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Giving up learning from failures? An examination of learning from one's own failures in the context of heart surgeons

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Abstract

Research Summary: We reassess existing theories on individual failure learning and propose an inverted-U-shaped relationship between an individual's accumulated failures and learning, based on a theoretical framework that jointly considers the opportunity, motivation, and perceived ability to learn. Using data on 307 California-based cardiothoracic surgeons who performed coronary artery bypass graft surgeries in 133 hospitals between 2003 and 2018, we find compelling evidence that individuals reach a threshold at which they discontinue learning from their own failures. We also find that this threshold is higher for surgeons who had higher perceived ability to learn. This article aims to shed new light on the relationship between individuals' failure experience and their learning, and advance our understanding of the microfoundations of organizational learning, an important basis of firm performance.

Managerial Summary: This article explores how individuals learn from their own failures. Contrary to prior

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theories, we propose a non-monotonic relationship between accumulated failures and learning: as a function of failures, an individual's performance will initially increase, then taper off, and finally decrease. Analyzing data on 307 cardiothoracic surgeons operating coronary artery bypass graft surgeries, we find such an inverted-U-shaped pattern. Notably, surgeons with higher perceived ability to learn—those with elite training, certified expertise, and specialization in patient care—reached the tipping point later than their counterparts. Our findings imply that repeated failures can have both beneficial and harmful impacts on individuals' learning processes, and therefore, both impacts must be simultaneously considered for understanding and improving individuals' performance.

KEYWORDS

individual learning; individual-level heterogeneity in learning; learning from failures; microfoundations of organizational learning; opportunity, motivation, and perceived ability to learn

1 | INTRODUCTION

Individual learning is an important microfoundation of organizational learning (Argote, 2013; Argote et al., 2021; Kim, 1998), and individuals' own failure experiences have been highlighted as important sources of individual learning (Ellis & Davidi, 2005; Wilhelm et al., 2019). Failures have been defined as undesired performance outcomes that deviate from expected organizational goals (Dahlin et al., 2018). In line with the experiential learning literature (Argote & Miron-Spektor, 2011; Kolb, 2015; Levitt & March, 1988; Sitkin, 1992), researchers have often viewed failure cases as units of experience and theorized that accumulated failures will lead to learning and improved performance for individuals, and ultimately for organizations (Avgerinos et al., 2020; Dahlin et al., 2018; Desai, 2015). A close examination of the literature on this topic, however, reveals that theories and findings on individual learning from one's own failures are inconsistent.

Some research has found that individuals effectively learn from their own failures (e.g., Avgerinos et al., 2020; Ellis & Davidi, 2005; Wilhelm et al., 2019). These findings are consistent with theories that suggest that failures facilitate cognitive processes—such as seeking causal explanations—that lead to learning (Ellis & Davidi, 2005; Hastie, 1984; Louis & Sutton, 1991; Taylor, 1991; Wong & Weiner, 1981), and subsequently trigger actions of updating knowledge to avoid repeating similar failures in the future (Ellis et al., 2006; Zakay et al., 2004). However, other studies have found that individuals do *not* effectively learn from their own failures or even perform worse after experiencing them (Deichmann & Ende, 2014; Diwas et al., 2013; Eggers & Song, 2015; Eskreis-Winkler & Fishbach, 2019). The dominant theories in this stream of literature argue this is due to failures evoking negative emotions such as shame, embarrassment, helplessness, fear, burnout, and loss of self-esteem (Cannon & Edmondson, 2005; Dahl & Werr, 2021; Roulet, 2020; Seo et al., 2004; Shepherd & Cardon, 2009; Staw et al., 1981; Vogus et al., 2020; Zhao, 2011) or triggering attribution biases that lead to individuals disassociating themselves from their own failures (Diwas et al., 2013; Jordan & Audia, 2012).

Altogether, studies have revealed starkly contrasting findings and have provided different but compelling theories to explain these results. From an overarching theoretical standpoint, however, it is unlikely that failures trigger only processes conducive for learning and not those that prevent learning, and vice versa. Rather, these processes are likely to coexist but vary in their relative strengths, where one dominates the other under certain conditions. Understanding this dynamic process would be crucial to better predicting how a particular failure would affect learning. This understanding becomes especially important in contexts where failures carry high stakes, can occur repeatedly and accumulate over time, and significantly impact the emotions, motivations, and behaviors of constituents, ultimately influencing organizational performance. Such contexts include a variety of organizations, such as research laboratories (Khanna et al., 2016; Shepherd et al., 2011), manufacturing firms (Haunschild & Rhee, 2004; Maslach, 2016), and hospitals (Desai, 2015; Diwas et al., 2013; Lee et al., 2021).

In this article, we synthesize existing theories on the effect of individuals' own failures on their learning and propose a *non-monotonic* relationship between them: individuals' performance will initially increase, then taper off, and finally decrease as a function of failure experiences. Building on a theoretical framework on individuals' own failure learning that jointly considers the opportunity, motivation, and perceived ability to learn from these failures (cf., Dahlin et al., 2018), we first propose that there will be an inverted-U relationship between one's own accumulated failures and their learning due to opposing effects of the opportunity and motivation to learn. Then, we propose that this relationship will be moderated by an individual's perceived ability to learn.

We test our hypotheses using data on 307 California-based cardiothoracic surgeons who performed isolated coronary artery bypass graft (CABG) surgeries in 133 hospitals between 2003 and 2018. In this context, failures are patient deaths resulting from CABG surgeries, and individual learning is captured through improvements in surgeons' surgery performance after such experiences. Our results confirmed the inverted-U-shaped relationship between individuals' own accumulated failures and individual learning; surgeons' performance increased as a function of their accumulated failures up to a point but then decreased afterward. We also found that this inflection point came later for surgeons who were hypothesized to have higher perceived abilities to learn—namely those with elite training, with certified expertise, and specialized in patient care.

