Group Decision and Negotiation (2021) 30:945–982
https://doi.org/10.1007/s10726-021-09743-0

The Relationship Between Unlearning and Innovation Ambidexterity with the Performance of New Product Development Teams

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Accepted: 26 April 2021 / Published online: 25 May 2021

Abstract
Previous research has suggested that unlearning is not linked to performance improvements in a team setting. Further, unlearning may have deleterious effects on performance outcomes because when it happens, teams are likely to lose the way they perform tasks and the reasons for their operational existence. In contrast, this study predicts that teams can conduct exploitative and exploratory activities in a balanced manner predicated on unlearning practices to improve new product development (NPD) performance. We hypothesized that while unlearning allows NPD teams to balance exploitative and exploratory learning activities, simultaneous yet balanced exploitation and exploration at high levels, namely innovation ambidexterity, links unlearning practices to NPD performance. This occurs by providing task-relevant knowledge for the replacement of outdated routines and beliefs during NPD processes. Data were collected from 198 NPD teams (i.e., 464 individual participants). The examination of ordinary least squares regression-based path analyses revealed that innovation ambidexterity mediates the relationship of unlearning with NPD performance, operationalized as product development speed, cost, and product success. Overall, this study shows that the unlearning-performance relationship occurs through simultaneous exploitative and exploratory learning activities in a balanced manner.

Keywords Unlearning · Innovation ambidexterity · New product development team performance · Team learning theory · Ambidexterity measurement

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1 Introduction

Innovation is a value creation process which brings new ideas into the market (Schumpeter 1934). Research on *technology and innovation management* (TIM) suggests that market success of an invention (i.e., innovative outputs) requires the simultaneous yet balanced use of exploitative and exploratory learning activities, namely innovation ambidexterity (e.g., He and Wong 2004). Exploitative learning activities are rooted in one's past accomplishments and actions (Lin and McDonough III 2014). They include the refinement of existing knowledge and skills associated with incremental innovations in nature. Exploratory learning activities are rooted in trial-and-error cycles (Lin and McDonough III 2014). These activities include novel skill sets for the development of innovations that are radical in nature.

Edmondson et al. (2007) stressed that an important area for future research is to show how teams can effectively integrate exploitation and exploration. This is because processes, factors, and resources that are essential for the success of how teams exploit existing resources may differ from those that are used to explore new opportunities. While pursuing both learning activities in a balanced manner has positive learning and performance outcomes (March 1991; He and Wong 2004), still less is known about *the mechanism of how a team can match the magnitudes of exploitation and exploration* (Brix 2019; Jansen et al. 2016; Úbeda-García et al. 2020). Gupta et al. (2006: 697) noted that "although near consensus exists on the need for balance between exploitation and exploration, there is considerably less clarity on how this balance can be achieved."

In this study, we propose that *unlearning*, defined as a change in routines and beliefs, is a team level reflective learning technique for achieving that balance. This is because unlearning is a mechanism that enables a team to detect and correct outdated routines and beliefs that typically hampers exploitative and exploratory learning cycles (Argyris and Schön 1974).

Previous studies have argued that unlearning per se has no relationship with performance outcomes (e.g., Akgün et al. 2006; Meyers and Wilemon 1989). These studies concluded that unlearning could paralyze team processes, hence hinder team performance (Akgün et al. 2006; Brown and Duguid 1991; Hedberg 1981). This is because when unlearning occurs, teams may lose the manner in which they operate tasks and hence the reason for their existence. Although unlearning has the potential to make room for new interpretative responses to shifts in the business environment, teams still need a mechanism to integrate new insights into operational processes (Brown and Duguid 1991).

Accordingly, in this study, we argue that in a team setting innovation ambidexterity may be such a mechanism that allows unlearning to improve performance. This may occur because, although exploitation and exploration have been characterized as two distinct dimensions of learning behaviors (Gupta et al. 2006), as we posit, they are in essence complementary to each other. In other words, pursuing these two activities in a combined manner facilitates further learning and thereby an improvement in performance outcomes (Katila and Ahuja 2002).

Nevertheless, this combination requires balancing exploitation and exploration at high levels (He and Wong 2004; Simsek 2009). The research on ambidexterity has mostly failed to show the importance of the balanced viewpoint of exploitation and exploration on performance regarding the combined effect (e.g., Cao et al. 2009; Chandrasekaran et al. 2012; Kostopoulos et al. 2015; Venugopal et al. 2020). The balanced view focuses on the absolute difference between exploitation and exploration, while the combined view sees these two activities as a combination by adding one to another or multiplying one with another. The combined view is important because it reflects the mutual exclusiveness of exploitation and exploration (cf., Gupta et al. 2006).

We also argue that the balanced view is crucial to show the level of “reciprocal dependency” among exploitation and exploration. In this regard, existing calculation method does not reflect the true nature of the predictive power of the balanced view on performance. This is because a balance between exploitation and exploration can occur at both low and high levels based on the available calculation method (Cao et al. 2009; Simsek 2009). Thus, a new approach for revealing that role is warranted. Following Cao et al.’s (2009) calculation methodology, and explaining the logic underlying our assertion (see Appendix 2), we propose that once a team synergistically combines the above-mentioned views, the output, innovation ambidexterity (i.e., a combination of the balanced and combined views of exploitation and exploration), is likely improve *new product development* (NPD) team performance in the form of accelerated product development speed, decreased product development costs, and increased market success of the newly developed product. Indeed, this understanding will truly define the notion of ambidexterity at team and organizational levels.

The results of our study show that combined yet balanced exploitation and exploration in the NPD teams serve as a mechanism for how unlearning enables improved performance. We found that innovation ambidexterity enables teams to link their reflective efforts, that is, unlearning implementations, to NPD performance. In this regard, our research makes a significant contribution to the literature on unlearning and innovation ambidexterity. Despite studies suggesting a negative or no relationship of unlearning with performance outcomes (e.g., Akgün et al. 2006; Meyers and Wilemon 1989). Our study shows that unlearning is indeed one of the main tools of NPD teams to balance exploitative and exploratory learning activities. In addition, the present study contributes to the literature by showing that unlearning and NPD performance outcomes is mediated by high levels of explorative and exploitative learning activities. Finally, this study contributes to the literature on measurement of ambidexterity by capturing a balance of exploitation with exploration at high levels of both activities. This methodological approach represents the unique nature of ambidexterity in research moving forward.

At the practitioner level, our study provides unique insights to NPD team leaders and managers. Using the results of our study, team leaders can enhance NPD performance by deliberately facilitating unlearning within the team concurrently with explorative and exploitative activities in a balanced way. In other words, NPD team leaders should note that activities that unlearning of old routines and beliefs alone is not sufficient to enhance NPD performance. While unlearning creates a contextual shift from an old state to a new one, team leaders should simultaneously facilitate explorative and exploitative learning activities to leverage the unlearning practices. Managers should not simply discard, but maximize the level of gains via incremental improvements, while simultaneously encouraging the team to go beyond what is already known and support the exploration of new possibilities in the business environments via experimentation and discovery in a balanced manner. At the end, these teams can increase the speed of the product development process, lower the cost of the project, and enhance the market success of a newly developed product, resulting in improved overall NPD performance.

We structure the remainder of the present article as follows. First, we review the concepts of unlearning and innovation ambidexterity. Second, we propose a theoretical framework and present our hypotheses. Third, we present the data analyses and the results. Finally, in the discussion section, we explain the contributions of our results to the literature, we describe the limitations of the study, and we suggest future research.

2 Conceptual Background

2.1 Unlearning

Unlearning is conceptualized in terms of a change in routines and beliefs (Akgün et al. 2006; Hedberg 1981). Routines are defined either as a "repetitive pattern of activity" (Nelson and Winter 1982: 97) or as interdependent behaviors adopted by team members to perform specific tasks (Wong et al. 2012). Uniformly held beliefs in the workplace bind individuals together in terms of their views regarding cause-effect relationships (Yang et al. 2014). In this regard, beliefs are defined as a general understanding that directs team members to undertake specified courses of action depending on prevailing situations (Akgün et al. 2006; Wong et al. 2012).

After reviewing 34 definitions of unlearning, Tsang and Zahra (2008) concluded that this concept refers to discarding or changing old routines and beliefs to make ways for new ones. Unlearning is the deliberate act of putting aside existing knowledge structures that teams will no longer use in a given context (Cegarra-Navarro and Wensley 2019). Nystrom and Starbuck (1984: 53) suggested that before making any attempt to develop new ideas, teams "must first unlearn old ones by discovering their inadequacies and then discarding them" to deliberately respond to changes in business environments. Baker and Sinkula (1999: 413) contended that "when organizations proactively question long-held routines, assumptions, and beliefs, they are engaging in the practice of unlearning." Lee and Sukoco (2011) proposed that team members need to engage in unlearning to overcome resistance to new ideas and facilitate fresh approaches to successfully address the detrimental effects of old routines and beliefs. This perspective is consistent with Ruíz et al. (2017). They argued that unlearning is an action that takes place when people need to update knowledge, routines, processes, or protocols (i.e., specific knowledge structures) that may overtime become obsolete or may need to be altered as business markets require. In summary, unlearning is not only a reactive response to ongoing changes. It also includes proactively questioning knowledge structures such as “long-held routines, assumptions, and beliefs” (Baker and Sinkula 1999: 413). Consistent with these approaches, we operationalized unlearning as a team’s ability to create a cognitive sphere for new insights through reflective discussions of shared routines (e.g., operations) and beliefs (e.g., strategies) in team sessions.

2.2 Innovation Ambidexterity

Scholars refer to ambidexterity when describing firms that effectively exploit the sources available to them, while, at the same time, exploring new opportunities beyond their known boundaries at high levels (e.g., Simsek 2009). Exploitation (e.g., improving existing product through revealing performance gaps) and exploration (e.g., creating a new product through conducting research and development activities) are different forms of learning processes through which innovation emerges in a team setting (Jansen et al. 2016). In March’s (1991) work, exploitation refers to learning activities for the purpose of modifying existing products and making operations efficient, whereas exploration refers to learning activities carried out with experimentation and discovery, and thereby developing new products. In this study, we conceptualized ambidexterity as an innovation-oriented learning process in which team members collectively exploit the value of existing resources and competencies for improving available products, while simultaneously exploring new knowledge and methods for the development of novel products in a balanced manner at high levels (Gupta et al. 2006; He and Wong 2004; Simsek 2009).

