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RESEARCH ARTICLE

How does team learning from failure facilitate new product performance? The double-edged moderating effect of collective efficacy

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Abstract Learning from failure can foster innovation, but how a new product development (NPD) team's learning from failure affects new product performance requires more insights. In particular, the question remains on how collective efficacy, which discerns team members' belief to achieve desired goals, affects team learning from failure towards improving new product performance. Using social cognitive theory complemented by sensemaking and attribution theories, we examine the effects of NPD teams' (experiential and vicarious) learning from failure on new product performance and the moderating effects of collective efficacy on these relationships. With survey data collected from 398 responses within 152 NPD teams in Chinese high-tech small and medium-sized enterprises, we find that both experiential and vicarious learning from failure enhance new product performance in terms of speed to market and product innovativeness. Further, as collective efficacy increases, the positive effect of experiential learning from failure on speed to market is strengthened. However, the positive effect of vicarious learning from failure on product innovativeness is weakened. Our results suggest that NPD teams can benefit from experiential and vicarious learning from failure to improve new product performance but must pay attention to the double-edged effect of collective efficacy.

Plain English Summary Failure is a common occurrence in the high-tech industry, especially when it comes to new product development (NPD). However, how NPD teams learn from failure can greatly affect their new product performance—their ability to develop superior novel products and take them to market faster than competitors. NPD teams can learn from their own failure experience (i.e., experiential learning) and that of other NPD teams (i.e., vicarious learning). However, how they believe in their collective power to produce desired results (i.e., collective efficacy) may change the effects of their learning from failure on new product performance. Based on 398 responses within 152 NPD teams in Chinese high-tech small and medium-sized enterprises, we take an evidence-based approach to

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unpack these relationships. Although experiential and vicarious team learning from failure improves the speed to market and product innovativeness, collective efficacy has double-edged effects on these relationships. Notably, a high level of collective efficacy enables an NPD team to benefit from experiential learning from failure to improve the speed to market. However, it undermines the effort of vicarious learning from failure to enhance product innovativeness. Thus, our study cautions NPD teams on regulating their collective efficacy to benefit new product performance.

Keywords Learning from failure · Experiential learning · Vicarious learning · Collective efficacy · Social cognitive theory · New product development team · Small and medium-sized enterprises

JEL Classification D83 · D91 · L26 · O31 · O32

1 Introduction

New product development (NPD) is crucial for the survival and success of high-tech firms, as it determines their new product performance, including speed to market and product innovativeness (Zhang & Wu, 2013). NPD teams' ability to develop superior novel products and take products to market faster than competitors offers vital lifelines (Lovelace et al., 2001). NPD carries inherent risks and uncertain outcomes (D'Este et al., 2018), making failure an inevitable part of the innovation process (Hu et al., 2017; Tzabbar et al., 2023). A project fails when it fails to meet its initial aspirations (Shepherd et al., 2014). However, failure in an innovation project can act as a catalyst for sensemaking efforts (Morais-Storz et al., 2020), highlighting areas of improvement and providing valuable learning opportunities (Baxter et al., 2023; Garzón-Vico et al., 2020; Gottschalk & Müller, 2022). Such learning can be applied in future projects (Shepherd et al., 2011). This is especially crucial for small and medium-sized enterprises (SMEs) with limited resources (Forsman, 2021).

Indeed, scholars have consistently emphasized the significance of learning from failure in pursuing innovation, predominantly at the organizational level (e.g., Carmeli & Dothan, 2017; Danneels & Vestal, 2020; Kim & Lee, 2020; Semrau et al., 2021; Yu et al., 2014). While this body of literature elicits organizational conditions under which learning from failure may improve innovation performance, the intricacies of learning from failure at the team level, such as in NPD teams, are overshadowed (Rauter et al., 2018). Theoretical advancement and empirical evidence on learning from failure in the research context of NPD teams is limited. This is problematic due to the crucial role of NPD teams acting in innovation activities. For instance, NPD teams are the front line for generating innovative ideas and transforming them into new products or services (Edmondson & Nembhard, 2009; Liu et al., 2015), making the lack of theoretical and empirical insights into NPD teams' learning from failure and new product performance especially problematic for NPD managers in high-tech SMEs.

NPD teams' ability to learn from failure to improve new product performance is as important as their ability to prevent NPD failure in the first place. Thus, understanding how teams learn from failure is an important issue that needs to be addressed to develop theory and practice on learning from failure (Rauter et al., 2018). Further, recent studies stress the need to examine experiential and vicarious learning to fully understand learning from failure and their effects on subsequent performance. However, once again, attention has been focused on either the individual level (e.g., Diwas et al., 2013; Lapré & Cravey, 2022) or the firm level (e.g., Carmeli and Dothan, 2017; Garzón-Vico et al., 2020; Madsen & Desai, 2010). NPD teams can learn from their own NPD project failures and other teams' failures in the firm. The latter is equally important, as firms, especially for SMEs, usually have limited resources and time to experiment with all possible outcomes to increase their likelihood of success (Garzón-Vico et al., 2020; Myers, 2021).

However, to the best of our knowledge, no prior study has examined how teams engaging in experiential and vicarious learning from failure can enhance new product performance. Experiential and vicarious learning from failure can work differently (Carmeli & Dothan, 2017), especially in NPD teams, because of the emotional and cognitive differences attached to learning from their own versus others' failures (Shepherd et al., 2013). Informed by social cognitive theory (henceforth SCT), which argues that individuals learn from their own experience and by observing others' actions (Bandura, 1986), our study simultaneously focuses on the two salient learning modes from failure within NPD teams. Firstly, our study focuses on learning from the NPD team's own failure (i.e., experiential learning from failure) and other NPD teams' failure (i.e., vicarious learning from failure) and examines their effects on new product performance in high-tech firms. Hence, our first research question is: *do NPD teams' experiential and vicarious learning from failure affect new product performance?*

Further, SCT asserts that learning occurs in a social context with social reinforcement (Bandura, 1986). It discerns how people motivate and regulate behavior to acquire knowledge and competence (Bandura, 2012) and how collective cognition underpins social and team learning (Shepherd & Krueger, 2002). Indeed, prior research has empirically verified that collective efficacy, as a motivational team process, influences the innovation performance of NPD teams in China (Liu et al., 2015). Our study builds on this but further examines how collective efficacy influences the effects of NPD teams' experiential and vicarious learning from failure on new product performance. Collective efficacy as a motivational factor is expected to transform failure experience into new knowledge through effortful cognitive processing (Danneels & Vestal, 2020). This is an eminent issue surrounding the effectiveness of NPD team learning from failure towards improved new product performance. This leads to our second research question: *what role does collective efficacy play in the effects of experiential and vicarious learning from failure on new product performance?*

To address these two research questions, we used survey data collected at two points of time from 398 respondents within 152 NPD teams in high-tech SMEs in Shanghai, China. Our study contributes to research on team learning from failure (Cannon & Edmondson, 2001; Carmeli et al., 2012) and extends the research on how to improve new product performance (Sivasubramaniam et al., 2012) drawing on SCT, which is complemented by sensemaking and attribution theories. First, our study departs from conventional research, which predominantly examines learning from failure at the organizational or individual level. By specifically exploring NPD teams' experiential and vicarious learning from failure, we uncover the underlying transformation mechanism that connects various forms of learning from failure to new product performance (Carmeli and Dothan, 2017) at the team level. This novel perspective paves the way for further research, offering a fresh and unexplored avenue of inquiry in this domain. Second, our study distinguishes the different types of learning from failure in NPD teams and clarifies their effects on new product performance. Our findings have vital implications on effective team learning to tackle failure and inform subsequent innovation (Carmeli et al., 2012). Thus, our study extends new product performance research (Sivasubramaniam et al., 2012) through the perspective of team learning from failure and offers practical implications for NPD teams to maximize the value of NPD project failures. Finally, we incorporate learning from failure as a cognitive team process and collective efficacy as a motivational factor to explain how NPD teams transform failure experience into new product performance within SMEs. By shedding light on the double-edged effect of collective efficacy within the context of innovation failure (Shepherd et al., 2016), our research shifts the discourse from the importance of learning from failure to understanding how such learning contributes to new product performance.

