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Time is running out: How design thinking shapes team innovation under time constraints

Marco Balzano [a,b,*], Guido Bortoluzzi [c]

[a] Department of Management, Ca' Foscari University of Venice, Venice, Italy
[b] KTO Research Center SKEMA Business School, Sophia-Antipolis, France
[c] DEAMS, University of Trieste, Trieste, Italy

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ABSTRACT

Design thinking as a problem-solving framework has garnered significant attention for its reliance on abductive reasoning and human-centeredness. Existing literature has underscored the importance of these elements in fostering an array of organizational outcomes and enhancing the overall stakeholder satisfaction. However, less is known about how these reasoning approaches influence team innovation quality, particularly in time-constrained settings. The present study aims to fill this gap by focusing on team dynamics and examining the effects of abductive reasoning and human-centeredness on team innovation quality. We conduct an empirical analysis involving seven teams, each undertaking multiple innovation decisions under time constraints in a laboratory game context. Our results suggest an interplay between the reasoning approaches and team innovation quality. Specifically, teams that relied more on abductive reasoning in time-constrained tasks tended to make lower-quality decisions, while teams that were highly human-centered produced decisions of higher quality. Importantly, team size emerged as a key moderating variable. Larger teams were found to exert an even more negative impact of abductive reasoning on team innovation quality while amplifying the positive effects of human-centeredness.

1. Introduction

Design thinking has emerged as a transformative paradigm for solving complex problems and developing innovative solutions, providing an alternative to traditional analytical methods (Magistretti, Dell'Era, et al., 2022, 2023; Meinel et al., 2020; Sahakian & Ben Mahmoud-Jouini, 2023; Wang, 2022). Design thinking explores both the problem space and the solution space. The problem space involves understanding and articulating user challenges and their persistence (Buchanan, 1992; Mortati et al., 2023; Pham et al., 2023). The solution space focuses on ideating, developing, and iterating innovative solutions, transitioning from understanding problems to refining solutions (Carlgren et al., 2016). This leverages innovative and technical skills to create original and effective solutions (Cai et al., 2023; Magistretti et al., 2024). Accordingly, the growing prominence of design thinking in the solution space has become apparent in several sectors. For example, in healthcare, design thinking has been instrumental in the redesign of patient experiences, leading to improved treatment outcomes (Altman et al., 2018). In the domain of public policy, design thinking has facilitated the creation of citizen-centric solutions that account for the complexities of human behavior (Lee et al., 2017). The multidisciplinary influence of design thinking underscores its potential for engendering innovative solutions (Meinel et al., 2020; Verganti et al., 2021). The power of design thinking to bring about meaningful change can be traced back to its fundamental principles, chief among which are abductive reasoning and human-centeredness to foster innovative solutions (Magistretti, Bianchi, et al., 2022; Nakata & Hwang, 2020; Robbins & Fu, 2022).

Human-centeredness leads to outcomes that are more aligned with user needs and preferences (Nakata & Hwang, 2020), enhancing the perceived quality of decisions. A case study on user-friendly public transportation systems described in Sirendi and Taveter (2016), for instance, illustrates how human-centered design can significantly impact the utility and effectiveness of a service. On the other hand, design thinking heavily relies on abductive reasoning, which in turn requires a series of rigorous steps. In constrained settings, therefore, adopting agile forms of reasoning can lead to a more prompt and higher-quality output.

* Corresponding author. Ca' Foscari University of Venice, Venice, Italy.
E-mail addresses: marco.balzano@unive.it (M. Balzano), guido.bortoluzzi@deams.units.it (G. Bortoluzzi).

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Moreover, literature has increasingly emphasized the role of team size in affecting the quality of decisional outcomes (e.g., Dooley & Fryxell, 1999; Wechtler et al., 2023). On the one hand, larger teams, while benefiting from diverse perspectives, also bring the challenge of increased complexity in communication and coordination (Espinosa et al., 2004). These intricacies can exacerbate the limitations of abductive reasoning, as more voices and viewpoints may lead to longer deliberation times and reduced team innovation quality. For example, software development projects with extensive teams may face difficulties in arriving at quick yet effective solutions due to these complexities (Pendharkar & Rodger, 2009). On the other hand, larger teams can leverage their size to enhance human-centered approaches, by allocating resources for more comprehensive user research (Collins & Clark, 2003), thereby potentially enhancing the quality of decision-making.

Surprisingly, despite the growing interest in design thinking as a paradigm for problem-solving and innovation, limited scholarly attention has been devoted to exploring the effects of abductive reasoning and human-centeredness on the quality of team decision-making outputs in time-constrained contexts. This gap in the literature is particularly concerning given the increasing demand for rapid decision-making in various organizational settings. In business environments where time is a limited resource and industry dynamics are constantly accelerating, managers often find themselves under significant time pressure. As "the clock is [incessantly] ticking" (Nadkarni et al., 2016), the application of appropriate mental schemas in ever-evolving settings becomes all the more necessary. In scenarios like this, it can be of vital importance to firms to be aware of the most effective ways of thinking for a specific situation and time constraints. It is with this in mind, that we have formulated the following research question:

How do abductive reasoning and human-centeredness affect the quality of team innovation outcomes in time-constrained settings, and to what extent does team size moderate these relationships?

To address this research question, we conducted an empirical analysis involving seven distinct teams, collectively responsible for 116 short-time decisions in a controlled laboratory game environment. The outcomes of the analysis indicate that abductive reasoning was found to adversely affect the team innovation outcomes when applied in time-sensitive scenarios. Conversely, a high degree of human-centeredness had a positive impact on innovation quality. Team size emerged as a significant moderating variable. Larger teams were observed to exacerbate the negative impact of abductive reasoning on team innovation quality. By contrast, the positive influence of human-centeredness was amplified in larger team settings.

Overall, this study offers multiple contributions to theory and practice. Firstly, it expands our theoretical understanding of design thinking in solution spaces by unpacking the differential impact of abductive reasoning and human-centeredness on team innovation quality in time-constrained situations. It provides empirical evidence to substantiate the benefits of human-centeredness, while simultaneously challenging the unconditional applicability of abductive reasoning. This resonates with existing studies that emphasize the challenges related to design thinking (e.g., Carlgren & Ben Mahmoud-Jouini, 2022). Secondly, this study contributes to the ongoing literature on time-constrained decision--making processes (e.g., Allen, 2011) and the speed of decision-making (e.g., Kocher & Sutter, 2006). Specifically, it offers up new reflections on the necessity of adopting appropriate cognitive schemas to face time-constraints in decision-making processes. Lastly, it offers novel insights related to the academic interest in unveiling optimal team size (Chen et al., 2008; Garcia Martinez, Zouaghi, & Garcia Marco, 2017; Kratzer et al., 2008; Rahmani et al., 2018), underscoring the dual role of large team composition in determining team decision quality outputs. Given the time-sensitive nature of many contemporary decision-making contexts, organizations need to assess their problem-solving approach based on the decision-making setting. Organizations typically favor more human-centered approaches, especially in the context of larger teams, to enhance the innovative outcomes coming from their decisions, particularly those made under time constraints.