March (1991) theorized that, albeit the beneficial effects of pursuing both exploitation and exploration, there is incompatibility between them. This is because organizational units who are responsible for exploitation and exploration compete for scarce resources. That is, resources devoted to exploitative learning activities generally mean fewer resources left for exploratory learning activities, and vice versa (Gupta et al. 2006). Yet, the argument on resource scarcity is not true for all types of resources. For example, information and knowledge, as cognitive resources, are infinite (Gupta et al. 2006). In this regard, Katila and Ahuja (2002) found that the interaction between exploitation and exploration have a prospective impact on product development. Departing from March’s (1991) incompatibility argument, they conceptualized exploitation and exploration as not two ends of a unidimensional scale, performed by a single organizational unit, but as two distinct dimensions of learning behavior. Hence, they are mutually exclusive activities (Gupta et al. 2006).

Building on March’s (1991) argument, He and Wong (2004) were the first to propose the absolute difference between exploitation and exploration to reveal the level of balance among them. An organizational entity should pursue balanced high levels of exploitative and explorative learning activities to eliminate a success or failure trap (Levinthal and March 1993). That is, an organizational entity should achieve a balance between exploitation and exploration to avoid a success trap, excessive exploitation, or a failure trap, an endless cycle of search and discovery (Úbeda-García et al. 2020). However, this approach (and its measurement) does not reflect the interaction of exploitation with exploration which was proposed by Katila and

Ahuja (2002). This interaction is important because the predictive power of these two activities on performance depends on it (cf., Gupta et al. 2006).

While existing perspectives discussed above have contributed to our understanding of ambidexterity, we argue that they do not reflect the true nature of ambidexterity as it stands. This is because dexterity refers to the ability to manipulate resources exploitatively and exploratively in a skillful manner (Simsek 2009; Trombly and Scott 1989). Robotics (Zhou et al. 2018) and cardiovascular medicine (Raghavan 2007) sciences suggest that skillful pursuit of dexterity requires both control (i.e., balance) and actuation (i.e., combination). In a similar fashion, ambidexterity in an organizational setting requires control of exploitative and exploratory activities to produce reciprocal dependency, while simultaneously executing these two. Balance is necessary to effectively manipulate infinite resources without paralyzing each other and destroying one another's interests.

Hence, based on the contingency approach that emphasises the configurational perspective (Cao et al., 2009; Miller 1981; Venkatraman 1989), we argue that the true nature of ambidexterity is to be revealed when congruence is achieved among exploitation and exploration, and when different configurations of exploitation and exploration dynamically interact (He and Wong 2004; Venkatraman 1989). These are the combinative and balanced configurations of exploitation and exploration. Ambidexterity in this regard should be a product of a "synergistic interaction" of the two configurations of exploitation and exploration (Cao et al. 2009; Miller 1981; Sutcliffe et al. 2000). In this way, these two configurations, exploitation and exploration, become "tightly interdependent" yet "mutually supportive" parts of something beyond a sum of its parts (Nilsson 2010). We explain this further in Appendix 2.

2.3 Criterion Variables

We examined NPD team performance using three well-known performance indicators: product development speed, product development cost, and new product success. Product development speed is measured in terms of how quickly an idea moves from conception to a product in the market (Chen et al. 2010). Product development cost is related to the actual cost of the project adhering to (or lowering) the estimated cost (Lewis et al. 2002). New product success refers to meeting or exceeding expectations to increase sales, boost profits, expand market share, and satisfy customers (Cooper and Kleinschmidt 1987).

3 Theory

Little is known about the mechanisms that enable teams to create a balance between exploitative and exploratory learning activities (Brix 2019; Jansen et al. 2016; Úbeda-García et al. 2020). We posit that, beginning with reflective unlearning, NPD teams need to create a clear cognitive path and mental space for conducting exploitative learning activities, while simultaneously benefiting from exploratory ones in a balanced manner. Because learning often requires unlearning (Nystrom and

Starbuck 1984; Peschl 2019). Action science (Argyris and Schön 1974) states that learning is the iterative process of detecting and correcting errors[1] (Argyris 2004), and then linking a goal to a desired performance level through an action. This occurs by eliminating errors. Learning in this regard is characterized either as single-loop or double-loop learning (Argyris and Schön 1974; Argyris 2004).

Single-loop learning occurs when the correction of an error (i.e., a taskrelated-problem) is achieved by only changing routines, not by changing the team's underlying beliefs (Argyris 2004). For example, when a team reflects on its performance metrics, it can identify the gap between the goal it set and the performance it has achieved. To eliminate the gap, the team should adjust its activities through unlearning outdated routines, methods, and operational procedures. On the one hand, single loop learning is based on the concept of a good enough/sufficient explanation as opposed to an optimal one. Double-loop learning, on the other hand, occurs when the correction of an error is achieved after changing both routines and the beliefs underlying them (Argyris 2004). When a team encounters an unexpected situation, such as an unfamiliar gap between a goal and desired performance, there may be situations where changing routines is necessary but not sufficient. In such situations, the team must also change the belief systems that govern its operational strategies.

The extent to which teams reflect upon their goals and methods for attaining them, their prior performance metrics may incrementally or radically permit them to learn and then prepare for upcoming performance episodes (Edmondson 2002; Marks et al. 2001). Single-loop learning is a first-order change or improvement. This fits with the characterization of the reflection-exploitation relationship in team learning theory. Double-loop learning is a second-order change or innovation. It is characterized as the reflection-exploration relationship in team learning theory (Argyris and Schön 1974).

A balanced approach to exploitative and exploratory learning is necessary because failure to manage the tensions among them can result in a success trap, namely too much exploitation at the expense of exploration. A failure trap occurs when there is too much exploration at the expense of exploitation (Levinthal and March 1993). For example, in a qualitative study of twelve teams, Edmondson (2002) concluded that when teams only engage in performance improvements but fail to learn,[2] inefficiencies (such as increased product development costs for product development teams) the firm's near-term profitability is threatened. When teams were only responsible for innovation (e.g., developing new strategies or products), they again failed to learn. Moreover, the firm often missed critical market opportunities that impeded its competitiveness. A focus on a breakdown between the iterative process of reflection (insight) and action enabled the teams to benefit from both exploitative and exploratory learning activities (Edmondson 2002). Thus, we

[1] Argyris (2004) defines error as any mismatch between an intention (a goal) and an implementation (a performance).

[2] Edmondson (2002) defined failure to learn as a mismatch between current routines and changes required to fit environmental conditions.

suggest that unlearning is a mechanism that enables a team to match exploitative with exploratory activities.

We further argue that innovation ambidexterity eliminates disorienting effects of unlearning on performance because it enables a team to exploit existing knowledge properties and explore new possibilities in a simultaneous, yet balanced way (Jansen et al. 2006). In their taxonomy, Marks et al. (2001) identified a recurring phase model of team processes defined "as members' interdependent acts that convert inputs to outcomes through cognitive, verbal, and behavioral activities directed toward organizing taskwork to achieve collective goals (p 357)." Ambidexterity, as a dynamic capability (O'Reilly III and Tushman 2007), is defined as "processes that use resources—specifically the processes to integrate, reconfigure, gain and release resources—to match and even create market change" (Eisenhardt and Martin 2000: p. 1107). Thus, teams may use innovation ambidexterity as a leveraging mechanism to link changed routines and beliefs to attain desired outcomes. This likely occurs in two phases in a team setting. Sometimes teams reflect on past performance metrics and ongoing changes in business environments to plan for subsequent action (i.e., transition phase) (Açıkgöz et al. 2020). At other times, they may focus on activities related to goal pursuit (i.e., action/performance phase) (Marks et al. 2001).

Teams that reflect on the above-mentioned issues can unlearn non-functional frames of reference, namely routines and beliefs, in favor of new ones in transition phases (Becker 2019; Hedberg 1981). Then, these teams can convert new insights through the combinative/additive power of high levels of exploitation and exploration to performance outcomes in action/performance phases in a balanced way.

Vince (2008) proposed that the time taken for reflection is the starting point for unlearning. In this period, team members collectively reflect on the limitations of a team's performance (Peschl 2019). Unlearning in this regard is an ongoing, iterative process (Becker 2019). That is, the process of unlearning continues until the new forms of routines and, if necessary, beliefs are internalized (Rupcic 2019). Teams can link new routines and beliefs via innovation ambidexterity to performance. That is, the management of synchronous and/or simultaneous exploitative and exploratory activities involves information exchange and mutual adjustment of new routines and beliefs. Doing so is likely to enable a team to align the pace and sequencing of new inputs with goal accomplishment (Marks et al. 2001).

3.1 Hypotheses Development

3.1.1 Unlearning and Innovation Ambidexterity

We hypothesized that unlearning may be the mechanism to match exploitative and exploratory learning activities at high levels. This is because learning requires unlearning. This argument is illustrated by a case involving Apple.

Apple launched its first generation of iPod in 2001.[3] Up until 2007, the firm made several modifications to upgrade that product line. In 2007, Apple launched the first generation of iPhone models in addition to a new version of its iPod. This happened through unlearning a set of routines and beliefs about an existing product line (i.e., iPod).

In 2005, Steve Jobs publicly announced that: "The problem with a phone is that we're not very good going through orifices to get to the end users." Jobs had other reservations about 'a new product' as one former Apple executive who had daily meetings with him noted. That executive said that "[Jobs] wasn't convinced that smartphones were going to be for anyone but pocket protector crowd." When Tony Fadell, the father of the iPod and one of the creators of iPhone, showed Jobs one of the first prototypes of iPod that runs with the internet (a new version for switching from iPod to iPhone), his reaction was simply that it was a worthless effort (Merchant 2017). In addition to Jobs, Jony Ive (Apple's chief design officer), and other engineers, designers, and managers at Apple believed that "…cell phones sucked. They were terrible. Just pieces of junk" (Merchant 2017).

Nevertheless, a few people on the executive team successfully convinced Jobs that building a phone was a good market prospect for Apple. This change in Jobs' thinking took extensive effort, arguments, and back and forth emails. This reflection process resulted in unlearning existing routines and beliefs that had been holding Jobs captive.