2 Theoretical Background

2.1 Social Cognitive Theory

Our overarching theory is the SCT, which offers insights on the cognitive and motivational team process that underpins the underlying relationship between learning from failure and new product performance at the team level. First, according to SCT, learning is not simply behavioral; instead, it is a cognitive process that occurs in a social context. Collective cognition is a social artifact of shared cognitive maps rather than a simple sum of individual cognition (Shepherd & Krueger, 2002). Accordingly, team learning is not the sum of individual learning when adequate collective cognition is in place. Thus, we argue that experiential learning from failure and vicarious learning from failure are essential cognitive processes for NPD teams to facilitate new product performance.

Second, SCT considers how individuals act and the social environment in which individuals perform (Bandura, 2012). It suggests that motivation and performance achievement are moderated by a self-regulatory mechanism such as self-efficacy (Boudreaux et al., 2019). As one of the core constructs of SCT, collective efficacy is defined as "the people's shared beliefs in their collective power to produce desired results" (Bandura, 2000, p.75). In this study, we argue that collective efficacy, through its associated traditional motivational mechanism such as direction, effort, and persistence in teams (Liu et al., 2015), affects NPD teams' ability to transfer their learning from failure into new product performance.

Further, Rauter et al. (2018) highlight that SCT is insightful for explaining a wide array of team learning especially under challenging conditions such as failures and setbacks. Some scholars have recently verified that an NPD team's behavioral, cognitive, and motivational processes could jointly sharpen innovation performance (e.g., Chen et al., 2013; Liu et al., 2015). For instance, as a motivational team process, collective efficacy facilitates the effects of collaborative behavior and joint decision-making on innovation performance. However, it inhibits the positive effect of information exchange on the innovation performance of NPD teams in China (Liu et al., 2015). Thus, drawing on insights from SCT, our study predicts that NPD team learning from failure (as a cognitive team process) and collective efficacy (as a motivational team process) jointly affect new product performance, particularly in NPD teams.

In this study, we further draw insights from the attribution theory, which discerns how individuals cognitively appraise outcomes of achievement situations (Weiner, 1985) and hence complements the SCT to explain team learning from failure in the NPD context. Weiner's (1985) attribution theory classifies causal attributions along three key dimensions: locus of causality (whether the cause of an outcome is attributed to internal or external factors), stability (whether the cause of an outcome is attributed to relatively stable or variable factors), and controllability (whether the cause of an outcome is attributed to factors that are within or outside one's control). Harvey et al. (2014) articulate two additional dimensions: intentionality (the extent to which an outcome is attributed to deliberate or unintentional actions) and globality (the extent to which the factor attributed to the cause of an outcome is relevant across situations or specific to a task or a context). Within the entrepreneurial failure context, the recent work (e.g., Riar et al., 2021; Yamakawa & Cardon, 2015) on learning from failure particularly focuses on two dimensions of failure attribution: locus of causality referring to whether the failure is attributed to causes internal to the individual who failed or to causes external to the individual; and stability referring to whether the cause is perceived to be permanent (stable) or temporary (unstable). Like self-referent attributions, team attributions can also be classified along the same dimensions and are purported to influence collective behavior through the team's affective reactions and future expectancies (Harvey et al., 2014).

2.2 Learning from Failure in NPD Teams as a Sensemaking Process

Learning from failure can be seen as a sensemaking process (Morais-Storz et al., 2020; Shepherd et al., 2011, 2014) and is therefore defined as "the sense that one is acquiring, and can apply, knowledge and skills" (Spreitzer et al., 2005, p.538). In the sensemaking process, individuals scan the environment for relevant information, interpret that information to give it meaning, and then base their actions on these interpretations (Gioia & Chittipeddi, 1991; Weick, 1995). Cardon et al. (2011) suggest that sensemaking is often a social activity. Our study thus defines experiential learning from failure as a sensemaking process in which an NPD team "reflects upon the problems and errors it experiences, interprets and makes sense of why they occurred, and discusses what actions are needed to produce improved outcomes" (Carmeli et al., 2012, p.33). We also define vicarious learning from failure as a sensemaking process in which NPD teams reflect on and interpret the failure experiences of other NPD teams in the firm such that they can develop new insights and pathways to improve innovation (Bledow et al., 2017).

Although experiential and vicarious learning from failure involve behaviors for obtaining collective goals (Carmeli and Dothan, 2017), they differ in their sensemaking processes regarding scan, interpretation, and action, and how those activities lead to new product performance. First, the difference may exist in information scanning. Vicarious learning from failure may involve incomplete information on other NPD teams' failure and what can be directly learned is often explicit rather than tacit knowledge. It is also confounded by the lack of direct comparability between other NPD teams' experience of failed NPD projects and the team's task at hand. Second, within the NPD project failure context, the emotional difference in experiential and vicarious learning from failure will influence the information interpretation. As project failures bring negative emotions, such as grief, to project team members (Shepherd et al., 2013), experiential learning from failure entails stronger emotions than vicarious learning from failure due to the nature of reflecting on one's own NPD project failures. Thus, examining the potential difference in the effects of an NPD team's experiential and vicarious learning from failure on new product performance is essential and crucial.

New knowledge is created when individuals acquire information from failure experiences and effectively process it to revise their belief systems (Shepherd et al., 2011). Acting upon this new knowledge generated by learning from failure can lead to positive innovation outcomes such as NPD performance (Yu et al., 2014), firm innovation (Carmeli & Dothan, 2017), and firm innovativeness (Danneels & Vestal, 2020). To further clarify the underlying influencing mechanisms of team learning from failure on new product performance, we further differentiate between speed to the market (i.e., how quickly an NPD team takes the product to market) and product innovativeness (i.e., the novelty of a new product). Speed to market is related to NPD commercialization efficiency, while product innovativeness is relevant to NPD effectiveness which is vital for maintaining market share (Sivasubramaniam et al., 2012). This differentiation is critical as the types of NPD outcomes vary, particularly in high-tech industries (Mallick & Schroeder, 2005), which has been empirically supported in the context of Chinese ventures (Wen et al., 2020).

2.3 Collective Efficacy

According to SCT, collective efficacy reflects the shared beliefs of the team members in their team's capabilities to mobilize cognitive resources and stimulate motivation to achieve a designed level of attainments on specific tasks (Bandura, 2012). Previous research has primarily emphasized the positive effect of collective efficacy on individual innovative behavior in open innovation projects (Miyao et al., 2022) and organizational commitment (Chen et al., 2019). However, collective efficacy is not always beneficial for teams. For example, DeTienne et al. (2008) find that entrepreneurs are likelier to persist with their poorly performing firms when embedded in a team with high collective efficacy. Such persistence may lead to financial costs of poor performance, which are much larger than needed (e.g., Shepherd et al., 2016).

Although several scholars have reminded us that enough attention should be paid to the double-edged

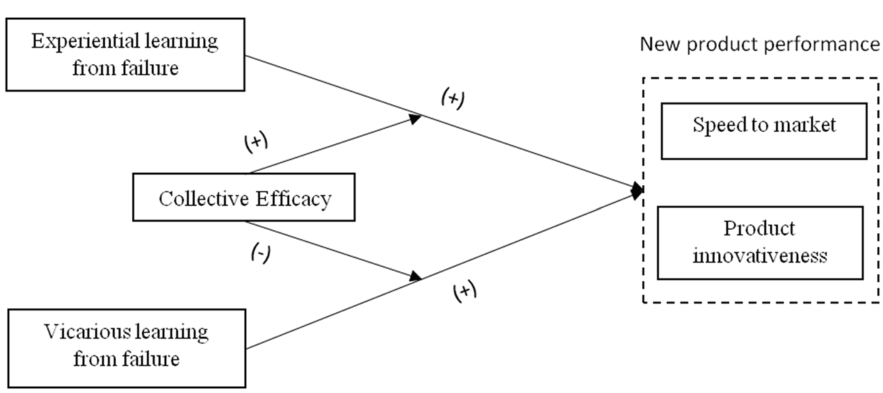


Fig. 1 Theoretical framework

effect of collective efficacy (e.g., Goncalo et al., 2010; Shepherd et al., 2016), there is still a lack of theoretical explanation and empirical evidence. An exception is a work by Liu et al. (2015), who have empirically verified that collective efficacy, as a vital enabler of shared goal commitment, could contribute to a high level of team willingness to innovate and perform through collaborative behavior and joint decision-making, but also may undermine the positive effect of information exchange on innovation performance. Our study builds on this insight but argues that collective efficacy might moderate relationships between an NPD team's experiential and vicarious learning from failure and new product performance (i.e., speed to market and product innovativeness) (see Fig. 1). Below, we blend SCT with sensemaking and attribution theories to develop our hypotheses.