2. Background and hypotheses development

2.1. *Design thinking in the solution space and the limits of abduction*

At its core, design thinking is a process that is often delineated into five iterative stages: empathize, define, ideate, prototype, and test (Micheli et al., 2019). These stages interconnect and inform one another, reflecting the dynamic nature of design thinking (Liedtka, 2018).

In design thinking, the problem space pertains to the domain where emphasis is placed on understanding and articulating the challenges at hand (Buchanan, 1992; Mortati et al., 2023; Pham et al., 2023). This space involves a thorough exploration of what challenges or difficulties users are encountering and why such challenges persist.

The solution space is where the actual ideation, the development, and the iteration of innovative solutions happens. These elements are accomplished through activities including brainstorming, creating prototypes, and testing solutions through iterative cycles. In the solution space, focus is moved from understanding the problem to actively exploring and refining solutions that address the identified issues (Carlgren et al., 2016). In this way, the solution space is dedicated to applying creativity and technical skills to formulate solutions that are effective and innovative (Cai et al., 2023; Magistretti et al., 2024).

In this paper, we focus our attention on the solution space of the design thinking approach. When working in a solution space, human-centeredness fosters empathy and inclusivity, ensuring that solutions are highly innovative and close to customers' preferences while abductive reasoning offers a way to propel innovation outcomes (Dew, 2007; Nakata & Hwang, 2020). This reasoning approach is advantageous as it allows for flexible decision-making that can lead to innovative solutions (Garbuio & Lin, 2021). However, decisions of strategic importance are often be made under different time and resource constraints. In some cases, managers have the time and resources needed to gather all the relevant contextual information, evaluate the alternatives, think about the final decision, postpone it and even revise it if they change their mind. In other cases, external or internal circumstances force managers to act quickly, without the time and the tools necessary to fully gather information, thoroughly evaluate alternatives, carefully consider the potential outcomes of the final decision and without the possibility of postponing the decision or even changing it at short notice. Examples of such situations could include reacting to an aggressive competitor's move, the emergence of a disruptive technology and/or business model, a sudden change in the regulatory regime, a communication emergency or, more in general, an unexpected endogenous or exogenous shock. Decisions like these must be made under time-constraints that can be dictated by external conditions or even self-imposed for competitive reasons. Making decisions under tight time-constraints is becoming increasingly frequent in organizations (Treffers et al., 2020).

As abduction requires the sequential application of multiple rigorous steps (Dunne & Dougherty, 2016; Golden-Biddle, 2020; Sætre & Van de Ven, 2021), it may present a range of challenges. In team contexts, design thinking relies highly on collaborative abduction and human-centeredness (Nakata & Hwang, 2020). The former dimension entails expansive and contextual learning. Through the mechanism of collaborative abduction, teams synthesize disparate viewpoints and insights, facilitating abductive leaps that yield innovative solutions. This process is augmented by cognitive tools such as mind mapping and brainstorming which serve to generate ideas and resolve cognitive tensions within the team, thereby promoting a culture of curiosity and open-mindedness. Teams that adopt design thinking also deal with its human-centered focus, encapsulated by the concept of "user empathy" (Carlgren et al., 2016). User empathy requires a team to continuously search for and process information relevant to design, thereby reinforcing a holistic view of the user experience.

Our claim is that when applied in time-sensitive or resource-constrained settings, the expedient nature of abductive reasoning can lead to biases and errors. Indeed, decision-makers have limited information and limited time to process it. This can easily lead, firstly, to type I errors (false positives), where decisions appear logical but are based on incorrect assumptions, and, secondly, to groupthink bias, or rather, an acritical convergence around a decision that pleases everyone but does not properly address the problem.

The multiple and iterative divergence and convergence exercises that characterize design thinking can help teams to avoid the trap of groupthink and jumping to decisions before considering all the potential drawbacks, but they require a number of time-consuming steps. A divergence exercise may require individuals to frame the problem independently and develop their own action plans. Then, in the convergence phase, individuals should challengeeach other and brainstorm to reconcile the different perspectives. However, not all scenarios allow individuals the necessary time to engage in this thorough process properly. If individuals choose this approach anyway, they may be overreaching, and the quality of their decisions may be suboptimal compared to more streamlined ways of thinking that can be pursued even when time is constrained.

To this end, teams may benefit from employing heuristics to enhance the speed and effectiveness of their decision-making processes (Kc, 2020). Heuristics, as cognitive shortcuts or "rules of thumb", facilitate quick judgments by schematizing complex problems (Lu et al., 2013). This schematization might enable rapid assessment and prioritization of critical factors, a feature exemplified by the ABC (Airway, Breathing, Circulation) heuristic commonly employed in emergency medical contexts (Bond & Cooper, 2006). Such heuristics can, for example, force managers to broaden the range of their decisions by using decision schemes based on real options reasoning (Trigeorgis & Reuer, 2017), which can be useful in reducing type I errors. Still, it is worth noting that no decision-making approach is entirely devoid of the potential for error or bias. Nonetheless, we contend that in settings where time is short, teams that are overly reliant on abductive reasoning may encounter significant challenges with respect to the quality of their decisions.

2.2. Abductive reasoning and quality of team innovation outcomes

In environments characterized by decision-making under conditions of incomplete information and time constraints, teams may employ abductive reasoning as a form of inferential logic (Calabretta & Gemser, 2015; Edmondson & Nembhard, 2009). This choice could be valuable given that abductive reasoning allows for the efficient formulation of plausible explanations based on the available data. However, it also introduces specific challenges that may affect decisional quality. The central point of this section is that the use of abductive reasoning may negatively influence the quality of outcomes in team-based decision-making processes for three main reasons.

Firstly, the time constraints inherent to many decision-making tasks are of particular concern. Time-limited conditions significantly restrict the capacity for thorough analysis and deliberation among team members (Kocher & Sutter, 2006), and this can be particularly pronounced when sequential, rigorous steps of abductive processes are involved (Sætre & Van de Ven, 2021). This is key as the time available for each team member to consider and communicate their thoughts becomes severely limited. Indeed, when considering the role of abductive reasoning, time constraints could potentially narrow the scope of considered alternatives and reduce the rigor in assessing the validity of underlying assumptions. Past research supports this point, noting that time-restricted decision-making could increase error rates (Treffers et al., 2020). Hence, in environments like this, the limitations of abductive reasoning might become exacerbated, increasing the risk of compromising decisional quality.

Secondly, the communicative challenges associated with "collaborative abduction" deserve scrutiny. Abductive reasoning often requires team members "to generate diverse ideas and to effectively manage tensions arising from collating divergent perspectives" (Nagaraj et al., 2020, p. 4). It should be emphasized that this is a not a trivial undertaking as multiple perspectives mean multiple opportunities for interpretation and misinterpretation. This process can be fraught with difficulty, leading to misunderstandings or misconstructions that may not be immediately obvious. Consequently, the likelihood of achieving high-quality innovation outcomes may be compromised due to suboptimal communication, especially in high-stakes or high-pressure environments.