By unlearning, one does not permanently lose the abandoned routines and beliefs. But it does reduce the influence of them for the sake of creating something new (Grisold et al. 2017). Apple explored a new set of routines and beliefs to develop iPhone, while simultaneously exploiting its existing knowledge structures to develop new versions of iPod models in highly effective manner. Unlearning led Apple to reduce the influence of its existing routines and beliefs while simultaneously utilizing new knowledge structures at high levels (Peschl 2019). Old and new knowledge structures and beliefs interact with each other in the process of mutual fade-out/fade-in to match exploitative and exploratory learning activities (Rupcic 2019). Thus, we tested the following hypothesis:

H1 Unlearning is positively related to innovation ambidexterity in NPD teams.

3.1.2 Mediation of Innovation Ambidexterity between Unlearning and Product Development Speed

The literature on NPD performance is still not clear whether cutting development time should be a goal when complex knowledge structures are to be acquired (e.g., Ali et al. 1995; Chen et al. 2010). For example, McDonough III (1993) argued that development time is a function of whether the product involves incremental or radical technology.

[3] See https://www.theverge.com/2017/6/13/15782200/one-device-secret-history-iphone-brian-merchant-book-excerpt.

We hypothesized that unlearning routines and beliefs, and establishing new procedures, rules, and/or mindsets may prevent a team from repetitive decision-making that blocks its members' collective efforts to create cause-and-effect relationships regarding exploitative and exploratory issues (Dickson 1992). The resulting potential, innovation ambidexterity, may lead a team to shorten product development cycle times through a probe-and-learn approach (Eisenhardt and Tabrizi 1995). That approach enables teams to mobilize know-how among exploitative and exploratory activities (Chen et al. 2010). That is, a team can perform incremental activities in a habitual way, such as developing a new version of an iPod, while at the same time it can test, iterate, and experiment with new operational procedures, tools, and technologies, such as the creation of first version of an iPhone. Recall that discarding what was old opened a way for both experimentation and improvement in Apple.

Shea and Cagan (1999) observed that manufacturing firms (e.g., Solectron, Jabil Circuits, and Flextronics) reduced cycle times by 10% to 40% by learning and integrating new technologies into design and production processes, such as computer-aided design, computer-aided manufacturing, and computer-aided production planning. Case studies on the implementation of concurrency[4] in firms (e.g., Boeing, Cummins Engine Co, Texas Instruments, IBM, Hewlett-Packard, and Thomson Consumer Electronics) reported savings of more than 60% in design cycle time (e.g., Swink et al. 1996). Process re-formalization as a result of unlearning or making unlearning as the integral part of the learning process may enable a team to execute parallel development activities. Such concurrency may eventually save the average time for improving an existing product and developing a new one. Thus, we tested the following hypothesis:

H2 Innovation ambidexterity mediates the relationship between unlearning and product development speed in NPD teams.

3.1.3 Mediation of Innovation Ambidexterity Between Unlearning and Product Development Cost

Previous research has argued that overlap in exploitative and exploratory activities can lead to extra development costs (e.g., Ha and Porteus 1995; Kessler 2000; Smith and Eppinger 1997). Yet, these costs might be repaid by benefits in downstream efficiencies and product novelty. That is, lowering average costs may occur because a concurrency in the development pipeline enables a team to create economies of scope. The "project and/or product platform" and "product families" lower overall development costs through pooling know-how and applying core capabilities over a long duration and across a broad scope in multiple situations (Prahalad and Hamel 1990). In support of this argument, Sher and Yang (2005) found that accumulated NPD process experience is related to lower product development costs. Hoppmann et al. (2011) revealed that lean product development is the result of a system of

[4] The extent to which stages of the NPD process overlap or are conducted concurrently (Tatikonda and Montoya-Weiss 2001).

highly interwoven elements which only in their concurrency lead to a cost-efficient product innovation process.

Unlearning reduces excessive "turf-guarding (i.e., strong functional norms)" that can lead to cost-traps as a result of conflict over project goals and/or restricted communication among different teams in a same business unit (Kessler 2000). Eliminating early mis-conceptualizations of product specs and conflicting goals is important for reducing development costs because it often leads to costly changes in the later stages of product development, such as design, production, and marketing (Cooper and Kleinschmidt 1987). Gupta and Souder (1998) reported that the cost incurred in the early stage of product development processes is estimated at no more than 8% of the total product costs yet decisions made at this stage determine as much as 80% of total costs. Unlearning is likely to prepare the ground for effective communication regarding exploitative and exploratory activities. That concurrency can minimize product development costs through leveraging the team's existing intellectual (e.g., knowledge resources) and physical resources (e.g., location, technology, human factor) (Kessler 2000). Moreover, exploratory activities leverage the knowledge and learning from exploitative activities. As one Apple executive, Tony Fadell, noted: "There would be no iPhone without the iPod." (Merchant 2017). Thus, we tested the following hypothesis:

H3 Innovation ambidexterity mediates the relationship between unlearning and lowering product development cost in NPD teams.

3.1.4 Mediation of Innovation Ambidexterity Between Unlearning and New Product Success

We hypothesized that innovation ambidexterity mediates the relationship of unlearning with new product success. This is because unlearning does away with rigid routines and beliefs across development processes as the action unfolds. This potentially eliminates process traps ahead of commercializing a new product. Although previous research has found no direct association between unlearning and new product success (e.g., Akgün et al. 2006), innovation ambidexterity is likely to find a relationship via learning, discovery, and experimentation regarding advancements in markets and technology.

Li (2013) has found that different types of learning modes enhance new product innovativeness in different ways. That is, in the implementation phase of an NPD project, exploitative learning activities have a relationship with incremental innovation, while, in the initiation phase, exploratory learning activities have a relationship with radical innovation in a team setting. By learning what has just been unlearned in improved ways, teams have a better chance of capitalizing on technology- and market-related opportunities, as this represents a way to succeed. If the teams put the knowledge of new techniques and methods into action via innovation ambidexterity, they may successfully introduce a new product into a market, in turn reaping the benefits of these opportunities (Crossan et al. 1999) via increasing profitability, reducing break-even time, and growing market share (Jayaram and Malhotra 2010). Hauptman and Hirji (1996) revealed that concurrency of problem-solving efforts pertaining to upstream decisions and downstream development is related to the success rate of new products. To that end, implementing newly acquired knowledge on developing new routines, rules, and procedures with improvements is the essential subsequent step in unlearning to increase the market success of a newly developed product (Akgün et al. 2006). Accordingly, we tested the following hypothesis:

H4 Innovation ambidexterity mediates the relationship between unlearning and new product success in NPD teams.

4 Research Methodology

4.1 Sample and Data Collection

The data were collected from team members employed by firms listed in the Istanbul Chamber of Industry and located in the Marmara region of Turkey. The firms located in this region typically develop new products and export them to markets abroad (e.g., the European Union, the Arabian countries, and Russia). They operate in line with a Western management style and European quality standards.

We studied NPD teams based on two specific criteria. First, we requested at least two members in each team to assess the survey items in order to avoid any plausible errors related to single source bias (Podsakoff et al. 2003). Second, to minimize response bias, we requested expert team members to assess the survey items (Kumar et al. 1993). These participants are in positions that have information about the financial situation of the firm, its operations, and its human capital.

We invited 246 NPD teams to participate in the survey. Of that number, 203 responded positively with an 81% response rate. We eliminated five survey questionnaires due to excessive missing data. Thus, the final sample included 464 team members drawn from 198 NPD teams. The teams had developed and launched new products in the following sectors: information technology (19%), materials (26%), healthcare (11%), consumer discretionary (63%), and industrials and consumer staples (8%).

We followed several procedures to control common method biases consistent with recommendations by Podsakoff et al. (2003). To avoid social desirability responses and to increase accuracy, anonymous paper-and-pencil questionnaires were distributed to all participants. To create a psychological separation, we prepared a cover story in which we noted that there is no relationship among any given item set. To reduce the participants' evaluation apprehension, and to make them less likely to edit their responses, we assured them that there are no right or wrong answers. To control for biases related to the question context (e.g., priming effects) or item embeddedness, we counterbalanced the order of the measurement of the predictor and criterion variables. The average time for each meeting with a participant was 15 min.

Tourangeau et al. (2000) noted that one of the most common problems in the comprehension stage of the response process to a questionnaire is item ambiguity. Thus, we carefully reworded the items that were developed by previous researchers.

This was done by (i) defining ambiguous/unfamiliar terms and concepts, (ii) providing practical examples when such terms/concepts were used, (iii) keeping items simple, specific, and concise, and (iv) avoiding double-barreled items. To reduce acquiescence bias, we also avoided the use of bipolar numerical scale values (e.g., –3 to + 3) and instead provided verbal labels for the midpoints of scales consistent with the recommendations of Tourangeau et al. (2000).

The descriptive statistics revealed that 81% of the respondents in the final sample are male, 66% have an undergraduate degree, 30% have a masters or associate degree, and 4% have a Ph.D. The majority of participants (58%) were born between 1981 and 1990; 36% of the respondents had 6 to 10 years of professional know-how in their respective fields.

4.2 Measures

The survey questionnaire was written in English based on several previous studies on unlearning, innovation ambidexterity, and NPD team performance. We performed a back-translation procedure to ensure translation accuracy (Brislin 1986). Then, we pilot-tested the survey questionnaire with nine engineers to ensure the accuracy of the survey items and to determine their content and face validity. All items were responded to on a 7-point Likert-type scale (from 1: Strongly Disagree to 7: Strongly Agree).

Unlearning This is a bi-dimensional construct which includes the dimensions of a change in routines and beliefs in a team setting. We adapted five items for assessing a change in routines and four items for assessing a change in beliefs from Akgün et al. (2006). For a change in routines, we asked the participants to identify any changes in the team decision-making processes, project plans, etc. that they had adopted during a product development process, regarding their shared routines. For the change in beliefs variable, we asked the participants, among other items, to identify technological and market changes adopted by their team before and after the development of a new product.

Innovation ambidexterity This too is a bi-dimensional construct consisting of exploitative and exploratory learning activities (He and Wong 2004). We measured exploitative learning by using three items adapted from Jansen et al. (2006) and five items adapted from Zhou and Wu (2010). Similarly, we measured exploratory learning using four items adapted from Jansen et al. (2006) and five items adapted from Zhou and Wu (2010). These items are shown in Appendix 1.