3 Hypotheses Development

3.1 Learning from Failure and New Product Performance

According to SCT, learning is a cognitive process that takes place in a social context and can occur purely through direct instruction or observation. We believe sensemaking theory (Gioia & Chittipeddi, 1991; Weick, 1995) can be linked to SCT as the social context process that facilitates experiential and vicarious learning. Specifically, we argue that experiential and vicarious learning from failure could be vital drivers of new product performance as they encourage internal and external searches for new information and solutions (i.e., scanning) and promotes profound comprehension of the meaning of information (i.e., interpretation), rather than reinforcing continued use and refinement of current ones.

First, we argue that experiential learning from failure facilitates new product performance regarding both speed to market and product innovativeness. On the one hand, experiential learning from failure can positively affect speed to market because it allows an NPD team to quickly gather information to fix problems that might have slowed down the NPD process. This can help a team get a product to market more quickly because they can address issues as they arise rather than waiting until the end of the development process to fix them. Further, experiential learning from failure allows the NPD team to develop a more "nuanced and intimate understanding of work processes" (Carmeli et al., 2012, p.45). The efficient work processes will speed up the iteration in the NPD process with timely feedback. Thus, experiential learning from failure can reduce the time for feedback and improvement on the new product, thus promoting efficient commercialization.

On the other hand, experiential learning from failure can also positively affect product innovativeness because it allows a team to reflect on their failures and try new approaches. This can lead to developing new ideas and approaches that might not have been considered otherwise. By asking questions like "why do we do the things in such and such a way" (see E1 in Appendix 1) and "is there a better way to produce the new product or provide the service" (see E5 in Appendix 1) after experiencing NPD project failures, an NPD team is more likely to get to the root cause of NPD project failures and develop a high level of mindfulness to see new possibilities (Levinthal & Rerup, 2006). Experiential learning from failure can also alter mental models because members can reflect on the gaps between existing and desired ends (Carmeli and Dothan, 2017). Explaining these gaps can foster new lines of thinking and lead the NPD team to seek and adopt new solutions to bridge them, improving product innovativeness. When NPD team members come together to review past decisions and examine failures for lessons learned, they explore the root causes of failure and make improvements, which will help them quickly develop knowledge superior to their competitors in improving the speed to market and product innovativeness. We thus hypothesize:

> **H1:** Experiential learning from failure positively affects: (a) speed to market; (b) product innovativeness.

According to SCT, the individuals would adjust how they act by learning from others' failures (Bledow et al., 2017; Diwas et al., 2013). Similarly, in the NPD process, NPD teams can also learn from other NPD teams' failures in the firm, which can extend the scope of information scanning and deepen their comprehension of new information, thus facilitating both the speed to market and product innovativeness in the NPD process.

First, vicarious learning from failure, through gathering information about other teams' NPD failure, can positively affect speed to market by helping an NPD team avoid making the same mistakes that others have made to identify best practices and avoid common pitfalls. For example, if a team learns about an NPD project failure that occurred in the firm, they may be able to identify potential problems and take steps to avoid them, which can help them get their product to market more quickly. Further, vicarious learning from failure is not a passive but rather an active learning process that requires flexibility and willingness to make major changes swiftly to respond effectively to constantly changing conditions (Carmeli and Dothan, 2017). Through vicarious learning from other NPD teams' failures in the firm, reflecting and reframing their problems, the NPD team will become more flexible and adaptive. Hence, vicarious learning from failure will enhance their capacity to develop novel solutions quickly and update their NPD process to achieve prompt response, thus facilitating market speed.

On the other hand, vicarious learning from failure can also positively affect product innovativeness by exposing an NPD team to a wider range of experiences and approaches. By learning about the failures of other NPD teams, the NPD team can gain new insights and ideas that might not have been considered otherwise. Moreover, vicarious learning is not just about rejecting poor practices that others have employed but can be seen as a way whereby NPD teams experiment and create new knowledge by cultivating a nuanced interpretation and causal inferences (Kim & Miner, 2007). Thus, the project failures of other NPD teams in the firm can be harnessed to draw new insights for new knowledge creation by reconfiguring processes, promoting product innovativeness. We hypothesize the following:

> **H2:** Vicarious learning from failure positively affects: (a) speed to market; (b) product innovativeness.

3.2 The Moderating Effects of Collective Efficacy

Following SCT, collective efficacy affects what people choose to do as a group, how much effort they put into the group's objectives, and their persistence when group efforts fail to produce desired outcomes (Bandura, 2012). Within the NPD context, collective efficacy can motivate the NPD teams' sensemaking that involves the reciprocal interaction of information seeking, meaning ascription and action, contributing to new product performance. Further, Yamakawa and Cardon (2015) highlight that causal ascription (i.e., attribution) of failure informs learning from failure as "it is through the sense making/interpretation of the experience that learning happens" (Rae & Carswell, 2001, 154). Thus, below we will blend SCT with sensemaking and attribution theories to elaborate how collective efficacy moderates the relationship between learning from failure and new product development within NPD teams.

First, informed by the sensemaking theory, collective efficacy will strengthen the positive effect of experiential learning from failure on speed to market and product innovativeness through enhancing the NPD team's capability of information seeking and interpretation. On the one hand, an NPD team with high collective efficacy will likely have strong communication and collaboration skills, which can also contribute to a more efficient and effective NPD process. Indeed, Liu et al. (2015) find that the positive relationship between information exchange and innovation performance will increase with collective efficacy in NPD teams. Thus, NPD teams with high collective efficacy could stimulate themselves to obtain and process information from prior failures and commercialize NPD projects efficiently. This will maximize the positive effect of experiential learning from failure on the speed to market.

On the other hand, collective efficacy can strengthen the positive relationship between experiential learning from failure and product innovativeness as it promotes a culture of continuous learning and quality improvement. Indeed, the NPD teams with a high collective efficacy generally have high commitments to generate and implement innovative ideas for new products (Liu et al., 2015). Within such an innovation-friendly team climate, the NPD teams are more likely to be open to interpreting their prior experience of NPD failure and develop novel solutions to improve product innovativeness (Ernst, 2002).

Second, based on attribution theory, team members have an innate tendency to make sense of failure experiences by acting as 'naïve psychologists' (Eberly et al., 2011; Heider, 1958). When analyzing the root cause of failure experience, whether team members attribute the cause to internal or external factors it influences their subsequent behaviors (Weiner, 1985). For example, when the root cause is attributed to internal factors (such as the lack of skills within the NPD team), team members are more likely to feel in control and seriously address the root cause and overcome internal barriers (such as improving NPD skills) in a subsequent NPD process. Conversely, when the root cause is attributed to external factors (such as the changing market conditions), team members may feel less in control regarding learning from failure experience. Thus, through attribution, the team members attempt to (re)establish control over their failure experience and improve their ability in subsequent NPD processes. Teams with a high level of collective efficacy have a shared belief on their ability to recognize and tackle their own failure experience, accompanied by a strong sense of control to overcome internal barriers, and mobilize cognitive resources and stimulate motivation to achieve a designed level of attainments on specific tasks (Bandura, 2012). Thus, an NPD team with high collective efficacy will put efforts to maximize the value of learning from their own failure experience to propel the speed to market and product innovativeness. We thus argue:

H3: Collective efficacy strengthens the positive relationship between experiential learning from failure and (a) speed to market; and (b) product innovativeness.