Our study makes important contributions to several streams of literature. First, by developing and testing a revised theoretical model on individual failure learning, we contribute to the literature on individual failure learning in organizations (Avgerinos et al., 2020; Diwas et al., 2013; Lapré & Cravey, 2022; Shepherd et al., 2011; Wilhelm et al., 2019). Particularly, we theorize and show a novel inverted-U-shaped relationship between individuals' own accumulated failures and learning. Our results suggest that accumulating one's own failures simultaneously triggers both forces that increase the opportunity to learn and decrease the motivation to learn; thus, learning outcomes will depend on which force is dominating. Second, our study also has important implications for the literature on organizational learning (Argote, 2013; Argote et al., 2021; Argote & Miron-Spektor, 2011). We find that even within the same organization, there is individual-level heterogeneity in the amount of one's own failure learning depending on an individual's qualifications or past experiences that shape their perceived ability to learn. Because organizational learning is influenced by the levels of learning achieved by individuals, our study highlights the need for greater attention to the antecedents of such individual-level heterogeneity. Finally, our study has implications for the organization design and strategic human capital literature, particularly in the areas of hiring and training. Especially, our results suggest that organizations can improve performance by hiring employees who are more resilient to repeated failures or training them to become so. Overall, the goal of our paper is to shed new light on the relationship between individuals' own failures and learning and to open up exciting opportunities for research on the microfoundations of organizational learning, an important basis of firm performance.

2 | THEORY AND HYPOTHESES

Failure learning has been defined as "the process by which individuals, groups, or organizations identify error or failure events, analyze such events to find their causes, and search for and implement solutions to prevent similar errors or failures in the future" (Dahlin et al., 2018, p. 254). Essentially, failure learning is a type of experiential learning that involves individuals, groups, or organizations learning from failure experiences. Although some experiential learning may occur somewhat unconsciously or automatically (Dutton & Thomas, 1984; Lapré et al., 2000), failure learning has been argued to require analytical learning—a process that involves active decision making that uses information about a prior experience to reshape future routines (Dahlin et al., 2018; Reason, 1990). In this regard, it is important to understand how individuals—the core decision makers in organizations—learn from their failures.

Intriguingly, the literature on individual learning from failure has shown contrasting results. On the one hand, some studies have found that individuals learn from their own failures. For example, in the context of Israeli soldiers, Ellis and Davidi (2005) found that individuals developed rich mental models of causal relationships between task inputs and outputs after their own failures. Similarly, Avgerinos et al. (2020) found that cardiothoracic surgeons went through a process of "sensemaking" after experiencing failures, which improved their performance over time. These findings parallel theories that argue that failures generate valuable information for learning and trigger cognitive processes or actions that help individuals update existing knowledge structures to improve performance (Ellis et al., 2006; Ellis & Davidi, 2005; Hastie, 1984; Louis & Sutton, 1991; Taylor, 1991; Wong & Weiner, 1981; Zakay et al., 2004).

On the other hand, researchers have found that individuals do not effectively learn from their own failures or even perform worse after experiencing them. For example, in a lab experiment, Eskreis-Winkler and Fishbach (2019) found that individuals could not learn from failure feedback because they "tuned out" from learning to protect their egos (see also Roulet, 2020). Diwas et al. (2013) also found that cardiothoracic surgeons did not learn and even performed worse after their own surgical failures due to self-serving attributions. Similarly, Eggers and Song (2015) found that serial entrepreneurs whose ventures failed tended to blame the external environment and moved on to creating a subsequent venture in a different industry instead of trying to learn from their failures. Altogether, these findings are consistent with the theories suggesting that failures trigger negative emotions (Cannon & Edmondson, 2005; Seo et al., 2004; Shepherd & Cardon, 2009; Staw et al., 1981; Vogus et al., 2020; Zhao, 2011) or attribution biases (Diwas et al., 2013; Jordan & Audia, 2012), which lead individuals to disengage from learning from their own failures.

Though these prior results provide valuable insights independently, they collectively suggest that existing theories and findings are incomplete. Notably, recent studies have started to examine the boundary conditions under which individuals are more likely to learn from their own failures (e.g., Avgerinos et al., 2020; Lapré & Cravey, 2022; Shepherd et al., 2011; Wilhelm et al., 2019). For example, Avgerinos et al. (2020) found that individuals may not learn from their recent failures because it takes time to make sense of them. Shepherd et al. (2011) theorized that learning from one's own failures depends on individuals' ability to cope with failures and on organizational culture of failure tolerance. Wilhelm et al. (2019) found that employees are more likely to learn from their failures if they work in psychologically safe teams with well-developed transactive memory systems. Finally, Lapré and Cravey (2022) suggested that failure learning depends on the frequency of failures and whether an objective root-cause-analysis can be conducted on failures.

Overall, prior studies have advanced our understanding of individual failure learning; however, at least three important limitations remain. First, a large portion of studies on individual failure learning examine the effect of only a *single* failure on learning (Ellis et al., 2006; Shepherd et al., 2011; Wilhelm et al., 2019). Such research designs limit examining the effect of a failure in different ranges (low/moderate/high) of accumulated failures. Second, these studies often assume a single average effect of failures on learning without allowing for the potential heterogeneous effects of failures (Diwas et al., 2013; Ellis & Davidi, 2005; Lapré & Cravey, 2022; Zakay et al., 2004). This precludes the possibility that the positive and negative effects of failures on learning interact with each other to form other intricate patterns of learning, such as non-monotonic relationships between failure experiences and learning. Third, prior studies lack theorization and evidence about when and why failure learning rates vary for different individuals (with exceptions such as Shepherd et al., 2011). This is a large gap in the literature because organizations are comprised of individuals with different characteristics, which create heterogeneity in their learning patterns (Lee, 2019; Reagans et al., 2005). Altogether, addressing these limitations will enable a better understanding of the effects of individuals' own failures on learning.