We first employed an *exploratory factor analysis* (EFA) for assessing innovation ambidexterity. To facilitate interpretation as well as to assess the underlying dimensions of the given items, we used the principal component analysis extraction with the oblique promax rotation method. We also applied the *Kaiser–Meyer–Olkin* (KMO) measure of sampling adequacy index and Bartlett's test of sphericity to assess the appropriateness of sample adequacy. The value of KMO (0.91) was significantly above the threshold value of 0.7. The Barlett's test was significant

($\chi^2 = 2085.47$; d.f. = 136, $p < 0.001$). This indicates the appropriateness of the factor analysis with the data. Two factors with eigenvalues greater than one and no cross loadings emerged. Factor 1 containing eight items was interpreted as measuring exploitative learning. Factor 2, containing nine items, was interpreted as measuring exploratory learning. The factor loadings ranged between 0.45 and 0.95. All factor loadings are above the suggested threshold value of 0.40 (Hair et al. 2010). The eigenvalues, used as the threshold value to retain factors, were 7.19 and 6.47 for each of the dimensions, respectively. Those values are evidence of discriminant validity.

The constructs were also subjected to a *confirmatory factor analysis* (CFA) through the maximum likelihood method. The results indicated that the overall fit values were satisfactory: $\chi^2_{(104)} = 147.57$, *comparative fit index* (CFI) = 0.98, *incremental fit index* (IFI) = 0.98, *Tucker–Lewis index* (TLI) = 0.97, and *root mean square error of approximation* (RMSEA) = 0.05.

To calculate a balance between exploitation and exploration, we used the absolute difference of exploitation and exploration (He and Wong 2004). In this study, we name the absolute difference between exploitation and exploration as the "balanced configuration of exploitation and exploration" (hereafter B). The B scores varied from 0 to 2.25. To facilitate interpretation, we reversed those differences by subtracting them from 7 (because exploitation and exploration were measured on scales from 1 to 7) so that a higher value indicates the greater B score (Cao et al. 2009).

There are typically two approaches for the measurements of the explanatory power of exploitation and exploration. The "additive interaction (hereafter A[5])" (Gisi 1996) is calculated by adding exploitation to exploration (i.e., Xploit + Xplore), while the "multiplicative interaction (hereafter M)" (Katila and Ahuja 2002) is calculated by multiplying exploitation with exploration (Xploit*Xplore). We named these two different configurations as the "additive configuration of exploitation and exploration" and the "multiplicative configuration of exploitation and exploration", respectively. We also used "the combinative configuration of exploitation and exploration (hereafter C)" as a general name for them because they simply represent the orthogonal interaction of exploitation and exploration (Gupta et al. 2006).

Then, by following Cao et al.'s (2009) strategy, we calculated ambidexterity scores by multiplying B scores with A scores[6] (BA scores) as the synergistic interaction of the balanced and additive configurations of exploitation and exploration (see Appendix 2 for details). To test our hypotheses, we used the BA scores in Model 3, though we also reported the results with the B scores in Model 1, and the A scores in Model 2 in Tables 5 and 6.

NPD team performance We used three variables to measure performance: *product development speed* (PDS), *product development cost* (PDC), and *new product success* (NPS). We measured PDS with five items adapted from Atuahene-Gima

[5] In the current research, we will use only A scores (instead of C scores) to explain our arguments.

[6] It is also possible to use M scores to calculate ambidexterity as BM scores (by multiplying B scores with M scores) (see Appendix 2 for details).

Table 1 Aggregation and reliability scores

Variable name	Inter-rater agreement	Intra-class correlation coefficient 1	Intra-class correlation coefficient 2	Cronbach's alpha	Average variance extracted	Composite reliability
Change in routines	.76	.54	.85	.87	.59	.84
Change in beliefs	.78	.58	.85	.86	.70	.90
Exploitative learning	.77	.42	.88	.88	.57	.91
Exploratory learning	.92	.50	.90	.90	.57	.92
Product development speed	.74	.52	.84	.84	.62	.89
Product development cost	.91	.64	.87	.88	.74	.92
New product success	.85	.69	.95	.95	.74	.96

(2003), PDC with three items adapted from Lewis et al. (2002), and NPS with nine items adapted from Cooper and Kleinschmidt (1987).

Control variables We included team size, team tenure, and industry as control variables. This is because previous research found both positive and negative relationships of them with team functioning and performance outcomes (cf., Horwitz and Horwitz 2007).

4.3 Measurement Analyses

4.3.1 Aggregation Analysis and Reliabilities

We aggregated the raw scores of the items by using the corresponding mean values of all team members' scores. We also assessed inter-rater agreement (r_{wg}) for each construct (James et al. 1984, 1993). The r_{wg} values range between zero (0-No agreement) and one (1-Perfect agreement). Inter-rater agreement shows if the participants have similar ratings at the team level, and it also determines the interchangeability between the respondents (Kozlowski and Hattrup 1992). The recommended threshold value for an acceptable inter-rater agreement is 0.60 (Glick 1985). The results revealed satisfactory r_{wg} values (see Table 1). The mean value of all r_{wg} was 0.82, a coefficient greater than the suggested cut-off value of 0.70 (Bliese 2000). The inter-rater agreement for the latent variables was therefore satisfactory.

The intra-class correlations (ICC-1 and ICC-2) were also assessed. ICC-1 shows the level of variance between respondents that could be accounted for differences in team membership, while ICC-2 shows the aggregate values' reliability at the team level. The obtained results in Table 1 reveal that ICC-1 values of all the constructs were greater than zero. The ANOVA test (*F*) was significant. ICC-2 values show that the values for the sets of perceptions for each construct are reliable estimates of the true score for the unit (James 1982). ICC-2 values were greater than the suggested value of 0.70 (Bliese 2000).

Other reliability scores are also above the suggested values (i.e., Cronbach's alpha, *average variance extracted* [AVE], and composite reliability) (Fornell and Larcker 1981). All scores in Table 1 suggest the unidimensionality of the measures.

4.3.2 Assessment of Common Method Variance

Harman's Single Factor (Harman 1960) was employed by utilizing an EFA analysis with all variables loaded onto a single factor without a rotation. This new common latent factor explained only 32.9% of the variance, which is less than the cut-off value of 50%. The common latent factor approach was also performed with a new latent variable in which all the observed items were connected to it (Podsakoff et al. 2003). The paths were constrained to be equal and the variance of the common factor was constrained to be one. The common latent variable value was 0.35 and the square of that score yielded a *common method variance* (CMV) value of 0.12, far below the threshold value of 0.50.

The marker-variable method was also performed (Lindell and Whitney 2001). A marker-variable with low or no correlation with the latent variables was chosen, then the items of the marker variables as well as the latent variables in the model were connected to a common factor by constraining the path to be equal, and the variance of the common factor to be one. The results indicated that the common latent factor value decreased to 0.28. The square of that score yielded a CMV value of 0.08, that is far less than the cut-off value of 0.50.

Finally, Kock (2015) proposed that a model with greater than 3.3 *variance inflation factors* (VIFs) is an indication of a CMV issue. The results of VIFs analysis showed that the VIFs values ranged between 1.13 and 1.28, values lower than the suggested threshold value of 3.3. Therefore, it would appear that the proposed model was not affected by common method bias.

4.3.3 Model Fit and Validity Tests

The final sample size is 464 individual team members. This sample size is sufficient for CFA analyses by employing *structural equation modeling* (SEM) based on the rule of sample to item ratio of 5-to-1 (Gorsuch 1983; Hatcher 1994; Suhr 2006). The current research incorporated 44 items (see Table 2). Therefore, the minimum sample size should be 220. The final sample size of 464 team members is significantly higher than what is recommended. Additionally, Kline (2016) advised a guideline to select a sample for the SEM analysis for which a sample of 100 is considered as small, 100 to 200 as medium, and 200 or more as large. Based on these criteria, a final sample size of 464 participants is sufficient for the SEM-based one factor CFA

Table 2 Model fitness and convergent validity

Variable name	Parameter[a]	Standardized coefficient	t-value[b]
Change in routines	λ_{CIR1}	.72	Scaling
	λ_{CIR2}	.92	11.19
	λ_{CIR3}	.68	9.46
	λ_{CIR4}	.70	9.06
	λ_{CIR5}	.76	9.05
Change in beliefs	λ_{CIB1}	.66	Scaling
	λ_{CIB2}	.77	9.05
	λ_{CIB3}	.93	7.05
	λ_{CIB4}	.72	5.41
Exploitative learning	λ_{EXI1}	.53	Scaling
	λ_{EXI2}	.64	10.85
	λ_{EXI3}	.54	6.00
	λ_{EXI4}	.70	7.12
	λ_{EXI5}	.79	7.55
	λ_{EXI6}	.88	7.96
	λ_{EXI7}	.81	7.66
	λ_{EXI8}	.71	7.14
Exploratory learning	λ_{EXR1}	.46	Scaling
	λ_{EXR2}	.70	6.24
	λ_{EXR3}	.72	6.25
	λ_{EXR4}	.55	5.55
	λ_{EXR5}	.81	6.53
	λ_{EXR6}	.81	6.54
	λ_{EXR7}	.91	6.78
	λ_{EXR8}	.78	6.50
	λ_{EXR9}	.62	6.40
Product development speed	λ_{PDS1}	.73	Scaling
	λ_{PDS2}	.78	13.07
	λ_{PDS3}	.71	7.04
	λ_{PDS4}	.67	5.91
	λ_{PDS5}	.76	6.29
Product development cost	λ_{PDC1}	.87	Scaling
	λ_{PDC2}	.89	16.28
	λ_{PDC3}	.78	13.33
	λ_{PDC4}	.70	11.39
New product success	λ_{NPS1}	.72	Scaling
	λ_{NPS2}	.89	13.77
	λNP_{S3}	.92	12.92
	λ_{NPS4}	.86	12.06
	λ_{NPS5}	.84	11.36
	λ_{NPS6}	.89	11.13
	λ_{NPS7}	.89	11.95

Table 2 (continued)

Variable name	Parameter[a]	Standardized coefficient	t-value[b]
	λ_{NPS8}	.78	12.14
	λNP_{S9}	.76	10.64

$\chi^2_{(832)} = 1259.93$, χ^2/d.f. = 1.51, CFI = 0.93, IFI = 0.93, TLI = 0.92, RMSEA = 0.05

CIR Change in Routines, *CIB* Change in Beliefs, *EXI* Exploitative Learning, *EXR* Exploratory Learning, *PDS* Product Development Speed, *PDC* Product Development Cost, *NPS* New Product Success

[a]λ parameters indicate paths from measurement items to first-order constructs

[b]Scaling denotes λ value of indicator set to 1 to enable latent factor identification

analyses (Anderson and Gerbing 1988). Our SEM analysis using AMOS software showed that the models fit sufficiently ($\chi^2_{(832)} = 1259.93$, χ^2/d.f. = 1.51, CFI = 0.93, IFI = 0.93, TLI = 0.92, RMSEA = 0.05). All item loadings were significant at $p = 0.001$ level with the lowest factor loading of 0.46, supporting convergent validity (see Table 2).