Drawing on SCT, the positive effect of vicarious learning from failure on speed to market and product innovativeness would be weakened due to NPD team members' self-confidence in their ability, associated with a high level of collective efficacy. NPD teams with a high level of collective efficacy usually have a high level of confidence in their team's capability to complete specific tasks (Goncalo et al., 2010). In this case, NPD teams are less likely to consult with and listen to peers outside their teams (Minson & Mueller, 2012). They may be unable or unwilling to apply and practice the lessons learned from the project failures of other NPD teams in the firm (Madsen & Desai, 2010), thereby undermining the new knowledge transferred from vicarious learning from failure.

Further, concerning learning from others' experiences, the globality dimension of attribution theory (Harvey et al., 2014) is worth considering. What makes a difference is an NPD team's perception on to what extent the cause of other teams' failure experience is specific to their task or context and to what extent such cause is relevant across different NPD teams. NPD teams with a high level of collective efficacy have a high level of self-belief and confidence in their ability. They therefore are more likely to consider other teams' NPD failures not directly relevant to their own. When their collective efficacy is extremely high, such NPD teams may completely neglect others' NPD failures. A high level of collective efficacy may breed selective ignorance, which undermines learning from others' failure experiences and motivation for performance improvement (Harvey et al., 2014). This could lead to the dysfunctional effect of vicarious learning from failure on new product performance. Thus:

H4: Collective efficacy weakens the positive relationship between vicarious learning from failure and (a) speed to market; and (b) product innovativeness.

4 Methods

4.1 Sampling

We collected survey data from high-tech firms in Shanghai, China. China provides a stimulating environment for the high-tech firms to accelerate NPD projects (Zhang & Wu, 2013). Shanghai, as one of the most high-tech cities in China, has an extremely high concentration of high-tech sectors. By nature, high-tech SMEs rely on NPD teams to improve their new product performance and competitive advantage (Tao et al., 2023). However, failure is common in NPD projects due to high uncertainty, especially associated with breakthrough innovation (Hu et al., 2017). NPD teams in high-tech firms in Shanghai provide our study with an appropriate research setting, and a similar context has proved productive in prior research (e.g., Tao et al., 2023; Tjosvold et al., 2004).

We obtained a list of 1812 high-tech SMEs, officially issued by *the Science and Technology Commission of Shanghai Municipality* on 5th June 2017, covering all the 16 administrative districts of Shanghai. Details of the executives and their firms were obtained from each company's registration records on *China's National Enterprise Credit Information Publicity System.* We surveyed all the 1812 high-tech SMEs in 2018 via an initial online survey, followed by three waves of reminders (via email, telephone, and on-site visit).

The questionnaire was initially written in English and then translated into Chinese by one bilingual co-author whose native language is Chinese. We followed an independent bilingual researcher's rigorous and iterative back-translation process. We compared the original and back-translated versions until they reached conceptual, categorial, and functional consensus. The questionnaire was also pre-tested with two British academics with expert knowledge in innovation and cross-cultural questionnaire surveys. Following this, a pilot study was conducted with 10 NPD project leaders in different high-tech firms in China. Feedback from the pretest and the pilot study was incorporated into the final questionnaire.

The respondents were NPD project team leaders whom the executives of the high-tech firms nominated and core NPD team members with whom the team leader shared the strategic decision-making process. They were expected to have comprehensive knowledge of the NPD process (Liu et al., 2015; Tang et al., 2015; Tao et al., 2023). Survey data were collected at two points of time from more than one respondent from each NPD team. First, team members were asked to complete experiential and vicarious learning from failure and collective efficacy. Team leaders were asked to answer the NPD team-related questions, such as the team age, team size, and the number of ongoing projects in the firm. Six months later, we asked the same team leaders to assess the new product performance of the NPD projects they had managed since the last survey. We finally obtained 398 usable responses within 152 NPD teams from 52 firms. We further compared the team age and team size of the late respondents with those of the early respondents, resulting in no significant differences in a t-test, providing evidence of the lack of non-response bias.

4.2 Measures, Reliability, and Validity

We adapted mature scales to maximize construct validity and asked the respondents to answer on a Likert-type scale, with options ranging from 1 = "strongly disagree" to 7 = "strongly agree." The Cronbach's alpha for the main study variables was acceptable (see Appendix, Table 3).

Learning from failure To assess experiential learning from failure and vicarious learning from failure, we adapted the scale employed by Carmeli and Dothan, (2017) from an organizational level to the team level. Specifically, experiential learning from failure was measured by five items; for example, "when NPD team members make a mistake, they inform the team leader to enable others to learn from it". We used four items to measure vicarious learning from failure; for example, "we constantly look at failures of other NPD teams in the firm to gain new insights into our own work processes."

Collective efficacy Collective efficacy was measured using a seven-item modified by Liu et al., (2015), focusing on NPD teams in the Chinese technology ventures. The respondents were asked to answer questions on the NPD teams' shared belief about their capabilities to perform NPD tasks successfully.

New product performance Following Zhang and Wu, (2013), we differentiated between speed to market and product innovativeness to measure new product performance. Speed to market was assessed relative to their team's time goals, industry conditions, expected speed-to-market, and expected speed-to-development. Product innovativeness was assessed by gauging the extent to which the new products developed by their teams were novel to the industry. This subjective measurement is suitable as numerous studies have demonstrated that subjective measures are consistently associated with objective performance measures (Morgan et al., 2018).

Further, objective measures are extremely challenging and, at best, would be weak or distant proxies unrelated to the firm's specific goals. They would require a subjective judgment by the researcher as to what constitutes novelty in an industry; managers are better placed to make that judgment. Most importantly, this measure has been validated to compare new product performance with what constitutes novelty in high-tech firms in China (Zhang & Wu, 2013).

Control variables We controlled for team age (i.e., the number of years since the NPD team being founded) and team size (i.e., the number of full-time equivalent team members) as their positive effects on innovation were verified by Sivasubramaniam et al., (2012). Further, as "a larger number of NPD projects tends to experience a higher number of failures" (Hu et al., 2017, p.48), we controlled for "the number of ongoing NPD projects" in operation in the firm. We controlled for business ownership (Yang & Tsou, 2020) and industry type (Torres de Oliveira et al., 2022) as their effects on innovation were found among Chinese firms. The state-owned and other industry types were further set as dummy variables separately.

We applied confirmatory factor analyses to assess our model's goodness of fit. The fit indices (see Appendix, Table 3) illustrated that our measurement model fitted the data very well ($\chi2$ (289) = 353.535; CFI = 0.972; TLI = 0.968; RMSEA = 0.038; $p = 0.006$) and was better than the one-factor model ($\chi2$ (343) = 507.031, CFI = 0.821, TLI = 0.838, RMSEA = 0.066, $p = 0.000$). Coefficient alpha reliability (α) and composite reliability (CR) indices exceeded the accepted 0.7 threshold. We further employed two methods to assess convergent validity. First, all the calculated average variances extracted (AVE) of study variables were greater than the minimum threshold of 0.5 (Fornell & Larcker, 1981), except for experiential learning from failure (AVE = 0.439). However, the CR of experiential learning from failure (CR = 0.793) was higher than 0.6; thus, the convergent validity was still adequate. Second, the path coefficients from latent constructs to their corresponding items were all statistically significant (i.e., t > 2.0). All items loaded significantly onto their corresponding latent constructs, with the lowest $t = 6.708$, providing evidence of convergent validity. Besides, all the square roots of AVEs were higher than the correlations, thus, discriminant validity was also satisfactory (Fornell & Larcker, 1981).

4.3 Common Method Variance Tests

Our study collected data at two points in time from two to six informants in each NPD team to mitigate the risk of common method bias (Tang et al., 2015). We also adopted the following procedures: (1) Before the survey, we conducted a pilot study to eliminate the ambiguity of item wording and context and placed the independent variables away from the dependent variables. (2) During the survey, we assured the respondents that their answers were confidential and that there were no right or wrong answers to the questions in the survey to reduce the respondents' evaluation apprehension and social desirability. (3) As our sample size is less than ten times the observed variables for factor analysis (Nunnally, 1967), the confirmatory factor analysis is thus not suitable for examining the common method variance in this study. Thus, the Harman single-factor test was further employed in exploratory factor analysis, and the result showed that the first factor only explained 20.325%, suggesting that there was no dominant factor. Overall, common method bias was not a concern in our study.