In the next section, we synthesize the existing literature and develop a revised theory for the relationship between individuals' own accumulated failures and learning. Our theory is particularly applicable to contexts where failures have high stakes, occur repeatedly, accumulate over time, and significantly impact individuals' emotions, motivations, and behaviors. We develop our hypotheses in the context of cardiothoracic surgery, a highly pertinent setting, and empirically test them using data on surgeons who encounter repeated failures in the form of patient deaths.

2.1 | Individual learning from failures: An interplay of the opportunity, motivation, and ability

In a recent review of the literature on learning from failures, Dahlin et al. (2018) advised researchers to develop theoretically sounder frameworks by being mindful of the mechanisms that affect learning from failures. Especially, they suggested that an interplay of three factors—the *opportunity*, *motivation*, and *ability to learn*—will determine the effectiveness of one's learning from failures. The *opportunity to learn* is the scope and amount of information available for an individual to learn from failures; the *motivation to learn* refers to an individual's desire to put in efforts to learn from past failures and prevent future failures; the *ability to learn* is an individual's capacity to understand causes of failures and to find/implement solutions to prevent future failures.

Extending Dahlin and colleagues' framework, we theorize in the following sections that the main relationship between an individual's own accumulated failures and learning will be driven by an individual's *opportunity* and *motivation to learn*, and that this relationship will be moderated by their *perceived ability to learn*, particularly through its effect on their motivation to learn.

2.2 | Accumulation of failures and the opportunity and motivation to learn

We expect one's opportunity and motivation to learn to work in parallel but in opposite directions as individuals accumulate failures. As aforementioned, the opportunity to learn from failures refers to the scope and amount of information to learn from failures (Dahlin et al., 2018). In many organizational contexts, individuals experience comparable failures repeatedly (Lapré & Cravey, 2022). For example, in our study's empirical context, surgeons repeatedly experience patient deaths from surgeries. Although the types of failures are similar, the details of each failure differ. Thus, each new failure offers unique knowledge that can synergistically modify and extend the existing knowledge of these individuals, opening up opportunities for improving task performance.

Additional failures will provide useful learning opportunities especially in complex task environments of modern organizations where recent experience can continue to provide novel information. In our empirical context, surgeons constantly face new surgery techniques, changes in coordination patterns with other hospital members, advancements in hospital technologies, and increasing heterogeneity in patient conditions (Bakaeen, 2017; Bogdanovic et al., 2015; ElBardissi et al., 2012; Head et al., 2013; Kimmaliardjuk et al., 2015; Sellke et al., 2010; Tørring et al., 2019). In these contexts, failures occurring at different points in time can increase individuals' quantity of knowledge by providing knowledge that they lacked or increase the quality of knowledge by updating incomplete or incorrect knowledge (Lai, 2021). In this regard, we expect that the opportunities to learn will increase as failures accumulate.

At the same time, and in contrast, we expect additional units of failure experience to decrease individuals' *motivation to learn* from their own failures. Earlier, we defined the motivation to learn as the desire to put in efforts to learn from failures and to improve subsequent performance. Prior literature has suggested that failures are important motivators for drawing lessons from experiences (Ellis & Davidi, 2005; Sitkin, 1992; Weiner, 1985), and that negative outcomes will trigger search for alternative solutions (Sitkin, 1992; Weiner, 2000; Zakay et al., 2004). Thus, when individuals encounter initial failures in their tasks, we expect them to be highly motivated to analyze and draw lessons from them to enhance their subsequent performance. This motivation to learn would be particularly high in contexts like ours (i.e., cardiothoracic surgery), where failures are high-stakes events (i.e., patient deaths) that are sought to be avoided.

However, as these failures repeat and accumulate over time, the initial high motivation to learn from one's own failures is likely to diminish. Prior literature has found that failures, especially repeated failures, dampen the motivation to learn, due to negative emotions triggered by failures (Shepherd et al., 2013). In specific, individuals involved in failures often experience emotions such as embarrassment, fear, frustration, pain, anxiety, disappointment, depression, and a loss of self-esteem (Dahl & Werr, 2021; Edmondson, 2004; Roulet, 2020; Shepherd et al., 2011). These emotions are particularly intense when the consequences of failures are severe, and high levels of these emotions accumulated through repeated failures would ultimately hinder the motivation to learn from one's own failures (Seo et al., 2004; Zhao, 2011).

Furthermore, repeated failures can trigger attribution biases, which can also reduce the motivation to learn from one's own failures. For example, Diwas et al. (2013) found that cardiac surgeons learned from others' repeated failures but not from their own. The authors explain that this is due to individuals attributing others' failures to controllable factors such as effort and their own failures to uncontrollable factors such as bad luck (see also Weiner, 1974, 2000). When a failure is perceived as uncontrollable, the motivation to learn from it will be reduced (Bandura, 1977; Lapré & Cravey, 2022). Attribution bias is also related to individuals feeling threats to their self-image when they fail (Eskreis-Winkler & Fishbach, 2019; Jordan & Audia, 2012; Roulet, 2020). To preserve a positive self-image, when individuals experience repeated failures, they engage in self-enhancing behaviors such as ignoring failures and taking on lower performance standards (Audia & Brion, 2007; Eskreis-Winkler & Fishbach, 2019; Jordan & Audia, 2012).