To assess discriminant validity, we followed Bagozzi et al.'s (1991) recommendation for which 42 models were calculated with the restriction of unity, one at a time, for the individual factor correlations. The fit values of χ^2 for the restricted as well as the original model were compared by subtracting them from each other. The change between these models was significant since the difference between them was greater than 3.84 in each model (Anderson and Gerbing 1988). These results, reported in Table 3, suggest evidence of discriminant validity.

4.4 Hypothesis Testing

To test our hypotheses, we only used the BA scores (innovation ambidexterity). Before testing the hypotheses, we looked at the dyadic relationships among the constructs. As shown in Table 4, the correlations of unlearning with innovation ambidexterity ($\beta = 0.23$, $p < 0.01$) is significant and positive.

Regarding the unlearning-performance relationship, the correlation between unlearning and PDC ($\beta = 0.17$, $p < 0.05$) is significant and positive. However, the correlations of unlearning with PDS ($\beta = 0.09$) and NPS ($\beta = 0.11$) are not significant. Regarding the ambidexterity-performance relationship, the correlations of innovation ambidexterity with PDS ($\beta = 0.42$, $p < 0.01$), PDC ($\beta = 0.53$, $p < 0.01$) and NPS ($\beta = 0.56$, $p < 0.01$) are significant and positive. Regarding control variables, team size has a significant, positive relationship with both PDC and NPS. Team tenure has a significant, positive relationship with NPS. Industry has a significant, positive relationship with PDC. None of them has a relationship with innovation ambidexterity, and PDS.

We created three models to show differences among the B, A, and BA scores. However, again, we only used the BA scores to test our hypotheses (Fig. 1). Models

Table 3 Discriminant validity

Model no.	Model			Unconstrained (χ^2/d.f.)	Constrained (χ^2/d.f.)	$\Delta\chi^2$
1–2	Change in routines	⇔	Change in beliefs	36.69/19	66.31/20	29.62
3–4	Change in routines	⇔	Exploitative learning	72.19/58	183.40/59	111.21
5–6	Change in routines	⇔	Exploratory learning	81.60/62	196.46/63	114.86
7–8	Change in routines	⇔	Product development speed	28/22	87.65/23	59.65
9–10	Change in routines	⇔	Product development cost	24.41/23	98.57/24	74.16
11–12	Change in routines	⇔	New product success	60.9/54	155.26/55	94.36
13–14	Change in beliefs	⇔	Exploitative learning	47.78/46	132.41/47	84.63
15–16	Change in beliefs	⇔	Exploratory learning	72.78/49	163.55/50	90.77
17–18	Change in beliefs	⇔	Product development speed	11.37/13	53.32/14	41.95
19–20	Change in beliefs	⇔	Product development cost	26.78/15	98.07/16	71.29
21–22	Change in beliefs	⇔	New product success	48.77/41	131.90/42	83.13
23–24	Exploitative learning	⇔	Exploratory learning	147.57/104	220.85/105	73.28
25–26	Exploitative learning	⇔	Product development speed	63.54/52	105.75/53	42.21
27–28	Exploitative learning	⇔	Product development cost	73.14/50	121.97/51	48.83
29–30	Exploitative learning	⇔	New product success	110.29/96	164.19/97	53.9
31–32	Exploratory learning	⇔	Product development speed	94.32/56	154.97/57	60.65
33–34	Exploratory learning	⇔	Product development cost	91.43/53	166.85/54	75.42
35–36	Exploratory learning	⇔	New product success	150.63/104	226.15/105	75.52
37–38	Product development speed	⇔	Product development cost	27.60/17	35.93/18	8.33
39–40	Product development speed	⇔	New product success	65.34/48	94.70/49	29.36
41–42	Product development cost	⇔	New product success	92.77/45	133.04/46	40.27

$\Delta\chi^2$: Change in chi-square

χ^2/d.f.: Chi-square relative to its degree of freedom

Table 4 Correlations and descriptive statistics

No.	Variable name	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Product development speed	–													
2	Product development cost	.58**	–												
3	New product success	.47**	.53**	–											
4	Change in routines	.16*	.17*	.18*	–										
5	Change in beliefs	–.0	.11	.02	.37**	–									
6	Exploitative learning	.36**	.54**	.56**	.27**	.0	–								
7	Exploratory learning	.38**	.46**	.52**	.35**	.07	.65**	–							
8	Unlearning	.09	.17*	.11	.80**	.85**	.15*	.24**	–						
9	Balanced configuration	.24**	.23**	.23**	.15*	.11	.13	.45**	.16*	–					
10	Additive configuration	.41**	.55**	.59**	.34**	.04	.9**	.92**	.22**	.33**	–				
11	Innovation ambidexterity	.42**	.53**	.56**	.32**	.07	.76**	.91**	.23**	.67**	.92**	–			
12	Team size	.13	.16*	.23**	.01	–.09	.1	.07	–.06	–.01	.1	.07	–		
13	Team tenure	–.01	.07	.18*	–.1	.04	.16*	.08	–.03	.04	.13	.12	.08	–	
14	Industry	.11	.19**	–.01	–.07	.08	.04	.04	.01	.08	.04	.06	–.01	.05	–
	Mean	5.00	5.42	5.4	5.11	3.95	5.82	5.66	4.53	6.54	11.48	75.2	2.23	2.01	3.7
	Standard deviation	.95	.86	.84	.93	1.06	.67	.75	.82	.41	1.29	10.73	1.09	.81	3.4

*$p < .05$, **$p < .01$

Balanced Configuration (B scores) is the absolute difference of exploitation and exploration

Additive Configuration (A scores) is the additive interaction of exploitation and exploration

Innovation Ambidexterity (BA scores) is the synergistic interaction of Balanced Configuration and Additive Configuration of exploitation and exploration

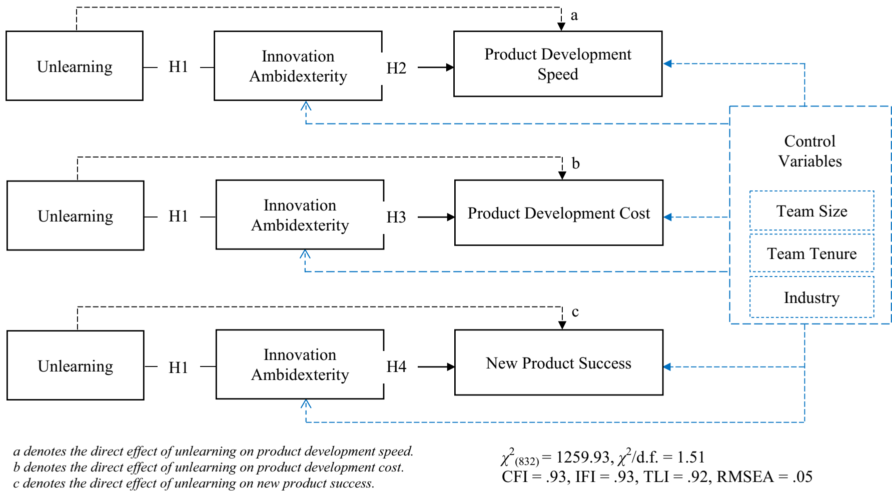

Fig. 1 The hypothesized relationships

1, 2, and 3 include unlearning as a predictor variable (X) and PDS, PDC, and NPS as criterion variables (Ys). Model 1 includes the balanced configuration of exploitation and exploration (B scores), Model 2 includes the additive configuration of exploitation and exploration (A scores), and Model 3 includes innovation ambidexterity (BA scores), as a mediator variable (M).

We then created nine sub models. Model 1.1, 2.1 and 3.1 include PDS as a first criterion variable (Y), Models 1.2, 2.2, and 3.2 include PDC as a second criterion variable (Y), and Models 1.3, 2.3, and 3.3 include NPS as a third criterion variable (Y). The control variables were also included in the analyses. We tested the hypotheses by employing the ordinary least squares regression-based path analyses through running PROCESS macro in SPSS software (Hayes 2017). We selected Model 4 in PROCESS macro to test the mediation hypotheses. Preacher et al. (2007) recommended 5.000 bootstrap resamples to obtain the 95% confidence interval of indirect effects. Bias-corrected bootstrapping approach is used since it is an assumption-free methodology. In addition, it controls for Type 1 errors.

Regarding Hypothesis 1, the results yielded a significant, positive relationship of unlearning and innovation ambidexterity ($\beta = 3.07$, $p = 0.000$; see Parcel 1 at Model 3 in Table 5). None of the control variables have a significant relationship with innovation ambidexterity. The coefficient of determination is 8%. That is, eight percent of the variation in innovation ambidexterity was explained by the variation in both unlearning and the control variables. This supports Hypothesis 1 and suggests validation for the role of unlearning on innovation ambidexterity within the context of NPD teams.