Thirdly, when teams lean heavily on abductive reasoning, they may inadvertently stifle alternative ways of reasoning that could yield better outcomes. This is particularly relevant given that teams typically possess a diverse skill set that could be applied to different reasoning strategies. This can lead to suboptimal decisions by narrowing the range of possible solutions under consideration. For example, when limited time is available to make choices, teams might focus on heuristics to expedite decision-making. These heuristics can be particularly useful for schematizing complex problems or for acting on partial information when immediate action is required (Kc, 2020; Lu et al., 2013). Yet, if abductive reasoning dominates the decision-making process, these alternative heuristic strategies (potentially more effective) may be overlooked or underutilized. Restricting the methodological repertoire of a team can lead to less optimal innovation outcomes, particularly when the team faces decisions that would benefit from a more diverse set of reasoning approaches. Taken together, these arguments suggest the following hypothesis:

Hypothesis 1. In time-constrained settings, abductive reasoning negatively affects the quality of team innovation outcomes.

2.3. Human centeredness and quality of team innovation outcomes

In the management literature, human-centered approaches are gaining considerable attention, particularly in light of their capability to enhance the quality of team-based decision-making processes (Hehn et al., 2019). Prioritizing the needs, capabilities, and perspectives of end-users or consumers (Brown, 2008) lies at the core of these approaches. When these elements are integrated into decision-making, the resulting choices are presumed to be more attuned to the desires and requirements of stakeholders, thereby elevating their perceived quality (Elsbach & Stigliani, 2018). This could be especially salient in contexts such as new product development, where a deep understanding of end-users can influence the efficacy of decisions (Nakata & Hwang, 2020). Incorporating these user-centric elements into decision-making paradigms results in choices that are more closely aligned with stakeholder desires and requirements, thus heightening their perceived quality. Consequently, it is reasonable to expect that human-centeredness could beneficially affect the quality of team innovation outcomes. Overall, this expectation could be substantiated by three overarching arguments. Firstly, the role of empathetic understanding emerges as pivotal (Carlgren et al., 2016), particularly when navigating the complexities often associated with new product development such as non-routine technologies or pioneering innovations (Nakata & Hwang, 2020). In such contexts, empathy has a dual function; it enriches the moral compass and guides the decision-making process while also serving as a strategic lens through which the real-world applicability and reception of technologically complex solutions can be gauged.

Secondly, new importance is given to participatory inclusivity, especially when the new product development process involves multifaceted or complex analyses (Veryzer & Borja de Mozota, 2005). The aggregation of diverse perspectives within the team and from stakeholders offers a more nuanced and comprehensive understanding of the challenges at hand (Fong, 2003). This collective intelligence could push the team toward more innovative solutions and mitigate the risks associated with pioneering endeavors or technical complexities.

Thirdly, the principle of human-centeredness underscores the need for adaptive learning (Glen et al., 2014). The iterative feedback loops favored by a human-centered approach optimize performance and serve as channels for potentially significant course corrections or pivots. This is key in complex or pioneering new product development processes, offering a systematic method for continually refining the decision-making process in response to real-world feedback and emerging challenges (Nakata & Hwang, 2020). The following hypothesis serves as a conclusion:

Hypothesis 2. In time-constrained settings, human-centeredness positively affects the quality of team innovation outcomes.

2.4. *The negative interaction of team size and abductive reasoning*

Team size has been studied as both an asset and a liability in organizational literature. While larger teams offer diversified skills and perspectives, they also introduce complexities to the decision-making processes (Collins & Clark, 2003; Espinosa et al., 2004). From this perspective, we argue team size can be a negative moderating variable in the relationship between abductive reasoning and team innovation quality for multiple reasons.

Indeed, the intricacies of coordination might scale with team size (Mueller, 2012). In smaller teams, synthesizing diverse viewpoints is more manageable, thereby facilitating the effective application of abductive reasoning. As teams grow, effective synthesis becomes more complex. This results in a multiplication of viewpoints and an increased density of interpersonal interactions. From this angle, abductive reasoning becomes challenging within such intricate settings. Tasks such as aligning divergent interpretations or managing conflicting viewpoints become burdensome. Therefore, the procedural complexities can undermine the utility of abductive reasoning, leading to diminished team innovation quality.

Moreover, increased coordination complexities could also augment the risk of process loss (Mueller, 2012), where cognitive resources are diverted from decision-making in order to manage procedural tasks. This diversion impacts the effectiveness of abductive reasoning and contributes to degraded team innovation quality. Likewise, the cognitive overload might correlate with team size. Large teams naturally accommodate more informational inputs and perspectives. Although this diversity is beneficial in the ideation stage, it could become problematic during decision-making. Abductive reasoning requires operating with incomplete or ambiguous information (Sætre & Van de Ven, 2021), a task made more difficult with increased informational inputs in larger teams. The cognitive load can become significant, affecting working memory capacity and consequently, diminishing the effectiveness of abductive reasoning. Key attributes like focus and the capacity for integrative complexity could be compromised, leading to decreased team innovation quality. Building on these arguments, we propose:

Hypothesis 3. In time constrained settings, team size negatively moderates the negative relationship between abductive reasoning and team innovation quality.

2.5. *The positive interaction of team size and human-centeredness*

As part of this examination of human-centered approaches and their impact on decision-making, another dimension that warrants attention is the influence of team size. Within a human-centered framework, larger teams could possess the resources to engage in more exhaustive research about end-users or consumers, thus potentially improving the quality of decisions. It follows, therefore, that team size could positively moderate the positive relationship between human-centeredness and team innovation quality for a number of reasons. Firstly, a larger team could confer a distinct advantage in terms of disciplinary diversity (Bates et al., 2023) as a larger team naturally accommodates professionals from a range of backgrounds. This disciplinary diversity ensures that varied professional perspectives and skills are drawn together, creating a more nuanced approach to problem-solving (Pressman, 2018). This complexity could be particularly beneficial when addressing the multifaceted challenges inherent in a human-centered approach to decision-making.

Secondly, the benefits of specialized roles in larger teams become operationally significant. The presence of these roles, such as a user experience specialist or data analyst, acts as a focal point for the complex interplay between the technical and social aspects of the team's work (Belbin & Brown, 2022). By enabling accurate interpretation of end-user data and keeping the focus sharply on human-centered objectives, these roles could mitigate the operational complexities that tend to increase with team size.

Thirdly, we argue that the scope of resource allocation within larger teams could directly impact the comprehensiveness of research approaches. For example, larger teams (thus, typically with greater resources) can employ a mix of both quantitative and qualitative research methods, providing a more complete data set and thereby contributing to a more nuanced understanding of end-user needs. This type of in-depth research may not only offer benefits within the immediate context of a current project but may also serve as a repository of valuable insights for future initiatives.

In summary, a larger team provides a nuanced influence on the quality of decisions within a human-centered approach. The amalgamation of diverse perspectives, the stabilizing effect of specialized roles and the capacity for more comprehensive resource allocation all collectively contribute to this dynamic. With these considerations in mind, we propose the following hypothesis:

Hypothesis 4. In time constrained settings, team size positively moderates the positive relationship between human-centeredness and team innovation quality.

Fig. 1 summarizes our research model.

3. Methods

3.1. *Sample and setting*

The empirical context of this study was conducted in a laboratory game environment that was designed to simulate strategic development projects. This controlled setting was essential to the study as it offered an encapsulated yet complex microcosm within which the decision-making processes could be observed. The laboratory setting allowed for the rigorous manipulation and measurement of key variables, thereby enhancing the internal validity of the study (Wayne & Ferris, 1990). The study was conducted throughout the year 2023 allowing the teams multiple opportunities to interact and make decisions in a recurring yet dynamic manner, a factor that is deemed crucial for measuring and collecting the variables of interest.