Taken together, we posit that two latent mechanisms, the increasing opportunities to learn and the decreasing motivation to learn as individuals accumulated failures will interact to form an inverted-U-shaped relationship between individuals' own accumulated failures and learning. As discussed earlier, failure learning requires analytical learning (Dahlin et al., 2018; Reason, 1990). Hence, to effectively learn from their own failures, individuals will need sufficient levels of both the opportunity and motivation to learn.[1] At low levels of individuals' own accumulated failures, the motivation to learn will be high, but the opportunity to learn will be low because individuals would not have gathered enough information about the different causes of failures. Thus, despite high motivation, we expect an individual's learning performance to be relatively low in this range. However, as more information is acquired through accumulating failures, the opportunity to learn will increase. Although the motivation to learn may not be as high as initial periods due to the negative emotions and attribution bias triggered by the increasing number of failures, we still expect individuals to have sufficiently high motivation to learn during this period, especially since the focal task in hand is important (Zhao, 2011). Thus, we expect individuals' learning to be highest at moderate levels of accumulated failures. However, once the number of accumulated failures surpasses a certain point, we argue that individuals' motivation to learn from their own failures will be impaired by the overwhelming effect of negative emotions and attribution biases. This will result in individuals "giving up" on learning from their own failures. Although this cessation of learning could merely lead to performance stagnation, in fact, Diwas et al. (2013) showed that the lack of learning leads to *decreasing* individual task performance over time. This is because individuals are likely to continue behaving in ways that led to failures and not modify or extend their existing knowledge although the task environment around them is evolving (Diwas et al., 2013; Staw, 1981). Consistent with these arguments, we expect that individuals' learning performance will deteriorate at high levels of accumulated failures. Table 1 summarizes these arguments.

In our context of cardiothoracic surgery, failures are patient deaths resulting from surgery. These failures are high-stake events that occur repeatedly, accumulate over time, and have

[1]In other words, we are theorizing a multiplicative relationship (i.e., interaction) rather than an additive relationship because no learning will occur if either the opportunity or the motivation equals 0 (Haans et al., 2016).

TABLE 1 Summary of (1) how the opportunity and motivation to learn from one's own failures change as a function of accumulated failures and (2) how the two mechanisms interact to affect an individual's learning from those failures.

One's own accumulated failures	Opportunity × motivation to learn from one's own failures	Learning
Low	Low opportunity × high motivation	Low
Moderate	Moderate opportunity × moderate motivation	Peak
High	High opportunity × low motivation	Low

significant impacts on the operating surgeon's emotions, motivations, and behaviors (Desai, 2015; Diwas et al., 2013; Huckman & Pisano, 2006). Therefore, we hypothesize:

> **Hypothesis H1.** There will be an inverted-U-shaped relationship between a surgeon's own accumulated failures and learning, such that a surgeon's subsequent surgery performance will improve as a function of their own accumulated failures up to a point but will deteriorate once that point is passed.

2.3 | The moderating effect of individuals' perceived ability to learn

While we anticipate that all surgeons in our context will eventually reach a point where their motivation to learn diminishes (Zhao, 2011), some of them may reach this point later (i.e., at a higher level of accumulated failures) than others. We posit that individuals with higher *perceived abilities to learn*—those who regard themselves to be better than others at understanding the causes of their own failures and finding and implementing solutions to prevent them in the future—will reach that point later than their counterparts. This is because they will not only have higher initial motivation to learn but will also be less susceptible to negative emotions and attribution biases from repeated failures, enabling them to sustain high levels of motivation for longer periods. We build our arguments off the concept of *self-efficacy*, the "judgments of how well one can execute courses of action required to deal with prospective situations (Bandura, 1982, p. 122)." Because individuals put more effort when they believe "I can do this" (Bandura, 1977), perceived ability to learn will be an important driver of an individual's persistence and motivation to learn (Cook & Artino Jr, 2016; Zimmerman, 2000). In our context, surgeons who are more competent in surgeries are considered as having higher perceived abilities to learn; this is because task competence is often a result of possessing strong learning capabilities (see Cook & Artino Jr, 2016).

Importantly, our theory does not require individuals to actually have high ability to learn; rather, their mere beliefs that they are competent in learning from their own failures are sufficient for our proposed moderation effect, as such beliefs will positively affect their motivation to learn and trigger more persistent learning behaviors (Ajzen, 1991). In the next paragraphs, we elaborate on why higher perceived ability to learn will positively moderate the relationship between individuals' own accumulated failures and learning.

To begin with, individuals with higher perceived ability to learn will have higher baseline motivation to learn than their counterparts. Particularly, the social-cognitive theories of motivation (e.g., Bandura, 1986, 1997; Pajares, 2008; Schunk, 1991; Zimmerman, 2000) suggest that individuals' pursuit of their learning goals hinges on their beliefs about their capabilities, values, and interests. Similarly, expectancy-value theories (e.g., Eccles & Wigfield, 2002; Wigfield & Eccles, 2000) propose that the expectancy of success—a future-oriented belief in one's ability to accomplish an anticipated task—predicts both engagement in learning activities and learning achievement. Consequently, individuals who have stronger beliefs in their ability to execute a given task are likely to pursue higher learning goals. For example, Zimmerman et al. (1992) found that students with high self-efficacy set higher academic goals than those with low self-efficacy. The literature on goal-setting theory has suggested that pursuing higher (harder) goals will increase motivation, as long as those goals are not impossible to achieve (Locke & Latham, 1990, 2002, 2006). This implies that individuals with higher perceived ability to learn will start off with a larger "stock" of motivation to learn from their own failures, which will be depleted later than those with lower perceived ability as their failures accumulate.