Regarding the mediation hypotheses, in Model 3, innovation ambidexterity has a significant, positive relationship with PDS ($\beta = 0.04$, $p = 0.000$), while unlearning has no significant association with PDS. Team tenure has a significant, negative

Table 5 Hypothesis testing

		Model 1	Model 2	Model 3
Parcel 1	Unlearning	.08* (.04)	.36** (.11)	3.07** (.9)
	Team Size	–.0 (.03)	.12 (.08)	.77 (.68)
	Team Tenure	.02 (.04)	.21† (.11)	1.5 (.91)
	Industry	.01 (.01)	.21 (.01)	.18 (.22)
	R^2	.03	.08	.08
	DV_1: Product Development Speed			
Parcel 2	Unlearning	.07 (.08)	.0 (.08)	–.01 (.08)
	Balanced Configuration	.53** (.16)	–	–
	Additive Configuration	–	.3** (.05)	–
	Innovation Ambidexterity	–	–	.04** (.01)
	Team Size	.13* (.06)	.09 (.06)	.1† (.06)
	Team Tenure	–.03 (.08)	–08 (.08)	–.08* (.08)
	Industry	.03 (.02)	.03 (.02)	.03 (.02)
	R^2	.09	.19	.20
	DV_2: Product Development Cost			
Parcel 3	Unlearning	.15* (.07)	.06 (.06)	.06 (.06)
	Balanced Configuration	.41** (.14)	–	–
	Additive Configuration	–	.35** (.04)	–
	Innovation Ambidexterity	–	–	.04** (.01)
	Team Size	.14 (.05)	.09 (.05)	.1* (.05)
	Team Tenure	.04 (.07)	–.02 (.06)	–.01 (.06)
	Industry	.04* (.02)	.04* (.02)	.04* (.02)
	R^2	.13	.34	.32
	DV_3: New Product Success			
Parcel 4	Unlearning	.1 (.07)	–.0 (.06)	.00 (.06)
	Balanced Configuration	.44** (.14)	–	–
	Additive Configuration	–	.37** (.04)	–
	Innovation Ambidexterity	–	–	.04** (.01)
	Team Size	.17** (.05)	.13** (.04)	.14** (.05)
	Team Tenure	.16* (.07)	.1 (.06)	.11† (.06)
	Industry	–.01 (.02)	–.01 (.01)	–.01 (.01)
	R^2	.14	.39	.36

Model 1 includes Balanced Configuration (B scores) as a mediator

Model 2 includes Additive Configuration (A scores) as a mediator

Model 3 includes Innovation Ambidexterity (BA scores) as a mediator

Balanced Configuration is the absolute difference of exploitation and exploration

Additive Configuration is the additive interaction of exploitation and exploration

Innovation Ambidexterity is the synergistic interaction of Balanced Configuration and Additive Configuration of exploitation and exploration

The values in parenthesis are standard errors

$^{\dagger}p < .1$, $^{*}p < .05$, $^{**}p < .01$

R^2: The coefficient of determination

DV: Dependent variable

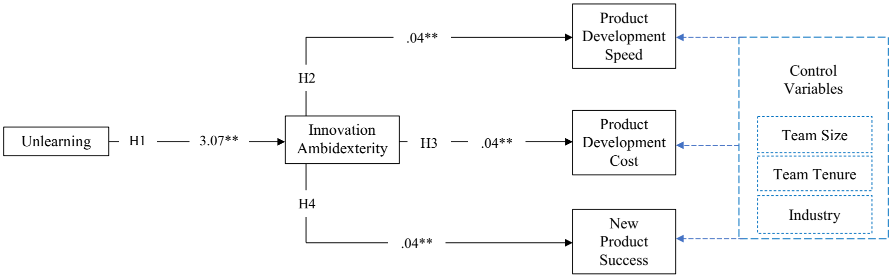

Fig. 2 The results of hypothesized relationships

relationship with PDS, while team size has a significant, positive one. The coefficient of determination is 20%. This result supports Hypothesis 2 as a first step (see Parcel 2 at Model 3 in Table 5).

Innovation ambidexterity is related to PDC ($\beta=0.04$, $p=0.000$), while unlearning is not. Team size ($\beta=0.1$, $p=0.032$) and industry ($\beta=0.04$, $p=0.01$) have significant, positive associations with PDC. The coefficient of determination was 32%. This result supports Hypothesis 3 as a first step (see Parcel 3 at Model 3 in Table 5).

Innovation ambidexterity is also associated with NPS ($\beta=0.04$, $p=0.000$). Yet again, unlearning is not related to the third performance indicator, namely NPS. Team size ($\beta=0.14$, $p=0.003$) and team tenure ($\beta=0.11$, $p=0.077$) have significant, positive relationships with NPS. The coefficient of determination was 36%. This result supports Hypothesis 4 as a first step (see Parcel 4 at Model 3 in Table 5).

We also depicted the results of hypothesized relationships in Fig. 2.

In the second step of testing the mediation hypotheses, we checked for the indirect and direct effects of the predictor on the criterion measures. The indirect relationships of unlearning with PDS, PDC, and NPS are all significant since the 95% confidence intervals do not include zero (see Table 6). Thus, innovation ambidexterity mediated the relationships between unlearning and the three NPD team performance indicators.

To determine if the mediation is partial or full, we examined direct effects. The mediation is considered to be full if the direct effect is not statistically significant; it is considered to be partial if the direct effect is statistically significant. The results revealed that the direct effects of unlearning on the NPD team performance indicators are not significant when controlling for innovation ambidexterity since the 95% confidence intervals include zero. Thus, innovation ambidexterity fully mediated the relationships of unlearning with PDS, PDC, and NPS (H2, H3, and H4: Model 3 in Table 6).

Regarding the differences among Models 1 and 2 in Table 5 and 6, the results showed that unlearning has a positive and significant relationship with the traditional ambidexterity configurations (i.e., the balanced and additive configurations). While balanced configuration does not have a mediating role between the unlearning-performance relationship, additive configuration shows that role. This finding is consistent with previous research (e.g., Cao et al. 2009; Chandrasekaran et al. 2012; Kostopoulos et al. 2015; Venugopal et al. 2020). In contrast, considering Model 3, the results showed that the synergistic interaction of balanced and additive configurations might be the way to eliminate the performance constraint of the balanced configuration.

5 Discussion

The current study makes at least two contributions to the literature on unlearning and innovation ambidexterity. Despite studies suggesting either a negative or no relationship between unlearning and performance (e.g., Akgün et al. 2006; Meyers and Wilemon 1989), this study shows that (i) unlearning enables NPD teams to match exploitative and exploratory learning activities at high levels, and that (ii) innovation ambidexterity enables NPD teams to link the results of reflective efforts, specifically unlearning implementations, to their performance.

Similar to Akgün et al.'s (2006) findings, we found a null relationship between unlearning and new product success (see Table 4). We were also unable to find a relationship of unlearning with product development speed. Thus, unlearning alone is not sufficient to enhance NPD team performance. Unlearning simply creates a contextual shift from an old state to a new one.

Nonetheless, a mechanism is needed to learn and implement new routines and beliefs (Akgün et al. 2006). That is, one needs intermediary processes, leveraging mechanisms, that will show unlearning to predict NPD team performance. The current research suggests that innovation ambidexterity is one such mediator. NPD teams maximize the level of gains via incremental improvements, while simultaneously benefiting from going beyond what is already known, and exploring new possibilities in the current environment via experimentation and discovery in a balanced manner. At the end, these teams can increase the speed of the product development process, lower the cost of the project, and enhance the market success of a newly developed product, resulting in improved overall performance.

We not only examined the mediation mechanism of innovation ambidexterity between unlearning and product market success (our third NPD team performance indicator), but we also included speed and cost of product development (our first two NPD team performance indicators). Previous empirical studies have only included new product success as a performance indicator in the unlearning-performance relationship (e.g., Akgün et al. 2006). While new product success represents team effectiveness, the literature has proposed that the speed and cost of product development processes signify the efficiency of a team processes. The present study provides evidence that innovation ambidexterity, as a leveraging mechanism, links a team's outputs of reflective thinking sessions, namely unlearned routines and beliefs, to the efficiency and effectiveness of that team.

Regarding ambidexterity, the literature is divided between structural and contextual approaches for explaining how one achieves it.[7] The findings of this study advance current understanding of the antecedents of innovation ambidexterity. That

[7] See O'Reilly and Tushman (2013) and Nosella et al. (2012) for a detailed review on these two perspectives.

is, the optimal balance for exploitation and exploration is contingent on the level of unlearning of established, yet outdated routines and beliefs that potentially hinder incremental and/or radical learning activities. “Exploitation of old certainties,” “exploration of new possibilities,” and sustaining the balance between them requires unlearning of outdated routines and beliefs. This finding contributes to the literature on contextual ambidexterity by showing that ambidexterity arises from team context (Gibson and Birkinshaw 2004).

Regarding the literature on operationalization of various dimensions of ambidexterity, we proposed a relatively new approach to calculate ambidexterity by utilizing previous measurements (He and Wong 2004; Cao et al. 2009). We found that unlearning is a mechanism to match exploitation and exploration at high levels. We also found support for the claim that innovation ambidexterity has a predictive power on performance outcomes and mediates the input–output relationship. Our results are consistent with Katila and Ahuja’s (2002) research who found that the interaction of search scope (exploring new knowledge) and depth (reusing existing knowledge properties) has a relationship with the number of new products introduced by firms’ research and development departments.

5.1 Theoretical Implications

Action science proposes that learning occurs either as a single-loop or double-loop by detecting and correcting errors (Argyris and Schön 1974; Argyris 2004). Team learning theory argues that exploitative and exploratory learning occurs as a result of reflective discussions in team meetings, retreats, and after-action reviews (Edmondson 2002; Marks et al. 2001). We propose that the characterization of the reflection-exploitation relationship in team learning theory is compatible with single loop learning, while the reflection-exploration relationship fits with double loop learning.

In that regard, revealing the relationship between unlearning and innovation ambidexterity extends team learning theory. This theory, however, does not provide the answer to how the reflection-learning process works. The results of the present study suggests that unlearning occurs as a result of reflective discussions that lead teams to learn both exploitatively and exploratively. We found relationships of unlearning with both exploitative and exploratory learning activities (see Table 4).

Prior to this study, team learning theory suffered from lack of a sound explanation regarding the creation of a balance between exploitative and exploratory learning activities (Edmondson et al. 2007). The extant literature on ambidexterity argued that the imbalance between those activities leads to either process and/or outcome traps. Edmondson (2002) found primary support for this claim in a qualitative study. The results of the present study suggest that by reflective unlearning, teams can develop innovation ambidexterity by balancing exploitation and exploration. This is because detecting performance errors and ongoing environmental changes by reflecting (Açıkgöz et al. 2020) and then correcting them through reflective unlearning may enable a team to create a balance to learn exploitative and exploratory ideas simultaneously at high levels. The present study found relationships of unlearning with the dimensions of ambidexterity (see Tables 4 and 5).

Overall, our findings extend team learning theory and contribute to an understanding of unlearning, a concept that has been under-researched in a team context (Klammer and Gueldenberg 2019).