4.4 Aggregation Tests

Relying on multiple respondents is more reliable than a single respondent, though it requires the assessment of the consistency of responses within a team (Carmeli et al., 2012). We employed an analysis of variance to assess this consistency. The results showed more variability in the ratings between teams than within teams ($p < 0.01$).

To justify the aggregation of team-level variables in this study (i.e., experiential learning from failure, vicarious learning from failure, and collective efficacy), we calculated the within-group agreement

Table 1 Descriptive statistics

Variables	1	2	3	4	5	6	7	8
1. Team age								
2. Team size	-0.026							
3. Number of ongoing NPD projects	-0.059	0.203**						
4. Collective efficacy	-0.055	0.122†	0.228**					
5. Experiential learning from failure	0.007	0.268**	0.148†	0.447***				
6. Vicarious learning from failure	-0.092	0.174*	-0.057	0.452***	0.454***			
7. Speed to market	-0.019	0.110	0.102	0.280***	0.297***	0.271**		
8. Product innovativeness	-0.015	0.108	-0.007	0.277**	0.382***	0.348***	0.300***	
Mean	4.442	12.105	6.145	5.443	5.400	5.212	4.942	5.481
SD	0.740	10.464	8.410	0.445	0.476	0.536	1.095	0.901

N = 152; SD = Standard deviation; †$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

index, namely r_{wg} of these variables (Biemann et al., 2012). The results illustrated that the median values of 0.968 for experiential learning from failure, 0.962 for vicarious learning from failure, and 0.972 for collective efficacy were above the 0.7 threshold. Thus, the aggregation was justified for these team-level variables.

We also computed the intra-class correlations (ICCs) to assess group member agreement (Biemann et al., 2012). ICC (1) indicates the extent of agreement among ratings from members of the same group. ICC (2) indicates whether groups could be differentiated based on the variables of interest. The values of ICC (1) and ICC (2) for the constructs for which we used multiple respondents were as follows: 0.143 and 0.736 for experiential learning from failure; 0.146 and 0.842 for vicarious learning from failure; and 0.154 and 0.796 for collective efficacy. These values were consistent with the conventional standards for aggregating individual responses into a team-level response (Biemann et al., 2012).

5 Results

This study used multiple regression analysis to test the hypotheses. We mean-centered all the study variables and interaction terms before conducting regression. Further, skewness and kurtosis were within the acceptable to -2 and + 2 range. Table 1 presents the bivariate correlations, means, and standard deviations of the main variables. Table 2 presents the results of hierarchical linear regression. The variance inflation factor (VIF) for each variable was below the threshold of 10 (i.e., the largest VIF was 8.191), while the tolerance is higher than the criteria of 0.1 (i.e., the lowest value of tolerance is 0.122), indicating that multicollinearity was not a serious concern in this study (Hair et al., 2006).

Model 1, as the base model, explained an insignificant amount of the variance in speed to market ($R^2 = 0.033$; $p > 0.1$), indicating that none of the control variables were significant. Model 2 suggested that both experiential learning from failure ($\beta = 0.200$, $p < 0.05$) and vicarious learning from failure ($\beta = 0.202$, $p < 0.05$) were positively associated with speed to market. Thus, Hypotheses 1a and 2a were supported.

Model 4 as the base model, with product innovativeness as the dependent variable, indicated that none of the control variables were significant. Model 5 suggested that both experiential learning from failure ($\beta = 0.288$, $p < 0.01$) and vicarious learning from failure ($\beta = 0.218$, $p < 0.05$) were positively associated with product innovativeness. Thus, Hypotheses 1b and 2b were supported.

Model 3 tested the moderating effects of collective efficacy. The results illustrated that the interaction term coefficient between collective efficacy and experiential learning from failure was statistically significant with speed to market ($\beta = 0.196$,

Table 2 Results of regression analyses

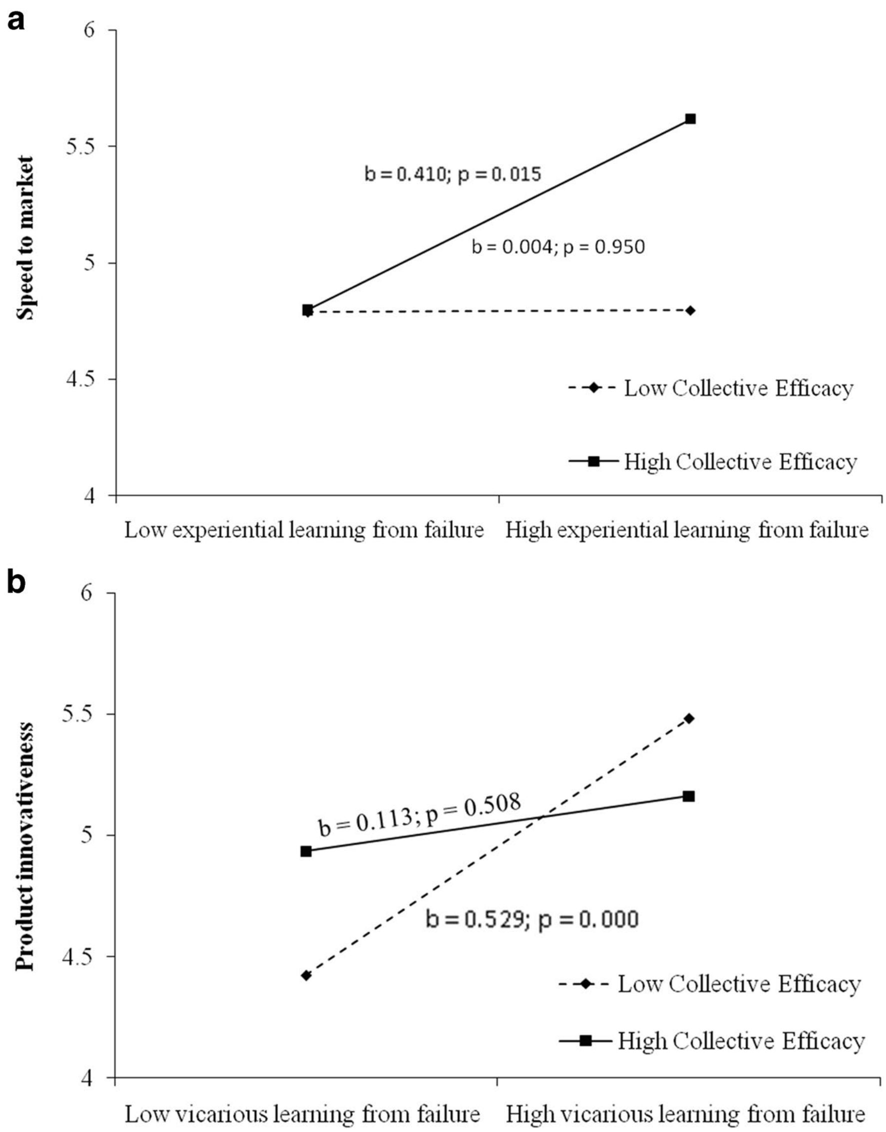
	Speed to market			Product innovativeness		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
Team age	-0.032 (0.086)	-0.020 (0.082)	-0.018 (0.081)	-0.006 (0.086)	0.006 (0.079)	0.011 (0.078)
Team size	0.081† (0.086)	0.010 (0.085)	0.017 (0.085)	0.110† (0.087)	-0.006 (0.082)	0.015 (0.082)
Number of ongoing NPD projects	0.080 (0.086)	0.088 (0.083)	0.028 (0.091)	-0.055 (0.086)	-0.052 (0.080)	-0.107 (0.088)
Joint share	0.144 (0.660)	0.074 (0.628)	0.081 (0.629)	0.266 (0.662)	0.174 (0.607)	0.305 (0.605)
Privately held	0.093 (0.611)	-0.147 (0.584)	-0.127 (0.586)	0.509* (0.613)	0.209† (0.565)	0.374† (0.564)
Foreign invested	0.144 (0.691)	0.146 (0.662)	0.223 (0.660)	0.352 (0.693)	-0.036 (0.640)	0.066 (0.635)
Electronic information	-0.132 (0.206)	-0.173 (0.196)	-0.142 (0.194)	0.044 (0.206)	-0.009 (0.189)	-0.048 (0.186)
New energy and materials	-0.082 (0.259)	-0.135 (0.252)	-0.150 (0.250)	0.036 (0.260)	-0.053 (0.243)	-0.129 (0.241)
New biotechnology	0.123 (0.288)	0.126 (0.277)	0.113 (0.277)	0.216 (0.288)	0.200 (0.267)	0.232 (0.266)
Independent variables						
H1a, H1b: Experiential learning from failure		**0.200* (0.094)**	0.164 (0.100)		**0.288** (0.091)**	**0.267** (0.097)**
H2a, H2b: Vicarious learning from failure		**0.202* (0.092)**	0.149 (0.102)		**0.218* (0.089)**	**0.235* (0.098)**
Interaction effects						
Collective efficacy			0.158 (0.110)			-0.029 (0.106)
H3a, H3b: Experiential learning from failure × Collective efficacy			**0.196* (0.093)**			-0.003 (0.089)
H4a, H4b: Vicarious learning from failure × Collective efficacy			0.007 (0.095)			**-0.235* (0.092)**
R-squared	0.033	0.138	0.180	0.167	0.441	0.492
Adjusted R-squared	0.028	0.070	0.096	0.028	0.195	0.242
Highest variance inflation factor	7.833	7.911	8.191	7.833	7.911	8.191
Lowest tolerance	0.128	0.126	0.122	0.128	0.126	0.122
F change	0.541	8.523***	2.345*	0.453	14.487***	2.848*