The laboratory game was conducted in Northeast Italy, facilitated by DITEDI, an ICT cluster financed by public funds to support firms operating in the ICT industry.[1] The initial call for teams' participation leveraged a combination of snowball sampling and a public announcement made by DITEDI. The ICT cluster invited potential participants to respond to the call by proposing a problem/project to be tackled using design thinking methodology. DITEDI then systematically selected the applicants (relying on an internal committee) to identify the best-fitting projects and firms. Projects dealing with new product/service development were prioritized.

Due to budgetary constraints, the number of firms that could be recruited was set at a maximum of seven. The adopted framework for the

[1] The official website of DITEDI is available at: https://www.ditedi.it/en/.

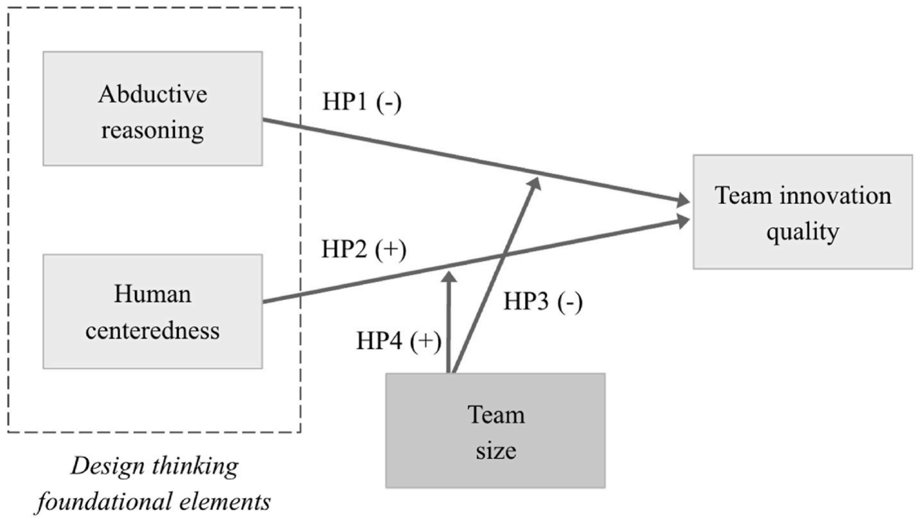

Fig. 1. Research model.

design thinking game was developed by an appointed business expert in innovation processes and design thinking, and included critical elements such as solution identification, uniqueness of the proposed solution, and target market definition. Overall, the framework employed can be considered a variation of the "Five Diamonds method for Explorative Business Process Management" described in Grisold et al. (2022). In Fig. 2 we report a graphical representation of the schema applied for our laboratory game.

Seven teams composed of a total of 27 people (entrepreneurs and managers) from real companies participated in the laboratory games/ study. Both start-ups and established corporations participated, and team sizes ranged from two (a recently established start-up) to five members.

For each team, the laboratory game then moved, as illustrated in Fig. 2, into the ideas generation phase, where participants (identified in the figure as P1, P2, and P3), were given 6 min to generate ideas to meet the outlined business opportunity independently. This divergence allowed for a wide array of creative solutions to surface, free from group influence or bias. Subsequently, teams were given 6 min to group their ideas into clusters (in the figure labeled A through E) during the first convergence round. In this phase, ideas were collectively shared, enabling participants to collaborate and refine each other's contributions. In clustering their ideas, teams engaged in the first type of decision within the laboratory game context. Following this, individuals and then teams were asked to prioritize the clusters in 12 min, assessing and ranking the clusters based on their potential value, impact, and feasibility. As an illustrative example, in Fig. 2, clusters are ordered as D, E, B, A, C, indicating a hierarchical valuation of their potential value, impact, and feasibility. In the case that the outcomes of each phase did not meet the expectations of a team, we included the possibility of looping back to earlier phases of the process, where previous phase could be performed from scratch again. At the end of the study, firms were challenged to translate the outputs of the laboratory game into tangible new products in their respective industries.

Overall, through this sequential and iterative process, the laboratory game harnessed both divergent and convergent thinking, facilitated by timed phases and structured decision-making. As explained above, each decision was time-constrained, depending on the nature of the specific task. Despite varying between the two decision types, the maximum available time per each decision was fixed *ex-ante* and was the same for each team. To facilitate the structured and timed aspects of this process, we employed the BUTTER interaction platform, integrating a MIRO module[2] specifically designed to manage the visual components of the "diamond framework". BUTTER's functionality allows users to set timers for each phase of activity, ensuring adherence to the designated time constraints. Participants were encouraged to make decisions within these allotted times; the platform allowed for time extensions if teams could not converge on a decision within the scheduled period. In these cases, decisions were flagged as "delayed", and a related variable was built into the analysis to control for the effects of delayed decisions on team innovation quality.

Table 1 summarizes the characteristics of the teams and their decisions.

3.2. Measures

3.2.1. Dependent variable

In this study, the dependent variable was the quality of decisions made by teams. To operationalize this construct, labeled "team innovation quality", we employed a laboratory-based experimental design involving various simulated game contexts. As anticipated, participating teams were required to make a set of decisions for each of the eight meetings. The number of decisions per team could vary from a minimum of 14 to a maximum of "n" depending on how many times teams decided to retrace their own steps. In our sample, the maximum number of decisions a team make was 18.

To ensure the reliability of this variable in the evaluation process, each decision made by the teams was subsequently appraised by a panel of three independent experts in the business field, distinct from the researchers conducting the study, similar to previous studies (Kahai & Cooper, 2003; Rogelberg & Rumery, 1996). Experts were selected based on their extensive experience in a field relevant to the projects being evaluated, including product development, design thinking, and business strategy. We identified potential experts through professional networks, academic associations, and industry groups, prioritizing individuals with a significant professional achievement in their respective fields. These experts independently rated the quality of each decision using a 7-point Likert scale, resulting in a total of 116 rated decisions. Their assessments were carried out independently of each other to minimize potential bias or undue influence. To assess the

[2] BUTTER is available at https://www.butter.us/, while MIRO is available at https://miro.com/. Last accessed May 22, 2024.