Second, we expect the motivation of individuals with higher perceived ability to learn to be less attenuated by the negative emotions triggered by their own failures than those of individuals with lower perceived ability to learn. Especially, error management research has shown that individuals with high self-efficacy have less negative emotional reactions to errors (Rybowiak et al., 1999), exhibiting the attitude of "no worries, can do" (Seckler et al., 2021). Prior studies have also suggested that individuals will persist through failures, despite feeling negative emotions, particularly when they feel that the causes of failures are fixable and under control (Bandura, 1997; Cook & Artino Jr, 2016; Lapré & Cravey, 2022; Zimmerman & Schunk, 2006). For example, in the context of Formula 1 racing, Lapré and Cravey (2022) found that despite the frustration and disappointment car racers feel when they cannot complete a race due to a car failure, they learn from these failures because they and their teams believe they are capable of objectively analyzing the root cause of the problem and fixing the car for the next race.

Finally, we anticipate that these individuals will be less susceptible to attribution biases after their own failures. As discussed earlier, individuals with stronger beliefs in their abilities to execute a task will pursue higher goals. The education literature has shown that individuals who set higher goals are less likely to attribute their worst marks to uncontrollable causes, such as teachers' skills, compared to their counterparts (Walkey et al., 2013). This implies that individuals with high perceived ability to learn will be more likely to attribute their own failures to controllable factors, such as their own effort (Weiner, 1985). Mirroring these findings, the medicine literature also notes that, on average, extensively trained experts are less likely to exhibit overconfidence and erroneously believe their diagnoses are correct compared to novices (Berner & Graber, 2008). Importantly, attribution theory suggests that individuals will continue to be motivated to learn from their own failures when they attribute them to internal and controllable factors (Diwas et al., 2013; Lapré & Cravey, 2022; Park et al., 2022).

In sum, we expect individuals with higher perceived ability to learn to persist longer in learning from their own failures than their counterparts through the mechanisms explained above. Hence, we predict that the inverted-U-shaped relationship between one's accumulated failures and learning hypothesized in H1 will shift to the right for these individuals, as depicted in Figure 1.[2]

In our context of cardiothoracic surgeons, we expect at least three types of surgeons to have higher perceived ability to learn than others: those (1) with elite training in cardiothoracic surgery, (2) with certified expertise in surgery, and (3) who specialize in patient care instead of other tasks (e.g., teaching). This conceptualization is consistent with Greenwood et al. (2019)

[2]Please see Haans et al. (2016) for the moderation of U-shaped relationships. Moderation could result from either a slope or intercept change in one of the latent processes underlying the U-shaped relationship. In our study, we are proposing that the moderation mainly occurs through the intercept change in the motivation to learn from failures.

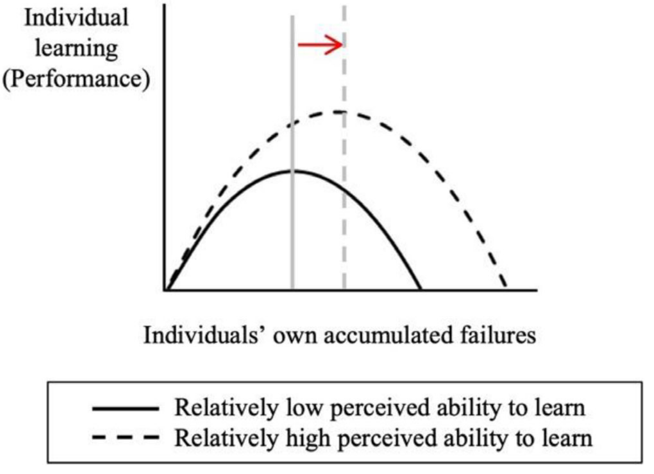

FIGURE 1 Illustration of the relationship between individuals' own accumulated failures and individual learning based on individuals' perceived ability to learn.

who proposed that cardiologists with elite education, board certification, and extensive task experience possess higher expertise than their counterparts.[3] Due to their confidence and skills in the task, and hence their elevated perceived ability to learn in the task, we argue these surgeons will maintain the motivation for learning from their own failures for a longer period than others.[4] Ultimately, we predict that these surgeons will cease learning from their own failures at a significantly later point (i.e., at higher levels of accumulated failures) than surgeons who perceive themselves to have lower ability to learn from their failures. Hence, we hypothesize:

> **Hypothesis H2.** The inflection point of the inverted-U-shaped relationship hypothesized in H1 will form at a later point for surgeons (a) with elite education, (b) with certified expertise, and (c) who specialize in patient care, compared to their counterparts.

3 | METHODS

3.1 | Empirical context, data, and sample

3.1.1 | Quantitative data

We test our hypotheses using comprehensive biannual data on cardiothoracic surgeons performing isolated CABG surgeries in California, reported by the California Department of Health

[3]Our three proxies loaded onto a common factor in an exploratory factor analysis using the Kaiser criteria.
[4]Notably, because confidence and skills in a task have been found to be highly correlated with a physician's perceived ability to learn within the task in healthcare settings (Cook & Artino Jr, 2016), they are operationalized similarly in our context. However, in other settings, perceived ability to learn may have to be captured independently. It is also worth noting that some studies have found that greater task experience may result in cognitive biases such as overconfidence or fear of failure, which could impede learning from failures (e.g., Gaba et al., 2023). However, such tendencies have been found to be weak in healthcare settings (Berner & Graber, 2008; Shepherd et al., 2019).