$N = 152$; Unstandardized coefficients are reported; Robust standard errors are provided in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

$p < 0.05$). We plotted these moderating effects by performing simple slope tests to probe this interaction further. We plotted values of speed to market for high and low levels of experiential learning from failure and collective efficacy (one standard deviation above and below the mean). Simple slope analyses (see Fig. 2a) further illustrated that the slope was significantly positive for high collective efficacy (b = 0.410; $p = 0.015$), while the slope was insignificant for low collective efficacy (b = 0.004; $p = 0.950$). Most importantly, as the differences between the slopes was statistically significant (t = 3.269, $p = 0.001$), we found support for Hypothesis 3a: collective efficacy has a significant, positive moderating effect on the positive relationship between experiential learning from failure and speed to market. However, the interaction term coefficient between collective efficacy and vicarious learning from failure was insignificant with speed to market (β = 0.007, $p > 0.1$). Thus, Hypothesis 3a was not supported.

The results in Model 6 showed that the interaction effect of vicarious learning from failure and collective efficacy on product innovativeness was negative and insignificant (β = -0.003, $p > 0.1$). Thus, Hypothesis 3b was not supported. However, the interaction term

Fig. 2 **a** Interaction term of experiential learning from failure and collective efficacy on speed to market. **b**. Interaction term of vicarious learning from failure and collective efficacy on product innovativeness



coefficient between collective efficacy and vicarious learning from failure was statistically significant with product innovativeness ($\beta = -0.235$, $p < 0.05$). Likewise, we further plotted these moderating effects and performed simple slope tests to probe these interactions. Simple slope analyses (see Fig. 2b) illustrated that the slope was significantly positive for low collective efficacy ($b = 0.529$; $p = 0.000$), while the slope was insignificant for high collective efficacy ($b = 0.113$; $p = 0.508$). As the difference between the slopes is statistically significant ($t = 3.350$, $p = 0.001$), Hypothesis 4b was supported: collective efficacy has a significant, negative moderating effect on the positive relationship between vicarious learning from failure and product innovativeness.

5.1 Robustness Checks

We conducted several tests to scrutinize our results. First, to address the potential issues of simple slope tests, which are based on significance tests of the slopes for a limited number and often arbitrarily chosen values of the moderator (Bauer & Curran, 2005), we further applied the Johnson–Neyman technique to probe the interaction effects with confidence bands. Figure 3a plots the confidence bands around

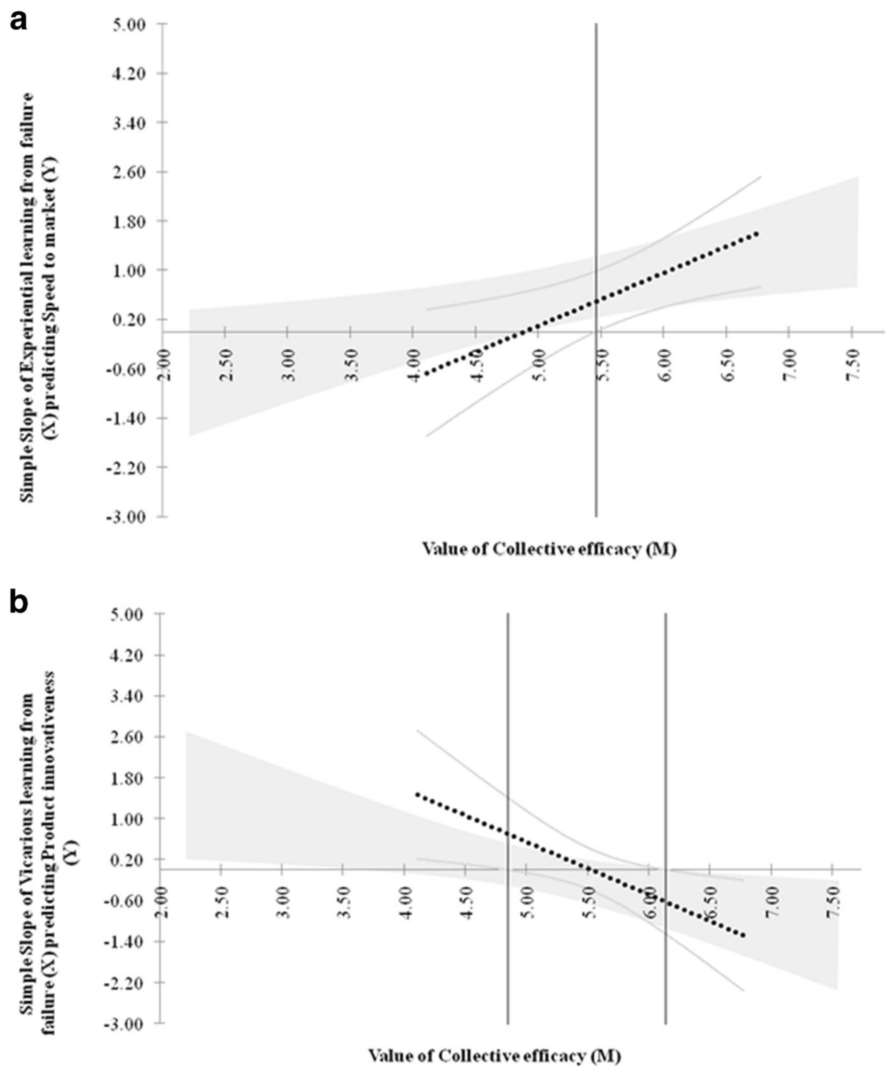


Fig. 3 **a** Johnson-Neyman regions of significance for the conditional effect of experiential learning from failure at values of collective efficacy. **b**. Johnson-Neyman regions of significance for the conditional effect of vicarious learning from failure at values of collective efficacy

the conditional effect (the dark line) of experiential learning from failure on speed to market across the distribution of collective efficacy (on the horizontal axis). The vertical axis represents the coefficient of the relationship between experiential learning from failure and speed to market (i.e., the conditional effect). The dashed lines in the diagram represent the upper and lower bounds of a 95% confidence interval around the conditional effect. The points at which the confidence interval is wholly above or below zero depict the range of values of the moderator collective efficacy for which there is a significant relationship between experiential learning from failure and speed to market. Applying the 95% region to calculate the regions of significance, we calculated the upper bound estimate (i.e., the value beyond which the coefficient becomes significantly positive) was 5.461. This effect is significantly positive when collective efficacy is at least 0.018 above the mean. Otherwise, the relationship between experiential learning from failure and speed to market is not significant. Thus, these results further support Hypothesis 3a.

