request.

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