5.2 Managerial Implications

Applying the concurrent approach to NPD projects is not common (Jayaram and Malhotra 2010). Instead, a sequential approach is widely used that creates inefficiencies in NPD processes (Jayaram and Malhotra 2010). A concurrent approach, as described in this study, is likely to prevent teams from a success or failure trap. For example, because of the diseconomies of time compression (cf., Cool et al. 2016), NPD teams often fail to explore new opportunities. The present study showed that the concurrent application of exploitative and exploratory learning activities enhances NPD team performance. Thus, team leaders should enhance an unlearning context by encouraging team members to match those two activities at high levels in order to avoid a success or failure trap. This also means the concurrent approach will also help NPD team leaders to understand the processes needed to support unlearning.

5.3 Limitations and Future Research

This study faces a few limitations that open up new venues for future research. One limitation is the use of a cross-sectional technique to collect data. Hence, causal inferences may be precluded. To limit this concern, we included innovation ambidexterity as a mediator as well as control variables (i.e., team size, team tenure, and industry) in our model.

Second, as this study was based solely on data from NPD teams located in a specific geographical area of Turkey, cross-cultural research based on data from NPD teams located in other geographical areas should be also conducted (e.g., Africa and South/North America).

Third, NPD teams in this study are composed of product development engineers. The literature suggests that engineering teams, specifically during idea development stage, may need to possess skills that are associated with exploratory learning activities. This is because they start with defining unknown problems and developing novel and uncharted novel solutions (Wenngren et al. 2016). Engineering teams in this regard may need more exploratory learning activities during the initial stages of product development, rather than a balanced approach as suggested in this paper. However, since our study does not differentiate between the stages of product development, future research should examine how the unlearning-ambidexterity-performance model may differ in different stages of development processes. In addition, since our data came solely from engineers and technicians with analytical mindsets, the way they unlearn or work with innovation ambidexterity may be different from that of the diverse teams. For example, artistic software developers, anthropologists, and social designers have the potential to change team formation with a non-analytical mindset. Future research should consider the role of diversity in team composition and how it may impact this process.

Lastly, while our study offers a prescription for NPD team managers and practitioners in handling unlearning and innovation ambidexterity, future research is needed to explore the organizational processes and mechanisms to do so. For example, while a practical method to spark unlearning might be using a challenger or a devil's advocate in team discussions (Akgün et al. 2006), future research can study how this is implemented in NPD teams.

6 Conclusions

In conclusion, from a theoretical perspective, the present study shows that unlearning enables matching exploitative and exploratory learning activities at high levels. Second, this study insights as to how this can be accomplished at high levels of those two activities collectively to enhance NPD team performance as a mediation of the unlearning-outcome relationship. From a methodological perspective, our study contributes to the literature by bringing forward a novel measurement approach to ambidexterity that captures a balance of exploitation with exploration at high levels.

Appendix 1

Innovation Ambidexterity

Exploitative Learning (adapted from Jansen et al. 2006; Zhou and Wu 2010).

- The team regularly implements small adaptations to existing products.
- The team makes improvements on the existing products to meet market demands.
- Lowering the costs of internal processes is an important objective of the team.
- The team frequently upgrades its knowledge base for existing products.
- The team enhances its abilities by searching for solutions to customer problems that are near to existing solutions.
- The team strengthens its skills to improve the efficiency of product development processes.
- The team strengthens its knowledge base to improve the efficiency of product development processes.
- The team utilizes its technologies that improve the productivity of product development operations.

Exploratory Learning (adapted from Jansen et al. 2006; Zhou and Wu 2010).

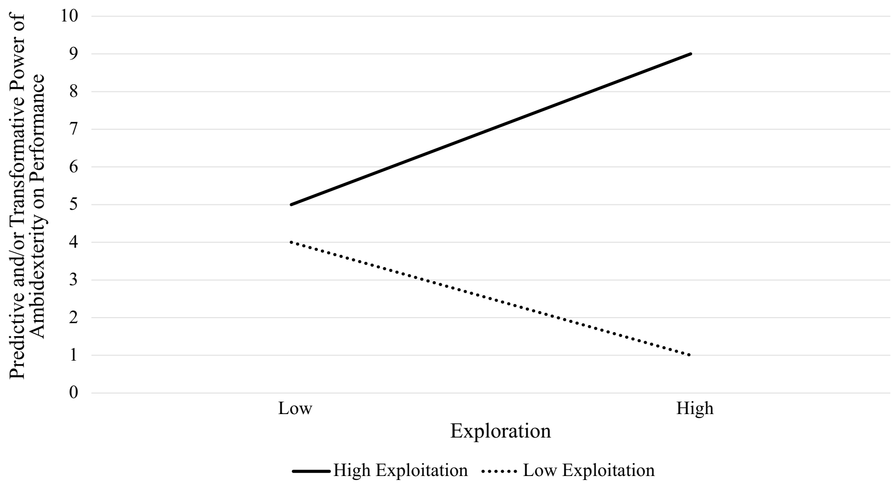

Fig. 3 An orthogonal interaction of exploitation and exploration (adapted from Gupta et al. 2006)

Table 6 Mediation analyses

	Model no.	Indirect effect			Direct effect			Hypothesis	Result
		Effect	LLCI	ULCI	Effect	LLCI	ULCI		
Model 1	Model 1.1	.04	–.0021	.0915	.07	–.0934	.2232	–	No mediation
	Model 1.2	.03	–.0016	.0682	.15	.0123	.2917	–	No mediation
	Model 1.3	.03	–.0016	.0787	.1	–.0393	.2332	–	No mediation
Model 2	Model 2.1	.11	.0293	.1929	.0	–.1508	.1527	–	Full mediation
	Model 2.2	.13	.0372	.2207	.06	–.0622	.1847	–	Full mediation
	Model 2.3	.13	.0450	.2316	–.0	–.1167	.1159	–	Full mediation
Model 3	Model 3.1	.11	.0363	.2048	–.01	–.1584	.1432	H2	Full mediation
	Model 3.2	.12	.0421	.2186	.06	–.0640	.1867	H3	Full mediation
	Model 3.3	.13	.0404	.2288	.0	–.1178	.1207	H4	Full mediation

Model 1 includes Balanced Configuration as a mediator

Model 2 includes Additive Configuration as a mediator

Model 3 includes Innovation Ambidexterity as a mediator

Models 1.1, 2.1, and 3.1 include Product Development Speed as a dependent variable

Models 1.2, 2.2, and 3.2 include Product Development Cost as a dependent variable

Models 1.3, 2.3, and 3.3 include New Product Success as a dependent variable

Team Size, Team Tenure, and Industry as the control variables were included in the analyses

LLCI Lower Limit Confidence Interval

ULCI Upper Limit Confidence Interval

Table 7 A hypothetical data set based on the 7-point Likert scale

Team no	Exploitation score	Exploration score	B score	A score C scores	M score	BA score Ambidexterity scores	BM score
Team 1	7	7	7	14	49	98	343
Team 2	7	6	6	13	42	78	252
Team 3	7	5	5	12	35	60	175
Team 4	7	4	4	11	28	44	112
Team 5	7	3	3	10	21	30	63
Team 6	7	2	2	9	14	18	28
Team 7	7	1	1	8	7	8	7
Team 8	6	6	7	12	36	84	252
Team 9	6	5	6	11	30	66	180
Team 10	6	4	5	10	24	50	120
Team 11	6	3	4	9	18	36	72
Team 12	6	2	3	8	12	24	36
Team 13	6	1	2	7	6	14	12
Team 14	5	5	7	10	25	70	175
Team 15	5	4	6	9	20	54	120
Team 16	5	3	5	8	15	40	75
Team 17	5	2	4	7	10	28	40
Team 18	5	1	3	6	5	18	15
Team 19	4	4	7	8	16	56	112
Team 20	4	3	6	7	12	42	72
Team 21	4	2	5	6	8	30	40
Team 22	4	1	4	5	4	20	16
Team 23	3	3	7	6	9	42	63
Team 24	3	2	6	5	6	30	36
Team 25	3	1	5	4	3	20	15
Team 26	2	2	7	4	4	28	28
Team 27	2	1	6	3	2	18	12
Team 28	1	1	7	2	1	14	7

B Score (B) = 7 —| Exploitation – Exploration |

A Score (A) = Exploitation + Exploration

M Score (M) = Exploitation * Exploration

BA Score = B*A

BM Score = B*M

- The team accepts new tasks that go beyond its existing operations.
- The team successfully develops new products that are entirely new to the firm.
- The team acquires new knowledge that is entirely new to the firm.
- The team frequently utilizes new opportunities in new markets.
- The team acquires new technologies that are entirely new to the firm.

- The team generates product development processes that are entirely new to the firm.
- The team learns entirely new product development skills that are important for innovation.
- The team learns totally new skills in applying new technologies.
- The team strengthens its product development skills in areas where it has no prior experience.

Appendix 2

Combinative Configuration of Exploitation and Exploration

The combinative configuration which reflects orthogonal interaction assumes that exploitation and exploration are independent yet complementary (Daft 1982; Nilsson 2010; Sutcliffe et al. 2000). Their independent existence depends on slack and/or infinite resources (e.g., information and knowledge) so that attention to one activity does not come at the expense of another (Gupta et al. 2006; Nilsson 2010). However, this perspective does not characterize whether there is a balance between exploitation and exploitation because such an interaction may not arise on the same resources. Thus, there is, at least, operationally, no direct relationship between exploitation and exploration (see Fig. 3). The highest value of an orthogonal interaction is mathematically expressed by 1 ($x \leq 1$) (Gisi 1996). In our hypothetical dataset in Table 7, it is a value of 14 for the additive configuration of exploitation and exploration (A) (i.e., 7 (Xploit) + 7 (Xplore) = 14). The degree of closeness to 1 represents a perfect combinative configuration of exploitation and exploration (C). For example, in Table 7, Team 13's A score is 7. So, the degree of its closeness to 1 is 0.5 (7/14 = 0.5).

In the combinative configuration of exploitation and exploration, one cannot understand whether there is a balance between exploitation and exploration by using the above-mentioned calculation (see Teams 5, 10, and 14's A scores in Table 7). Balance is important because it reflects the level of *reciprocal dependence* between exploitation and exploration. As a result, there will always be unknown situations of success or failure traps due to a possible imbalance between exploitation and exploration (Levithal and March 1993), even if an orthogonal interaction has a high value and a positive effect on performance.