Similarly, Fig. 3b plots the confidence bands around the conditional effect (the dark line) of vicarious learning from failure on product innovativeness across the distribution of collective efficacy (on the horizontal axis). The vertical axis represents the coefficient of the relationship between vicarious learning from failure on product innovativeness (i.e., the conditional effect). Applying the 95% region to calculate the regions of significance, we calculated the lower bound estimate (i.e., the value beyond which the coefficient becomes significantly positive) to be 4.846. In contrast, the upper bound estimate (i.e., the value beyond which the coefficient becomes significantly negative) was 6.139. That means that when the collective efficacy score is 0.597 below the mean (i.e., 5.443, see Table 1) or smaller, the effect of experiential learning from failure is significantly positive. In contrast, this effect is significantly negative when collective efficacy is at least 0.947 above the mean. In between these two values, the relationship between vicarious learning from failure on product innovativeness is not significant. Thus, these results further support Hypothesis 4b.

Further, we applied a two-stage Heckman procedure to account for the potential endogeneity of previous NPD failures. First, we estimated a first-stage probit model to assess the likelihood of a project failure. Absent better exclusion criteria, we generated two new variables, an industry failure rate, and a district failure rate—the ratios of the total number of NPD project failures to the overall number of NPD projects in an industry and district in the sample, respectively (Liu et al., 2019). Our sample for the first stage contains 177 observations, including 25 NPD project leaders without NPD failure experience. Secondly, we put the inverse Mills' ratio derived from the previous estimation, with other antecedent variables in the second-stage analysis of learning from failure. The results showed that all the hypotheses remained consistent, and the inverse Mills' ratio was statistically insignificant ($\beta = -1.590$; $p = 0.141$). Thus, the selection bias was not an issue in our study.

Finally, to test if the results were sensitive to the model's specification, the method based on OLS parameter estimation was replaced with maximum likelihood using Mplus 8.0. The robustness checks suggest that the magnitudes, directions, and sizes of the results were stable. Further, Funken et al., (2020) find that entrepreneurial self-efficacy has a positive effect on entrepreneurial learning, thus, experiential and vicarious learning from failure might be stimulated by collective efficacy. Therefore, we further tested the potential mediating roles of experiential and vicarious learning from failure in the relationship between collective efficacy and new product performance in Mplus 8.0. The insignificant results of the mediating effects rule out such alternative multiple mediation models.

6 Discussion

Drawing on SCT complemented with sensemaking and attribution theories, our study provides a nuanced view regarding the relationship between learning from failure and new product performance in NPD teams of high-tech SMEs. Specifically, our study examines experiential and vicarious learning from failure as important antecedents of new product performance regarding the speed to market and product innovativeness. It also provides novel insights into the double-edged moderating effect of collective efficacy: it enhances the positive effect of experiential learning from failure on the speed to market. However, it hampers the positive effect of vicarious learning from failure on product innovativeness.

Our results indicate that collective efficacy does not significantly moderate the relationship between experiential learning from failure and product innovativeness. One possible reason is that NPD teams with a high collective efficacy usually have a strong shared belief about their capabilities to perform NPD tasks successfully. Even when an NPD team has attributed own failure experience to internal causes, a high level of collective efficacy may prompt team members to reflect on experience and incrementally refine their NPD practice, which could lead to improved speed to market. However, their self-belief associated with a high level of collective efficacy may lead to their indifference in fundamentally challenging the status quo and coming up with radically new ideas required for product innovativeness. The findings also indicate that when collective efficacy is high, NPD teams are likely to fall back on their existing skills and capabilities derived from past success. While this approach may expedite the speed to market, it may not be so conductive to product innovativeness.

Similarly, collective efficacy's moderation effect on the relationship between vicarious learning from failure and speed to market is insignificant. One possible explanation based on attribution theory is that NPD teams with a high level of collective efficacy tend to develop a self-serving attributional bias that favors the group to which they belong to over others, and a low attributional globality bias (Harvey et al., 2014) that undermines learning from others' failure experience. Under the influence of such a cognitive process, NPD teams are more likely to perceive a low level of attributional globality of other teams' NPD failure and ignore their experience. This undermines the positive effect of vicarious learning from failure on speed to market and product innovativeness, to the extent that the effect of vicarious learning from failure on speed to market becomes insignificant. However, the damage to the effect of vicarious learning from failure on product innovativeness is even more severe because NPD teams are trapped in their complacency, and unwilling to absorb external, new knowledge required to develop innovative products.

It is worth noting that our survey data suggest that, when collective efficacy is at least 0.018 above the mean, the effect of experiential learning from failure on speed to market is significantly positive. However, when collective efficacy is at least 0.947 above the mean, the effect of vicarious learning from failure on product innovativeness is significantly negative. The results confirm the double-edged effect of collective efficacy: NPD teams' self-belief and confidence improves its chance of learning from failure experience to improve speed to market, but over confidence can lead to complacency, undermining their ability to learn from failure experience towards developing novel products. Thus, we have answered the recent call in the literature on learning from failure for more attention to the double-edged sword effect of collective efficacy (cf. Shepherd et al., 2016). Based on the above, our findings advance theory on team learning from failure in the NPD context, providing further nuance on the applications of SCT with sensemaking and attribution theories in the domain of learning from failure.

6.1 Theoretical Contributions

Our study contributes to the literature by taking a team-level lens (i.e., NPD team) and bringing together theoretical insights from SCT, sensemaking, and attribution theory to study the effects of learning from failure on new product performance. First, our study contributes to knowledge on learning from failure by elaborating on the heterogeneity in its effects on new product performance, especially within NPD teams, an overshadowed unit. The only existing research on learning from failure at the team level has primarily focused on its mediating role between top management team trust and decision quality (Hirak et al., 2012), as well as the relationship between the units' psychological safety climate and the units' performance (Carmeli et al., 2012). However, how NPD teams' experiential and vicarious learning from failure affect new product performance remains unclear. Such a knowledge gap is problematic as it restricts the ability of NPD team, particularly in the SMEs, to fully leverage the value of learning from failure to enhance new product performance.

Further, large organizations have dominated research on innovation failure (Forsman, 2021), the learning process (Argote et al., 2021) and learning from failure (e.g., Garzón-Vico et al., 2020; Madsen & Desai, 2010), while SMEs have been sidelined in research on learning from failure. Given that SMEs and larger organizations often follow different innovation strategies and learning behaviors (Manez et al., 2015), there is a need for further research on learning from failure in SMEs. Our study contributes to filling this gap in learning from failure by examining NPD teams in high-tech SMEs, rather than general teams primarily from large-scale ventures (Tjosvold et al., 2004). Thus, our study advances our knowledge on learning process in SMEs by shedding light on NPD teams' learning from failure.

Second, our theorizing based on SCT, and empirical evidence clarify the underlying influencing mechanisms of experiential and vicarious learning from failure on new product performance regarding the speed to market and product innovativeness. Previous research has presented distinct perspectives on the critical effects of either experiential learning from failure (e.g., Kim & Lee, 2020) or vicarious learning from failure (e.g., Kim & Miner, 2007) on organizational innovation. As a result, our understanding of the heterogeneous effects of learning from failure on innovation remains incomplete. This knowledge gap necessitates a scholarly call for further theoretical development and empirical evidence to explore the different types of learning from failure and their impact on innovation various levels within organizations (Rhaiem & Amara, 2021). While Carmeli and Dothan, (2017) delve into the effects of experiential and vicarious learning from failure on firm innovation, the existing literature falls short in comprehending the specific role of experiential and vicarious learning from failure in the NPD activity at the team level. Our study extends the research on the relationship between team learning from failure and new product performance by investigating how NPD teams adopt various forms of learning from failure to facilitate speed to market and product innovativeness. By doing so, we not only timely address the growing demand for research on the dynamics of team learning in the context of innovation (Harvey et al., 2023), but also advance the applicability of SCT in making accurate predictions about learning from failure and new product performance within high-tech SMEs' NPD teams.

Third, integrating SCT with sensemaking and attribution theory, our study explores the joint effects of learning from failure and collective efficacy in NPD teams on new product performance. Our study extends the research on new product performance by delving deeper into the team level at which learning from failure occurs and the sensemaking mechanism that drive post-failure learning and new knowledge creation. While existing literature has provided valuable insights into the significant impact of learning from failure on innovation (Rhaiem & Amara, 2021), "relatively little is known about the effect that key organizational members have on learning from failure and the impact of this learning on post-failure product innovation" (Tzabbar et al., 2023, p.2). To effectively address this research gap, our study specifically targets NPD teams and integrates learning from failure as a cognitive team process with collective efficacy as a motivational team process. This approach allows us to explore the joint impact of these factors on new product performance, shedding light on how they collaboratively enhance or hinder the NPD outcomes (Zhang & Wu, 2013).