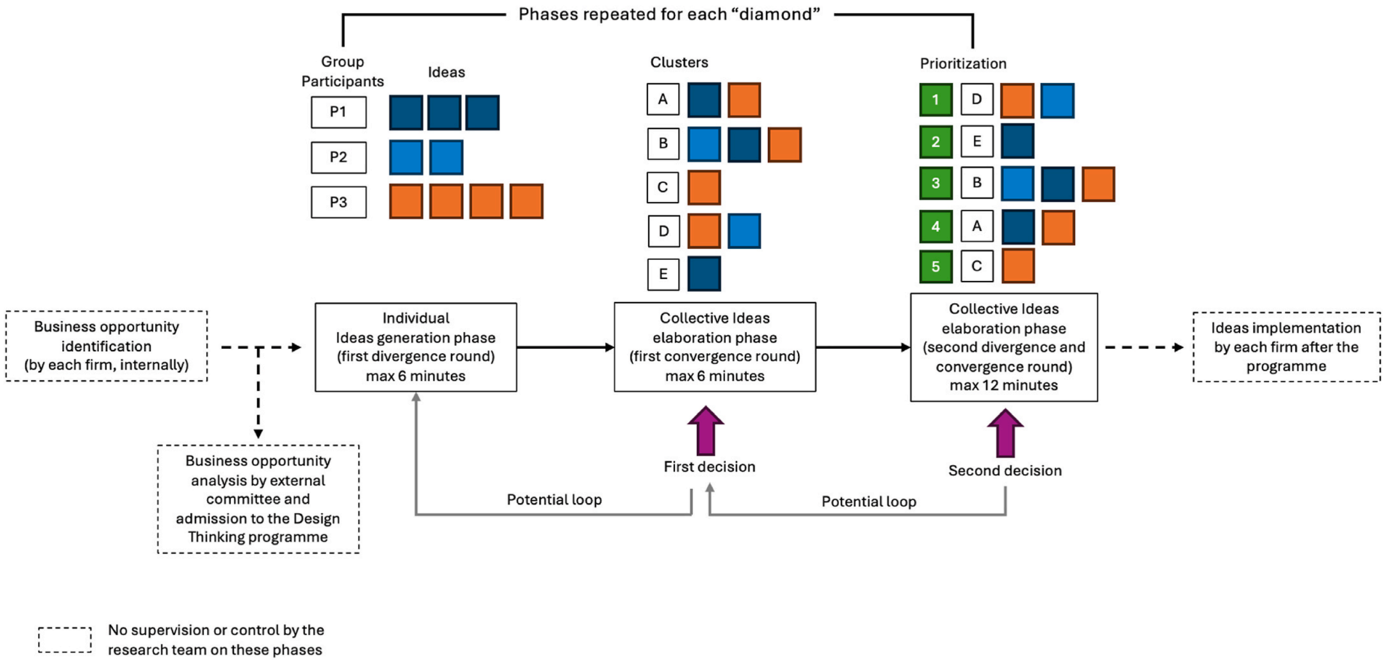

Fig. 2. Designing the laboratory game.

Table 1
Teams and decisions' characteristics.

Team	Number of decisions	Number of delayed decisions	Participants	Average speed of timely decisions (clusterization)	Average speed of timely decisions (prioritization)	Average speed of delayed decisions (clusterization)	Average speed of delayed decisions (prioritization)	Average team innovation quality
A	16	6	3	312.667	354.429	1103.333	–	4.843
B	16	6	5	300.333	560.750	759.000	1620.000	4.688
C	18	8	3	294.667	459.143	1239.400	767.333	3.361
D	18	15	4	300.667	–	1073.429	908.750	4.250
E	14	4	2	319.600	425.200	855.000	984.000	4.429
F	18	12	5	308.000	464.000	1095.429	938.400	4.778
G	16	10	5	360.000	383.200	1242.143	778.333	4.969
Total	116	61	27	308.727	433.333	1108.944	1001.880	4.457

validity of our dependent variable, this variable was subjected to inter-rater reliability analysis. Using the K-Alpha Calculator (Marzi et al., 2024), we obtained that the Krippendorff's Alpha inter-rater reliability coefficient for the quality ratings was 0.850, exceeding the suggested threshold, and thus enhancing the robustness of our team innovation quality variable. Following the expert evaluations, we synthesized these multiple ratings to create a composite measure of team innovation quality. This composite measure was calculated as the average of the three expert scores assigned to each decision.

3.2.2. *Independent and moderating variables*

In this study, we employed two independent variables: abductive reasoning and human-centeredness (Nakata & Hwang, 2020). To operationalize these latent constructs, we used a series of measurements. Table 2 provides a list of these measurements, alongside corresponding reliability coefficients for each construct. Specifically, the table shows two types of reliability metrics: Omega and the Average Variance Extracted (AVE). These metrics serve to assess the internal consistency and convergent validity of the latent variables, thereby enhancing the methodological rigor of the study. Maximum likelihood estimation was chosen as the estimation method, in alignment with weighted average techniques that are rooted in congeneric approaches. This methodological choice is supported by congeneric modelling, which advocates for increased accuracy and representativity in the estimation of latent constructs (McNeish & Wolf, 2020). To implement these statistical

Table 2
Items and reliability of latent variables.

	Omega	AVE
Imagine to be involved in a discussion about the development of a new product. To what extent the following sentences apply to your way of behaving? (Answer from 1 to 7 where 1 corresponds to "does not apply to me at all" and 7 to "it perfectly describes how I would behave"):		
Abductive reasoning (Nakata & Hwang, 2020)	0.85	0.59
- I'll try to push the boundaries of product ideas		
- I'll go beyond immediately observable solutions		
- I'll keep asking myself "what if" kind of questions (imagining different solutions) to discover new ideas		
- I'll try to challenge the "what is" or "assumed" in pursuit of novelty		
Human-centeredness (Nakata & Hwang, 2020)	0.91	0.72
- The product developed by our new product development team was technically complex to develop.		
- Our new product development team had to use non-routine technology to develop the product.		
- The development process associated with the product was relatively simple.		
- The development of this product required pioneering innovation.		
- The product developed by our new product development team is/was complex.		

procedures, we utilized the CLC Estimator software (Marzi et al., 2023). The Omega coefficient consistently exceeded the threshold of 0.70, thereby enhancing the measures' internal consistency and reliability (Groves et al., 2011). Additionally, the AVE exceeded the 0.50 criterion, lending support to the convergent validity of the constructs under investigation. Once these latent constructs had been estimated per participant, averages were computed among team members to obtain the team average latent scores, which were used in our analysis.

The variable for team size, which served as our moderating variable, was operationalized as a count variable that incorporated the number of individuals contributing to each decision-making process (Carpenter, 2002; Haleblian & Finkelstein, 1993). It is worth noticing that throughout the duration of the laboratory game, there were instances when teams operated with less than their maximum capacity of members. In such cases, adjustments were made to the team size variable to accurately reflect the actual number of participants. Such adjustments were also made in the cases of abductive reasoning and human-centeredness variables.

3.2.3. *Control variables*

In the analytical models, control variables were included to mitigate the influence of confounding factors on the relationship between the independent variables–abductive reasoning and human-centeredness–and the dependent variable of team innovation quality. The first control variable, average team industry experience, was calculated as the mean number of years that each team member has spent in their relevant industry. This variable was calculated on the basis of previous research (Tihanyi et al., 2000) and served to control domain-specific expertise and its potential impact on team innovation quality. The second control variable, gender ratio, was calculated as the number of female team members divided by the number of male team members (Van Emmerik et al., 2010). This was included to account for any gender-related effects on team innovation quality. In our sample of participants, 4 were female and 23 were male. Additionally, to control for idiosyncratic characteristics within teams, a teams' fixed effect variable, represented by a unique identifier for each team (Team ID), was incorporated following a similar logic to that of Dezsö and Ross (2012). This variable was instrumental in accounting for any unobserved heterogeneity constant within teams but that varied across teams. Moreover, as each meeting was held online and recorded, we could precisely retrieve data about the time taken to make each decision. Thus, the speed of the decision, measured in seconds, was introduced as a control variable to account for the temporal aspect of decision-making and its potential influence on the quality of the outcomes (Judge & Miller, 1991). Then, as we allowed for time extensions, we controlled for the potential effect of delayed decisions on team innovation quality. This was operationalized by creating a dummy variable which took the value of 0 for timely decisions, and 1 for delayed decisions. Finally, we controlled for the decision type, creating a categorical variable which took the value of 0 for clusterization decisions (the first decisions teams were invited to take in each round), and 1 for prioritization decisions (the second decisions).