Care Access and Information (HCAI). Our context is favorable for testing our theory for several reasons. First, high-stake failures that have significant impacts on individuals' emotions, motivations, and behaviors can be objectively measured using an established measure in the literature, namely *patient deaths* resulting from the surgeries (Desai, 2015; Diwas et al., 2013; Huckman & Pisano, 2006). Similarly, learning performance can be measured by examining improvements in subsequent task performance (i.e., surgery performance) following failure experiences (Argote, 2013; Argote et al., 2021; Dahlin et al., 2018). Second, individuals tend to experience multiple failures across time, allowing us to test the non-monotonic relationship between accumulated failures and learning. Third, we have access to fine-grained microdata on each surgeon's background (e.g., education, certification, and specialization), enabling us to capture how different types of individuals learn from their own failures in distinct ways.

We merged 10 data sources to build a panel dataset. First, we created the data of surgeons who performed isolated CABG surgeries in California. As it was mandatory for hospitals to submit this data to the HCAI, the data represented the entire population of 493 surgeons who performed isolated CABG surgeries in California from 2003 to 2018 (4446 observations). After creating lagged variables, our final sample included 2808 observations of 307 surgeons who experienced 4216 failures in 133 hospitals for eight periods from 2003 to 2018 (see Appendix A for details).

Next, we collected data for moderators and control variables. To test H2a (elite education), we collected data on each surgeon's cardiothoracic training hospitals. This data was hand collected from multiple websites (see Appendix B for details). We identified elite cardiothoracic training hospitals using the U.S. News & World Report's Best Hospitals for Cardiology and Heart Surgery list. This ranking was determined based on objective and quantifiable data on hospitals' patient care quality (e.g., surgery performance). To test H2b (certified expertise), we collected data on surgeons' Fellow of the American College of Surgeons (FACS) status through the websites listed in Appendix B. FACS designation was given only to surgeons who met exceptional qualification standards. To test H2c (specialization), we retrieved mandatory surveys filled out by surgeons, from the Medical Board of California website, which included information on how each surgeon allocated time across different tasks (e.g., patient care, research, etc.). Just as in universities where some faculty focus on research and some on teaching, some surgeons specialize in patient care (surgeries) over other tasks. We expect these surgeons who specialize in patient care to be better at understanding causes of surgical failures than others who specialize in other domains, and thus, will be more willing to learn from them. Finally, we used the HCAI's annual hospital utilization reports and the American Hospital Association's annual surveys to create control variables.

3.1.2 | Qualitative data

To supplement our quantitative data, we also held 30-min to 1-h long semi-structured interviews with 25 surgeons and physicians affiliated with 17 medical centers. These interviews were aimed at collecting qualitative data to gain deeper insights into our empirical context and corroborate the validity of our measures and findings (Appendix C provides a summary of the method, the interview format, and the informants). In addition to this interview data, we extensively reviewed books authored by practicing cardiothoracic surgeons and qualitative studies conducted in the context of healthcare to corroborate our quantitative findings.

3.2 | Measures

3.2.1 | Dependent variable

Following prior literature, we measured *learning from failures* as an increase in a surgeon's performance in the period after experiencing patient deaths (Desai, 2015; Diwas et al., 2013). Patient risk-adjusted mortality rate is one of the most commonly used surgical performance measures (Diwas et al., 2013; Huckman & Pisano, 2006). We captured each surgeon's performance by reverse coding patient risk-adjusted mortality rate into *patient risk-adjusted survival rate* (*RASR*), computed by subtracting patient risk-adjusted mortality rate from 1 (RASR = 1 means patient survival rate is 100%). To mitigate the risk of reverse causality, we measured *surgeons' patient RASR* at period $t + 1$ and the independent and control variables at period t.

3.2.2 | Independent variables

Following the literature on learning from failures, we measured *surgeon's own accumulated failures* in a focal hospital as the number of patient deaths experienced by a surgeon in a focal hospital up to period t (Desai, 2015; Diwas et al., 2013).[5] Importantly, all accumulated experience variables in our study (including control variables) were discounted using a discount factor between 0 and 1, to take into account potential knowledge depreciation (Huesch, 2009) and changes in the intensity of negative emotions toward failures (Avgerinos et al., 2020).[6] We used the best-fit method used in prior studies to calculate the appropriate discount factor for each experience variable (Argote et al., 1990; Desai, 2020) (see Appendix D for a note on calculating the discount factor). For *surgeon's own accumulated failures*, the discount factor was .90. To test the inverted-U-shaped relationship hypothesized in H1, we included this variable and the squared term of it (termed "*surgeon's own accumulated failures sq*" hereafter).

To test H2a, we created interaction terms between *elite education* and the single and squared term of *surgeon's own accumulated failures*. Cardiothoracic surgeons follow a standardized training path of medical school, general surgery residency, and cardiothoracic residency. Some also pursue advanced cardiothoracic fellowships. Our interviewees noted that surgeons receive their most important hands-on training during their cardiothoracic residency and fellowship, and thus the quality of training received at this level will greatly impact a surgeon's belief about their abilities to learn. Following prior research (Burke et al., 2007; Greenwood et al., 2019), we used the U.S. News & World Report ranking and coded *elite education* as 1 if a surgeon completed a cardiothoracic surgery residency or fellowship at the top 30 best hospitals for cardiology and heart surgery, and 0 otherwise.[7]

To test H2b, we created interaction terms between *certified expertise* and the single and squared term of *surgeon's own accumulated failures*. We coded *certified expertise* as 1 if surgeons had a FACS designation in period t, and 0 otherwise. As aforementioned, to become a FACS,

[5]We measured a surgeon's accumulated own failures at *each* hospital rather than across *all affiliated* hospitals because individuals' task experiences have been suggested to be hospital-specific in this context (Huckman & Pisano, 2006).
[6]The discount factor of 0 means that the effect of the experience depreciates immediately and 1 means that the effect of the experience does not depreciate over time.
[7]These were hospitals ranked top 30 at least once during 2011–2014. The year 2011 was the first year that we had public access to the ranking data and 2014 was the latest cardiothoracic training completion year for our sample surgeons.

surgeons had to meet exceptional standards set by the College, and thus we expect those with this designation to have higher perceived ability to learn from failures than surgeons who do not.