Furthermore, our study also contributes novel insights to the literature on collective efficacy by illuminating its dual moderating effect within innovation failure research (Baxter et al., 2023). The extant literature on collective efficacy has primarily focused on its positive effects (e.g., Chen et al., 2019; Miyao et al., 2022). While prior research on collective efficacy has predominantly focused on its positive effects (e.g., Chen et al., 2019; Miyao et al., 2022), several scholars have emphasized the need to pay attention to its potential double-edged nature (e.g., Goncalo et al., 2010; Liu et al., 2015; Shepherd et al., 2016). However, theoretical explanations and empirical evidence within the context of innovation failure, especially NPD project failure, remain largely limited. Our findings, particularly revealing the negative impact of collective efficacy on the relationship between vicarious learning from failure and product innovativeness, shed light on this construct's potential value in elucidating the darker side of an innovation process. Consequently, our study contributes to a more comprehensive understanding of the multifaceted role of collective efficacy by bridging it with team learning from failure to foster new product innovation. This enriches our comprehension of the intricate complexities inherent in the innovation process.

6.2 Managerial Implications

Our paper has several managerial implications for NPD teams. First, as it is common for NPD teams to encounter failure in high-tech firms, we argue that failure should not be perceived as being totally negative and the end of the innovation journey; rather, it should be considered a learning opportunity (Rhaiem & Amara, 2021) and a chance to stimulate innovation (Forsman, 2021). Ongoing and post-project reviews are a highly effective mechanism for stimulating learning in NPD teams (Goffin & Koners, 2011). The NPD team should be open about project failure in their firms and explore further refinements and experiments to advance new product performance. Our results indicate that experiential and vicarious learning from failure facilitates new product performance. Thus, NPD leaders must simultaneously consider experiential and vicarious learning from failure and promote them in the NPD process. However, we would not promote NPD project failure just for the opportunity to learn from them but recommend that such failure be viewed as a normal part of innovation process.

Further, it is recognized that a high level of collective efficacy does not work in all environments regarding all aspects of innovation (Liu et al., 2015). Although our study has verified the negative moderating effect of collective efficacy on the relationship between vicarious learning from failure and product innovativeness, we do not advocate against a blanket approach to reducing collective efficacy. Consistent with the first implication, NPD teams should reflect on their collective efficacy and analyze the root cause of failed projects of their own and those of other teams in the firm. Similarly, external NPD teams could also be utilized to share their experience of failed NPD projects, which can reduce the risks of making the similar mistakes in the NPD process. Thus, NPD teams need to ensure that their collective efficacy can be fully utilized for the benefits of new product performance but be mindful of its negative effect when it comes to vicarious learning from failure on product innovativeness.

6.3 Limitations and Future Research

Like all studies, ours has limitations, providing opportunities for future studies. First, focusing on the team level, our study explains how learning from failure affects new product performance. However, prior research has discussed the variance in responses to failure and learning from failure at multiple levels (e.g., Dahlin et al., 2018). Despite some commonalities, these actors have possible differences and even competing interests. For example, perceptions of project failure likely differ between the primary decision-maker accountable for the outcome and the project team members (Shepherd et al., 2014). Future research can adopt a multilevel perspective to explore how learning from failure affects new product innovation across different levels. For instance, based on the team-as-resource perspective and archival data, Wilhelm et al. (2019) further elaborate that employees are likelier to learn from their failure experience when they perceive medium-to-high levels of psychological safety from their team, particularly with a well-developed transactive memory system.

Second, our study only focuses on the effects of team learning from failure on new product performance. However, several scholars (e.g., Garzón-Vico et al., 2020; Diwas et al., 2013; Lapré & Cravey, 2022; Madsen & Desai, 2010) have argued that we should simultaneously consider both failure experience and success experience to fully understand the critical role of learning in innovation activities. Future studies can shed light on the nature of prior experience and the trajectory of project failure in the NPD process.

Third, our study uses data collected at two time points from multiple respondents. However, we cannot entirely rule out the reverse causality. Since learning from failure is regarded as a continuous influencer of innovation performance (e.g., Carmeli & Dothan, 2017; Danneels & Vestal, 2020; Yu et al., 2014), longitudinal designs are recommended to track the dynamics of team learning and its influence on innovation (e.g., Harvey et al., 2023).

Finally, our study is based on a single region; therefore, conclusions may be specific to the nature of the sample firms. Future research can collect data from wider geographical areas to increase the generalizability of findings. Emerging research has pointed out that a range of institutional factors can impede or enhance subsequent learning and performance (e.g., Lee et al., 2022), such as the stigmatization of entrepreneurial failure (Simmons et al., 2014) and social costs of business failure (Lee et al., 2021), which is a promising direction.

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Declarations

Conflict of interest None.

Appendix

Table 3 Measurements

Items	Standardized loading	t-value
Collective efficacy (α = 0.833; CR = 0.902; AVE = 0.650)		
C1. This NPD team has above average ability	1.000[a]	
C2. This NPD team is poor compared to other teams doing similar work (reverse-coded)	0.867	10.990
C3. This NPD team is not able to perform as well as it should (reverse-coded)	0.888	11.942
C4. The members of this NPD team have excellent job skills	0.825	10.513
C5. Some members of this NPD team should be fired due to lack of ability (reverse-coded)	0.961	13.188
C6. This NPD team is not very effective (reverse-coded)	0.883	13.141
C7. Some members in this NPD team cannot do their jobs well (reverse-coded)	0.855	11.762
Experiential learning from failure (α = 0.909; CR = 0.793; AVE = 0.439)		
E1. After a failed experience, a question such as "why do we do the things in such and such a way" is fully appreciated in our NPD project team	1.000[a]	
E2. When a team member makes a mistake, colleagues in the NPD project talk to him or her, not for the purpose of blaming him or her, but rather for the value of learning	0.889	6.814
E3. When team members make a mistake, they inform the relevant project leaders to enable others to learn from it	0.948	7.107
E4. When a problem concerning the lack of required resources to complete a task is raised, our team members provide an immediate solution, but also inform the management and the relevant NPD projects about the problem	0.978	6.708
E5. In our NPD project team, when something goes wrong, team members are encouraged to ask questions such as "is there a better way to produce the new product or provide the service."	0.960	7.356
Vicarious learning from failure (α = 0.875; CR = 0.869; AVE = 0.570)		
V1. We constantly look at failures of other NPD projects in the firm to gain new insights into our own NPD processes	1.000[a]	
V2. When other NPD projects in the firm experience a failure, we take notice and develop a deep awareness of why it emerged and the implications for our NPD project	0.908	10.118
V3. When other NPD projects in the firm experience a failure we ask, "why things are done in such and such a way"	0.916	9.618
V4. We regularly talk to our suppliers and customers to learn about failed experiences of other NPD projects in the firm	0.797	8.961
Product innovativeness (α = 0.934; CR = 0.906; AVE = 0.582)		
P1. Offering new ideas in our industry	1.000[a]	
P2. Challenging to existing ideas in our industry	0.716	9.110
P3. Very novel in our industry	0.855	10.048
P4. Creative	0.946	12.007
P5. Interesting	0.692	8.078
P6. Capable of generating ideas for other products	0.887	11.963
P7. Promoting fresh thinking	0.995	12.135
Speed to market (α = 0.913; CR = 0.925; AVE = 0.723)		
S1. Much faster than we expected	1.000[a]	
S2. Faster than the industry norm	0.903	13.934
S3. Far ahead of our time goals	0.871	12.637
S4. Faster than our typical product development time	0.989	14.055

[a]Fixed factor loading. α = Cronbach's alpha, CR = Composite Reliability, AVE = Average Variance Extracted

Model fit: $\chi^2 = 353.535$, d.f. = 289; DELTA2 = CFI = 0.972; TLI = 0.968; RMSEA = 0.038; p = 0.006.

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