3.3. *Analytical technique*

We used multiple linear regressions to test our hypotheses. The choice was influenced by the specific characteristics of our dataset and the nature of our research questions. Moreover, multiple linear regressions exhibit the capacity to investigate interaction effects (Allison, 1977, 1999). The statistical analysis was performed via Stata 17.0.

The structure of our analysis followed an incremental logic, wherein models were built step by step. We began with a foundational model focusing on control variables only. As we moved towards the richer models, main effects, interaction terms, and control variables were incorporated. This incremental approach ensured that we could compare models and discern the added value of each new variable or interaction term. By gradually introducing complexity, we were able to effectively isolate the unique contributions of different components to our dependent variable, ensuring a smoother interpretation of results, as well as a finer appreciation of improvements in R-squared values. Moreover, to correct for any potential heteroscedasticity in the data, we used the robust option.

4. Results

4.1. *Hypotheses testing*

In Table 3 we report the variables' descriptive statistics. As shown in the correlation matrix, the highest correlation coefficients are between speed of the decision and timely vs delayed decisions variables ($r = 0.791$; $p = 0.000$), teams' ID and gender ratio ($r = -0.533$; $p = 0.000$), and human-centeredness and team size ($r = 0.485$; $p = 0.000$). Human-centeredness and team size were the two key independent variables in this study. To assess potential multicollinearity issues, we computed variance inflation factors (VIF) scores for each of the variables. VIFs were below the threshold of 10 (Gujarati, 2003), thus minimizing the risks for multicollinearity issues in our regression analysis.

In Table 4, we present the results of our multiple linear regressions. Model 1 shows only the control variables. In Model 2 we insert our first independent variable (abductive reasoning) as it encompasses the first hypothesis of this study. In Model 3 we insert our second independent variable (human-centeredness) as it encompasses the second hypothesis of this study. Model 4 includes all main effects. Models 5 and 6 separately test the two interaction effects between abductive reasoning and team size, and human-centeredness and team size, respectively. Model 7 describes our full model, on which hypothesis testing primarily relies. To enhance the validity of our study, a mean-centered approach was employed to standardize all variables within the regression models, as suggested by Aiken et al. (1991).

To begin with, Hypothesis 1 posits that abductive reasoning negatively affects the quality of team innovation outcomes. As shown in Model 7, the estimated coefficient of abductive reasoning is negative and significant ($\beta = -0.441$; $p = 0.000$), thus providing support for Hypothesis 1. Hypothesis 2 posits that human-centeredness positively affects the quality of team innovation outcomes. The estimated coefficient of human-centeredness is positive and significant ($\beta = 1.543$; $p = 0.004$), thus providing support for Hypothesis 2. Hypothesis 3 posits that team size negatively moderates the negative relationship between abductive reasoning and team innovation quality. The estimated coefficient related to such an interaction is negative and significant ($\beta = -0.284$; $p = 0.003$), thus providing support for Hypothesis 3. To enhance the clarity of our analysis, in Fig. 3 we have plotted a significant interaction effect. As the figure shows, the slope of the relationship between abductive reasoning and team innovation quality changes with varying levels of team size, such that in larger teams, the baseline relationship becomes more negative as compared to the case of smaller teams.

Hypothesis 4 posits that team size positively moderates the positive relationship between human-centeredness and team innovation quality. The estimated coefficient related to this type of interaction is positive and significant ($\beta = 0.998$; $p = 0.022$). Hence, our analysis suggests support for Hypothesis 4. As is shown in Fig. 3, related to our Hypothesis 3, we have also provided a graph for Hypothesis 4 showing f the emerging interaction effect. As is clear from Fig. 4, in smaller teams, the relationship between human-centeredness and team innovation quality is flatter than in larger teams. Thus, in the latter case, the relationship between human-centeredness and team innovation quality proves to be more pronounced.

Looking at the effect sizes, we observe significant improvements in the explanatory power of the models. While Model 1, including controls, only explains 11.4 % of the total variance, the introduction of all independent variables in Model 4 increases the Adjusted R-squared

Table 3
Descriptive statistics.

	Mean	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. Team innovation quality	4.457	1.137	1.000	7.000	1.000									
2. Abductive reasoning	5.434	1.305	1.000	7.000	−0.172[a]	1.000								
3. Human-centeredness	5.221	0.911	2.940	6.218	0.107	0.321[d]	1.000							
4. Team size	3.336	0.923	2.000	5.000	0.138	0.031	0.485[d]	1.000						
5. Average team industry experience	4.126	3.112	1.000	11.667	−0.102	−0.026	0.227[b]	0.325[d]	1.000					
6. Gender ratio (Women/Men)	0.416	0.716	0.000	2.000	0.132	−0.363[d]	−0.011	−0.391[d]	−0.211[b]	1.000				
7. Teams' fixed effect	4.026	1.998	1.000	7.000	0.073	0.300[c]	−0.256[c]	0.193[b]	−0.158[a]	−0.533[d]	1.000			
8. Speed of the decision (in seconds)	741.905	432.357	186.000	2380.000	−0.036	0.125	0.154[a]	0.206[b]	0.117	−0.192[b]	0.114	1.000		
9. Timely vs delayed decisions	0.526	0.501	0.000	1.000	−0.036	0.081	0.127	0.122	0.217[b]	−0.191[b]	0.186[b]	0.791[d]	1.000	
10. Decision type	0.500	0.502	0.000	1.000	0.015	0.083	−0.012	−0.028	−0.050	−0.051	0.022	−0.148	−0.190[b]	1.000

[a] $p < .10$.
[b] $p < .05$.
[c] $p < .01$.
[d] $p < .001$. n = 116.

coefficient to 0.175. The full model (Model 7) shows the highest Adjusted R-squared coefficient, accounting for 20.5 % of the total variance.

Finally, as our analysis only considered seven teams, we explored the possibility of interaction effects between teams and team decision processes in relation to team innovation quality and we re-ran our full model including such interactions. Our results indicate that the interactions between the team and the team decision process are not significant when added to our full model. Importantly, the moderating relationships explored in our study hold their statistical significance, and the directional signs of these relationships are consistent across different analyses.

4.2. Robustness checks

To substantiate the validity and reliability of the results, several robustness checks were conducted. These checks aim to ensure that the results are not unduly sensitive to model specification, measurement methods, or specific data points. The first robustness check involves varying the panel of experts used for assessing team innovation quality (Cooksey, 1996). In the primary analysis, each decision was evaluated by a panel of three independent experts. For this robustness check, the analysis was re-run multiple times, each time omitting one expert's evaluation. The rationale behind this procedure was to ascertain the robustness of the dependent variable against potential idiosyncratic judgments of individual experts. The results were largely consistent with the original results, reinforcing the validity of our composite measure of team innovation quality. This means that in most cases, significant and non-significant coefficients and related signs reflected the model presented in Table 4.