To test H2c, we created interaction terms between *specialization* and the single and squared term of *surgeon's own accumulated failures*. Surgeons engage in various tasks including patient care, research, teaching, administration, and telemedicine. We operationalize surgeons who spent most time on patient care among these tasks (i.e., those who were specialized in surgery) as those with higher perceived ability to learn from failures. The surgeons in our data mandatorily reported to the Medical Board of California every 2 years how much time they spent on each task. We coded *specialization* as 1 if surgeons spent most time on patient care, and 0 otherwise.[8]

3.2.3 | Control variables

We controlled for various individual and hospital level characteristics that can affect surgeons' performance, including *surgeon's accumulated isolated CABG surgeries*, *surgeon's accumulated others' failures*, *surgeon's average surgery complexity*, *(surgeon's) multiple hospital affiliation*, *hospital's accumulated isolated CABG surgeries*, *hospital's accumulated inpatient surgeries*, *hospital's number of surgeons*, *hospital's trauma center*, *hospital's cardiac ICU*, *teaching hospital status*, *surgeon turnover*, and *number of hospitals in region* (see Appendix E for details on the construction of these variables). Table 2 reports the descriptive statistics and correlations for all the variables included in our analyses.

3.3 | Econometric models

Since our dependent variable (i.e., *surgeon's patient RASR*) is bounded by 0 and 1, we test our hypotheses using fractional logit regression models (Papke & Wooldridge, 1996). These log-linear models are most appropriate for our data, as some surgeons started accumulating surgery (and failure) experiences before the start of our data. Log-linear learning models have been used to yield unbiased coefficients when experience variables were left-censored in learning curve studies (Diwas et al., 2013; Lapré & Tsikriktsis, 2006). Equation (1) shows the model for testing H1:

$$ln\left[\frac{E(Patient\ RASR_{i,h,t+1}\,|\,\boldsymbol{X})}{1-E(Patient\ RASR_{i,h,t+1}\,|\,\boldsymbol{X})}\right]$$

$$=\beta_0+\beta_1 accum.own\,failures_{i,h,t}+\beta_2 accum.own\,failures_{i,h,t}{}^2$$

$$+\beta_3\boldsymbol{S_{i,t}}+\beta_4\boldsymbol{H_{h,t}}+\lambda_{i,h}+\tau_t+u_{i,h,t} \tag{1}$$

In this equation, i, h, and t indicate the surgeon, hospital, and period, respectively. The dependent variable was measured at period $t+1$ and the independent and control variables were measured at period t to mitigate reverse causality. $\boldsymbol{S_{i,t}}$ and $\boldsymbol{H_{h,t}}$ are vectors of surgeon- and

[8]We used responses from 2010 to 2016 as 2010 was the earliest available data. We imputed 2010 survey values for periods before 2010. The response rate was 96%. Missing values were coded as spending zero hours on the task. H1 and H2c were robust to dropping missing observations or using a measure based on a single-year response (year 2018).

TABLE 2 Descriptive statistics and correlations ($n = 2808$).

	Variables	Mean	SD	Min	Max	1	2	3	4	5	6
1	Surgeon's patient RASR	0.974	0.060	0.000	1.000						
2	Surgeon's accum. own failures	4.590	5.459	0.000	36.869	0.017					
3	Elite education	0.535	0.499	0.000	1.000	0.040	0.001				
4	Certified expertise	0.595	0.491	0.000	1.000	0.001	0.053	0.032			
5	Specialization	0.935	0.246	0.000	1.000	−0.017	0.088	0.045	0.069		
6	Surgeon's accum. iso-CABG surgeries	221.62	142.35	1.000	771.44	0.083	0.424	0.052	0.153	0.145	
7	Surgeon's accum. others' failures	5.209	5.569	0.000	61.000	0.010	0.089	0.018	−0.105	0.032	0.108
8	Surgeon's average surgery complexity	0.026	0.015	0.002	0.463	0.023	0.040	0.008	0.030	0.029	−0.032
9	Multiple hospital affiliation dummy	0.771	0.420	0.000	1.000	−0.004	−0.169	−0.067	0.056	0.087	0.223
10	Hospital's accum. iso-CABG surgeries	1070.3	1091.4	2.000	7669.6	0.055	0.411	0.084	−0.074	0.032	0.277
11	Hospital's accum. inpatient surgeries	35,093	28,561	202.0	192,706	0.037	0.130	0.108	0.020	−0.123	−0.118
12	Hospital's number of surgeons	5.340	2.180	1.000	13.000	0.011	−0.110	0.060	−0.033	−0.053	0.039
13	Hospital's trauma center dummy	0.312	0.463	0.000	1.000	−0.007	−0.009	0.031	0.007	−0.101	−0.101
14	Hospital's cardiac ICU dummy	0.755	0.430	0.000	1.000	0.029	0.086	0.074	−0.018	0.005	−0.016
15	Teaching hospital dummy	0.450	0.498	0.000	1.000	0.028	−0.008	0.007	0.068	−0.070	−0.145
16	Surgeon turnover	0.162	0.175	0.000	0.833	−0.035	−0.048	−0.079	−0.020	−0.032	−0.038
17	Number of hospitals in region	18.274	7.726	8.000	28.000	0.010	−0.120	0.024	−0.007	−0.087	−0.207
	Variables (continued)	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
8	Surgeon's average surgery complexity	0.049									
9	Multiple hospital affiliation dummy	−0.061	0.034								
10	Hospital's accum. iso-CABG surgeries	0.343	−0.119	−0.177							
11	Hospital's accum. inpatient surgeries	−0.054	−0.101	−0.309	0.420						
12	Hospital's number of surgeons	0.407	0.030	0.085	0.279	0.165					
13	Hospital's trauma center dummy	−0.049	−0.002	−0.139	−0.035	0.325	0.050				