Balanced Configuration of Exploitation and Exploration

To eliminate the lack of balance between exploitation and exploration, He and Wong (2004) proposed the calculation of the absolute difference between these two activities, namely the *balanced configuration of exploitation and exploration* (hereafter B).

The logic of balance is a win–win situation, where increased weight on exploitation does not imply a reduction of emphasis on exploration (March 1988; Osborn

1998; Tushman and O'Reilly 1996). In the case of imbalance, a win-lose situation, a tension between exploitation and exploration emerges because of the severe competition for controlling mutual organizational resources, resulting in obstructing the opponent. Thus, an absolute imbalance may mean too much of activities either devoted to exploitation or exploration. The literature suggests that too much of either, that is too much exploitation leads to a success trap, while too much exploration leads to a failure trap (Levithal and March 1993). This is because exploitation and exploration are self-reinforcing through consuming the other's resources (March 1991). This is characterized as an antithetical competition (Sutcliffe et al. 2000), mathematically an "antagonistic interaction" (Gisi 1996), between exploitation and exploration.

In the case of balance, each of these activities is expected to show an equal treatment for other's interests, in addition to self-interest. This is the starting point of being reciprocally dependent of exploitation and exploration peremptorily. A perfect balance can occur in two situations. In the first situation, prudence prevails because of trade-offs between exploitation and exploration (March 1991). Trade-offs may require a downward pressure for each of these activities' explanatory power (see Team 28's B score in Table 7). This is because a struggle for finding a balance between exploitation and exploration is likely to suppress each other's explanatory power. In an organizational context, this may be akin to investing in existing and new capabilities, but not devoting enough resources to either of them. That is the reason why a perfect balance at low values of these activities may occur, but still cannot be characterized as ambidexterity (Simsek 2009). Measurements based on absolute difference does not tell us whether that balance is achieved at low or high values of exploitation and exploration (see Team 1 and Team 28's B scores in Table 7). Absolute difference, as a level of balance, shows instead the degree of how much exploitation and exploration consider each other's interests. It represents reciprocal dependence.

In the second situation, the explanatory power of these activities can be unleashed in a controlled manner, i.e., a case of balancing exploitation and exploration at the highest value (see Team 1's B scores in Table 7). Yet, mathematically, as argued above, a value of absolute difference does not reflect that power. Another name of the absolute value is "modulus" which refers to the remainder in a calculation. Because an absolute value is computed by using the difference of exploitation and exploration, the result is indeed a face value. For example, in Table 7, Team 2 and Team 27's leftover values are the same, 1, though they have different values of exploitation and exploration. As a "magnitude" (i.e., the degree to which something is balanced), that value is the observed (or shown) result of a ranking (or ordering) of the balance between exploitation and exploration. Therefore, we still cannot know that difference is a result of whether low or high values of exploitation and exploration (see Team 2 and Team 27's exploitation, exploration, and B scores in Table 7). A perfect balance between exploitation and exploration is mathematically expressed by 0 ($x \geq 0$). The degree to which a value deviates from 0 represents an imbalance.

Previous research was systematically unable to find a predictive and/or transformative power of absolute difference on performance (or found a negative relationship), while finding a significant, positive role of orthogonal interaction on different performance outcomes (e.g., Cao et al. 2009; Chandrasekaran et al. 2012; Kostopoulos et al. 2015; Venugopal et al. 2020). A rare significant, positive effect of absolute difference on performance was reported by He and Wong (2004) by using a path analysis in which other variables (i.e., process and product innovation intensities) with seven control ones (thus, in total nine variables) were also modeled simultaneously on performance. These variables might obscure the direct relationship of absolute difference with performance.

Ambidexterity

Cao et al. (2009) preferred to use the notions of the *balanced dimension of ambidexterity* to describe an antagonistic interaction of exploitation and exploration (i.e., absolute difference), and the *combined dimension of ambidexterity* to describe an orthogonal interaction of them. Instead, we use the *balanced configuration of exploitation and exploration* (the *fit-as-matching* approach in the strategic management literature) and the *combinative configuration of exploitation and exploration* (the *fit-as-moderating* approach in the strategic management literature) based on the arguments of the strategic fit-as-Gestalts perspective (He and Wong 2004; Miller 1981; Venkatraman 1989). We recognize that (i) exploitation and exploration are interdependent, but not causal, and (ii) this interdependency should create an effect that is more than the sum of its parts. On the one hand, one of these configurations must reflect a level of balance between exploitation and exploration, on the other hand, another one must reflect a combination of exploitation and exploration. That is, the first one reflects the level of reciprocal dependence, while the second one reflects the level of explanatory power of exploitation and exploration. Thus, the significance of the resulting output, ambidexterity, can be best understood by making reference to the two configurations of exploitation and exploration, not just one of them (Cao et al. 2009; Miller 1981).

By definition, dexterity refers to the ability to manipulate resources (Trombly and Scott 1989) through controlling (i.e., balancing the interdependency among parts) and actuating its parts (e.g., Raghavan 2007; Zhou et al. 2018). In an organizational setting, ambidexterity requires balancing (i.e., control) exploitative and exploratory learning activities to produce reciprocal dependence, while simultaneously executing (i.e., actuation) them to reveal explanatory power (Gupta et al. 2006; Katila and Ahuja 2002). A balance is necessary to effectively manipulate relevant resources without incapacitating each other's activities. A simultaneous execution is needed to change the orientation of the manipulated resources from a given reference point to something beyond (Bicchi 2000). Ambidexterity in this regard is a product of a "synergistic interaction" (Miller 1981; Sutcliffe et al. 2000). A synergistic effect occurs when the outcome is more than a sum of its parts by multiplying the two configurations of exploitation and exploration.

Cao et al. (2009) used a similar methodology to calculate a synergistic interaction. They named the resulting output "the simultaneous pursuit of the balanced dimension of ambidexterity and the combined dimension of ambidexterity" (p. 784). We further argue that the synergistic interaction is an effective method that reflects the explanatory and transformative power of ambidexterity on performance in a balanced manner. In essence, it is ambidexterity. Mathematically, a synergistic interaction is expressed a value of bigger than 1 ($x > 1$) (Gisi 1996).

A Hypothetic Example

We illustrate our arguments in Table 7 via a hypothetical data set based on the 7-point Likert scale, showing exploitative and exploratory activity scores of different teams.[8]

For the face value argument, similar to Team 1, Team 28 achieved a perfect balance of exploitation and exploration. However, the real values that represent these two activities and thereby their orthogonal interaction scores are quite different. That might be a reason why past literature suggests that a perfect balance does not make one ambidextrous on its own (e.g., Simsek 2009). From the measurement perspective, this is because, first, a value of balance is a face value; second, a perfect balance can also occur at low values of exploitation and exploration (Cao et al. 2009). Nonetheless, we argue that by using a synergistical interaction, this constraint can be eliminated.

Regarding the balanced configuration of exploitation and exploration, the B scores for Teams 1, 8, 14, 19, 23, 26, and 28 are the same which yielded a value of 0 (to ease the interpretation of that score, we reversed it by subtracting it from 7 for which a higher value indicates a higher B, while a lower value shows lower B). But their A scores are different from each other, ranged from 2 to 14. In other words, although there is a perfect balance between exploitation and exploration, the A scores drifted apart, depending on the magnitude of these two activity scores. Thus, considering an absolute difference between exploitation and exploration as "ambidexterity" is a problem because the predictive and transformative power of ambidexterity on performance depends on an orthogonal interaction among these two activities and high levels of both can indeed increase each other's performance enhancing effect. This may be a reason why previous research was systematically unable to find the predictive and/or transformative power of B on performance, while finding a significant role of M (or A) on different performance outcomes (e.g., Cao et al. 2009; Chandrasekaran et al. 2012; Kostopoulos et al. 2015; Venugopal et al. 2020).

Regarding the combinative configuration of exploitation and exploration, in Table 7, Teams 5, 10, and 14's A scores are the same, 10. But their B scores are different from each other, ranged from 3 to 7. In this case, Team 14's B score is high, 7, while Team 5 has a relatively low score, 3. Thus, the A score, 10, does not reflect

[8] By using a similar data set, He and Wong (2004) and others (e.g., Cao et al. 2009) calculated the absolute differences of exploitation and exploration.

a balance between exploitation and exploration. In other words, an orthogonal interaction is still missing the balanced configuration of exploitation and exploration as also explained above. In our hypothetical case, an imbalance exists in Team 5's B score relative to Teams 10 and 14, but we cannot understand it from their A scores because these scores are the same for all three teams, 10.

We instead posit that the measurement of the multiplicative interaction of B with A scores of exploitation and exploration reflects the true nature of ambidexterity (hereafter BA[9]). This is because this measurement approach may eliminate the above-mentioned constraints. For example, when we take the synergistic interaction of Teams 5, 10, and 14's B with A scores, we find their BA scores. Those are 30, 50, and 70, respectively. Although their A scores were the same, their BA scores became different from each other. That is, B did a corrective impact (in terms of balance) on those teams' A scores and those scores now reflect the balance between the teams' exploitative and exploratory activities.

We further posit that by injecting B into A, one can promote or degrade its "traditional" ambidextrous potential exponentially. That is, if there are high levels of imbalance between one's exploitation and exploration scores relative to others, regardless of how high the value of A score one has, being ambidextrous may not be the case as well, in addition to low A scores or can be at least less ambidextrous (Simsek 2009). For example, as shown in Table 7, Team 6's A score, 9, is relatively higher than Teams 12, 16, 17, 19, 20, 21, 22, 23, 24, 25, and 26 (we named all of them *others* hereafter). This is because others' A scores are lower than 9. However, Team 6's B score, 2, is lower than others, ranged from 3 to 7. When we correct their A scores by multiplying with B, we have a very different situation. Team 6's BA score was stuck at 18, whereas others' same scores increased, ranged from 20 to 56. More importantly, some of the others' same scores skyrocketed, e.g., Teams 19, 23, and 26, depending on the level of balance between their exploitation and exploration scores. These arguments suggest that high B scores gave others an exponential/synergistic potential. Because these teams now have balanced higher BA scores than Team 6, they became more ambidextrous than Team 6 (Simsek 2009).

Acknowledgements The authors thank the first anonymous reviewer for her/his helpful suggestions and comments on earlier drafts.

[9] In this example, we only used B and A scores to calculate BA scores. Likewise, B and M scores can be used to calculate BM scores which is another way of ambidexterity.

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