The second robustness check employed Jackknife Resampling techniques (Efron & Tibshirani, 1994; Miller, 1974). This procedure involves running the regression models multiple times, excluding one team's data points each time. Our objective was to determine whether individual teams exerted undue influence on the overall model fit and estimates. Results from these analyses were confirmatory the original findings, reinforcing the idea that the results were not driven by specific outliers or influential observations.

The third robustness check pertains to the estimation of latent variables. In the primary analyses, latent scores for abductive reasoning and human-centeredness were estimated using congeneric models. To test the robustness of these estimates, parallel models were employed as an alternative method for estimating latent scores. Despite the different assumptions underlying these models, results were confirmatory, which substantiates the robustness of the latent variables employed in the study.

The fourth robustness check involved re-estimating the model without incorporating control variables (Bernerth et al., 2018). This exercise helped us to gauge to what extent the observed relationships were directly attributable to the independent variables studied. Results remained in alignment with the main findings, providing further assurance that the observed relationships are not artifacts of model specification or confounding variables.

5. Discussion

5.1. Theoretical implications

Overall, this study offers three main theoretical implications. Firstly, it contributes to the existing body of work on design thinking by elucidating the specific effects of abductive reasoning and human-centeredness on the innovation quality of team decisions made in time-sensitive environments. The empirical evidence derived from this study substantiates claims of human-centeredness being beneficial for decision-making (Nakata & Hwang, 2020). At the same time, this study questions the general applicability of abductive reasoning as an optimal

Table 4
Multiple linear regressions.

Variable	H	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Abductive reasoning	*1*		−0.151		−0.314[c]	−0.337[c]	−0.353[c]	−0.441[d]
			(0.092)		(0.116)	(0.112)	(0.112)	(0.115)
Human-centeredness	*2*			0.112	0.325[b]	0.288[b]	0.935[b]	1.372[c]
				(0.115)	(0.139)	(0.145)	(0.469)	(0.467)
Abd. reas. X Team size	*3*					−0.118		−0.284[c]
						(0.075)		(0.092)
Hum-cent. X Team size	*4*						0.474	0.881[b]
							(0.358)	(0.378)
Team size		0.257[c]	0.236[b]	0.192[a]	0.025	0.020	−0.165	−0.339[b]
		(0.088)	(0.090)	(0.106)	(0.115)	(0.115)	(0.177)	(0.170)
Average team industry experience		−0.080	−0.083	−0.074	−0.072	−0.054	−0.048	0.016
		(0.112)	(0.111)	(0.113)	(0.112)	(0.117)	(0.111)	(0.112)
Gender ratio		0.329[c]	0.278[b]	0.327[c]	0.216[a]	0.257[b]	0.003	−0.080
		(0.124)	(0.117)	(0.124)	(0.115)	(0.129)	(0.190)	(0.182)
Teams' fixed effect		0.225[a]	0.246[b]	0.271[b]	0.397[c]	0.428[c]	0.306[a]	0.299[a]
		(0.124)	(0.124)	(0.130)	(0.139)	(0.145)	(0.162)	(0.162)
Speed of the decision		−0.051	−0.025	−0.044	0.024	0.025	−0.007	−0.031
		(0.182)	(0.181)	(0.186)	(0.184)	(0.184)	(0.183)	(0.179)
Timely vs delayed decisions		0.018	0.002	−0.004	−0.081	−0.078	−0.056	−0.027
		(0.177)	(0.178)	(0.178)	(0.180)	(0.180)	(0.181)	(0.180)
Decision type		0.023	0.033	0.018	0.028	0.033	0.024	0.032
		(0.090)	(0.090)	(0.091)	(0.088)	(0.089)	(0.088)	(0.089)
N		116	116	116	116	116	116	116
Adjusted R-squared		0.114	0.133	0.122	0.175	0.180	0.185	0.205

Robust standard errors in parentheses.
[a] $p < .10$.
[b] $p < .05$.
[c] $p < .01$.
[d] $p < .001$. All variables have been standardized.

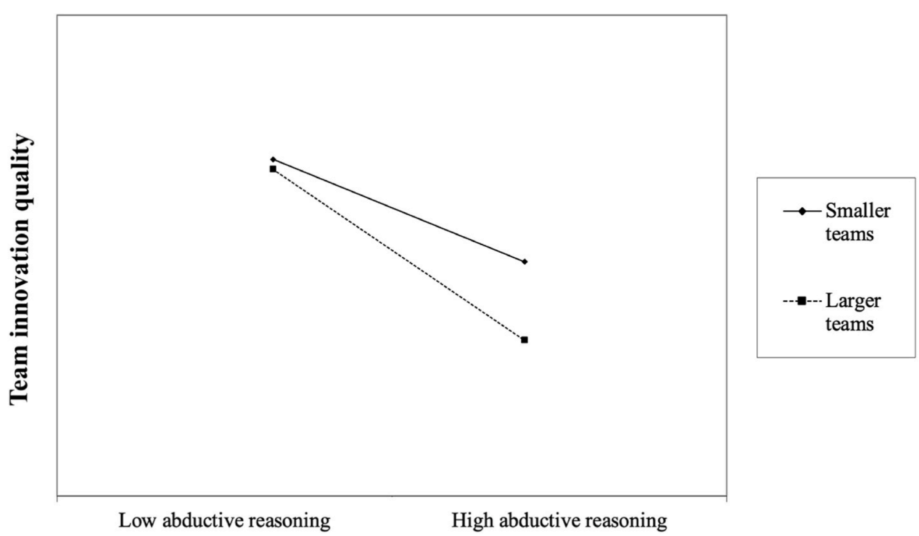

Fig. 3. The moderating role of team size on the relationship between abductive reasoning and team innovation quality.

strategy in all contexts. This dual contribution resonates with existing scholarship that identifies challenges and complexities in the design thinking framework (e.g., Carlgren & Ben Mahmoud-Jouini, 2022). The findings suggest that the theoretical modeling of design thinking should account for these context-specific strengths and limitations, thus nuancing its operational paradigms.

Secondly, the study contributes to the literature on decision-making under time constraints. By examining how design thinking principles manifest in these settings, it brings attention to the salient issue of cognitive schema appropriateness for quick decision-making. The study thereby supplements existing theories on the dynamics and speed of decision-making (e.g., Allen, 2011; Kocher & Sutter, 2006), introducing a perspective that interrogates the relevance of different reasoning approaches when time is of the essence. This opens avenues for further research that could delve into the selection and tailoring of cognitive schemas to match the decision-making environment.

Thirdly, the study sheds additional light on the effect of team size on innovation quality, an area that has garnered academic interest but remains partly underexplored (e.g., Rahmani et al., 2018). It posits that team size acts as a moderating variable that amplifies the existing tendencies of the decision-making approaches employed. Specifically, it accentuates both the positive and negative impacts of abductive reasoning and human-centeredness. This underlines the need for more granular research that can pinpoint optimal team sizes or configurations

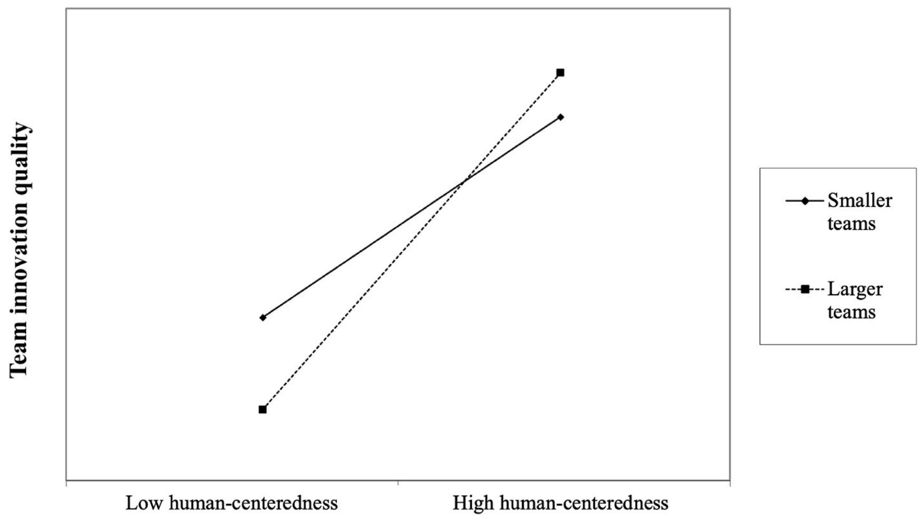

Fig. 4. The moderating role of team size on the relationship between human-centeredness and team innovation quality.

under various constraints, thereby enriching theoretical models of team dynamics and decision-making.

5.2. Practical implications

The results of this study can be translated into multiple actionable recommendations for enhancing management practice. From a broad perspective, managers should take a nuanced approach to applying design thinking principles, particularly abductive reasoning and human-centeredness, in various organizational settings.

Regarding the limitations of abductive reasoning in time-constrained environments, managers should be prepared to use alternative frameworks. In fast-paced situations, it would be advisable to have a set of predefined heuristics or rules of thumb that teams can quickly consult. Training modules can be developed to help team members practice applying these heuristics in simulated time-pressured conditions, thereby enhancing the likelihood of making innovation quality decisions rapidly.

Secondly, the fact that this study underscores the primacy of human-centeredness as positively impacting team innovation quality suggests that managers should actively instill a culture of empathy and user-focus. To implement this, they could initiate regular stakeholder meetings or deploy customer experience surveys as part of a project's life cycle. Managers could also set KPIs (key performance indicators) that directly measure the level of customer satisfaction or user engagement, thus tying team performance metrics to human-centered outcomes.

Thirdly, concerning the role of team size, managers have a critical decision to make when assembling a team for a project. Larger teams may bring in diverse perspectives but could dilute the decision-making quality due to complexities in communication. For larger teams, managers might employ specialized software for project management and communication to streamline interactions and facilitate easier decision-making. Alternatively, managers could consider a 'modular' approach to team formation, where subsets of larger teams tackle specific aspects of a problem, later integrating their findings into a comprehensive solution. In this perspective, managerial tools such as decision matrix charts could be used to weigh the trade-offs between different decision-making approaches and team sizes, depending on the specific constraints and requirements of the project at hand.

5.3. Key limitations

While this research contributes to the academic understanding of design thinking, decision-making processes under time constraints, and the variables affecting optimal team size, of course, it is not without limitations. First, the research was tied to budgetary constraints, which limited the scope of the study, particularly in terms of the number of participating teams. This financial constraint prevented the inclusion of a broader sample, potentially affecting the generalizability of the findings. Similarly, it is possible that Type II errors were also introduced due to the sample size. The relatively small number of participants may have reduced the study's statistical power, increasing the risk of failing to detect significant effects where present.

Secondly, and relatedly, the study did not include very large teams or single decision makers. The exclusion of these groups means that the results may not be applicable to settings where decision-making dynamics are significantly different, such as in larger teams with more complex coordination needs or in situations where a single individual makes decisions.

Thirdly, the study relied on self-reported latent variables, which can introduce bias due to the subjective nature of self-assessment. Participants may have overestimated or underestimated their behaviors and attitudes, leading to inaccuracies in the data collected.

Fourthly, the participating firms were from the ICT industry, which limits the applicability of the results to other sectors. The specific dynamics and innovation processes in ICT may not reflect those in different industries, thereby restricting the generalizability of the findings to a wider business context. Similarly, there was a gender disproportion, with significantly more male participants compared to females. This could have influenced the results, as diverse gender perspectives can impact decision-making processes and outcomes. Moreover, the participants were primarily entrepreneurs and managers, not employees. This focus might have skewed the findings, as decision-making processes and innovation dynamics can differ markedly between these roles and those of regular employees.

Additionally, the focus on short-term decision-making could be expanded to examine the implications for long-term, strategic decisions, thereby broadening the study's applicability to other time contexts. Another limitation pertains to the fact that the study did not explore the potential diminishing returns of human-centeredness. Future research could explore the optimal levels of human-centered focus in decision-making, illuminating the threshold beyond which this approach ceases to be beneficial and may even become counterproductive.

6. Conclusions

The present study was motivated by the increasingly high pace of industry dynamics where effective decisions must be made urgently under various constraints. Accordingly, this study engaged with a research gap in extant literature, particularly concerning the influences of abductive reasoning and human-centeredness on team innovation quality in time-constrained settings. Through a laboratory game context empirical analysis involving seven teams, the research elucidated the complex interplay between the cognitive frameworks of design thinking and the quality of team decisions. The study revealed that an over-reliance on abductive reasoning may adversely affect team innovation quality, whereas a pronounced focus on human-centeredness yielded more favorable outcomes. Team size functioned as a moderating variable, exacerbating the negative outcomes associated with abductive reasoning and enhancing the beneficial effects of a human-centered approach. Overall, the study provides novel theoretical and practical insights while establishing a foundation for future scholarly work. The limitations noted within the research framework serve to guide upcoming explorations aimed at offering a more comprehensive understanding of the intricate relationships between reasoning paradigms, team dynamics, and innovation quality.

Declarations of interest

None.

Data availability

Data available on request due to privacy/ethical restrictions: The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

CRediT authorship contribution statement

Marco Balzano: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Guido Bortoluzzi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Marco Balzano is PhD Candidate of Management attending a Double PhD Program between the Department of Management, Ca' Foscari University of Venice (Italy) and KTO Research, SKEMA Business School (France). He published in several international outlets including Technovation, IEEE Transactions on Engineering Management, and Journal of Small Business Management, among others, and presented the results of his research activity in international conferences including the AoM Conference, EURAM, R&D, IPDMC. His main research interests deal with the study of chance, business strategy, and innovation management.

Guido Bortoluzzi is Full Professor of Innovation Management and Entrepreneurship at the Department of Economics, Management, Mathematics and Statistics "Bruno de Finetti" of the University of Trieste (Italy) and Core Faculty member at the MIB Trieste School of Management. He has been visiting lecturer in several international Universities worldwide, including University of Northern Colorado (Greeley, U.S.), Lingnan (University) College (Guangzhou, PRC) and ISM University of Economics and Business (Vilnius, LT). His research interests deal with innovation management, creativity and start-ups. He has published the results of his research in several international journals, including Journal of Business Research, International Marketing Review, European Management Journal, Management Decision, Harvard Business Manager (HBR, German edition), European Journal of Innovation Management.