TABLE 2 (Continued)

	Variables (continued)	7	8	9	10	11	12	13	14	15	16
14	Hospital's cardiac ICU dummy	0.139	−0.027	−0.135	0.219	0.257	0.137	0.139			
15	Teaching hospital dummy	0.048	−0.006	−0.160	0.189	0.410	0.210	0.268	0.222		
16	Surgeon turnover	0.006	0.003	0.015	−0.044	−0.010	0.287	0.046	0.021	0.030	
17	Number of hospitals in region	−0.112	0.018	−0.012	−0.103	0.040	0.027	−0.070	−0.083	0.093	0.042

hospital-level control variables. We also included surgeon-hospital dyad fixed effects ($\lambda_{i,h}$) and period fixed effects (τ_t). We clustered the standard errors by surgeon-hospital dyads. In this model, H1 will be supported if *surgeon's own accumulated failures* (β_1) has a positive coefficient and *surgeon's own accumulated failures sq* (β_2) has a negative and statistically meaningful coefficient (Haans et al., 2016). $-\beta_1/2\beta_2$ is the inflection point at which surgeons cease learning.

Equation (2) shows the model that includes the interaction terms for testing H2a–c:

$$ln\left[\frac{E(Patient\ RASR_{i,h,t+1}\,|\,\boldsymbol{X})}{1-E(Patient\ RASR_{i,h,t+1}\,|\,\boldsymbol{X})}\right]$$

$$=\beta_0+\beta_1 accum.own\,failures_{i,h,t}+\beta_2 accum.own\,failures_{i,h,t}{}^2$$

$$+\beta_3 accum.own\,failures_{i,h,t}\times Z+\beta_4 accum.own\,failures_{i,h,t}{}^2\times Z$$

$$+\beta_5 Z+\beta_6\boldsymbol{S_{i,t}}+\beta_7\boldsymbol{H_{h,t}}+\lambda_{i,h}+\tau_t+u_{i,h,t} \tag{2}$$

Z represents *elite education*, *certified expertise*, and *specialization* for H2a–c, respectively. The inflection point for surgeons with low perceived ability to learn ($Z=0$) will form at $-\beta_1/2\beta_2$, whereas it will be at $-(\beta_1+\beta_3)/2(\beta_2+\beta_4)$ for surgeons with high perceived ability to learn ($Z=1$). Because we hypothesize that the inflection point comes later for surgeons with higher perceived ability to learn than others, H2a–c will be supported if $-(\beta_1+\beta_3)/2(\beta_2+\beta_4)$ is greater than $-\beta_1/2\beta_2$ and a Wald-type test rejects the null that the two are equal (Medappa & Srivastava, 2019).

Importantly, our empirical approach closely follows the latest guidelines for research on learning from failures recommended by Bennett and Snyder (2017). In their study, they analyzed placebo data, which by design, should not show a learning effect, and found that model specifications commonly used in failure learning research might erroneously indicate a significant learning effect where none exists. They specifically cautioned researchers about two empirical biases that prior literature on learning from failures have been prone to: the *induced slope effect*—which can occur when cumulative failures and successes (or their linear combinations) are included in a single model—and the *unit-root problem*—which can occur when using the cumulative history of failures as an independent variable. To mitigate the induced slope effect while not excluding a theoretically meaningful confounder, surgeons' total experience in isolated CABG surgeries, we controlled for each surgeon's total number of isolated CABG surgeries across *all affiliated hospitals*, instead of the *focal hospital* (see Appendix F for a comprehensive discussion on this model choice). Additionally, to address the unit root problem, we confirmed the absence of the unit root problem in our independent variable using the Fisher-type Phillips-Perron unit root test. Finally, we assessed potential mechanical effects in our analyses by conducting a placebo test (detailed in the robustness checks and Appendix H).

4 | RESULTS

4.1 | Empirical test of hypotheses

Table 3 shows the results of the analyses that tested our hypotheses. Model 1 includes the control variables only. *Surgeon's patient RASR* was positively associated with (1) *surgeon's*

TABLE 3 Fractional logit regression estimates for surgeon's patient risk-adjusted survival rate (RASR).

DEPENDENT VARIABLE: Surgeon's patient RASR (period $t + 1$)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
INDEPENDENT VARIABLES (period *t*)						
Surgeon's own accum. failures **(H1)**		0.245 (0.000)	0.301 (0.000)	0.310 (0.000)	0.640 (0.000)	0.724 (0.000)
Surgeon's own accum. failures sq **(H1)**		−0.005 (0.000)	−0.007 (0.000)	−0.008 (0.000)	−0.032 (0.003)	−0.035 (0.001)
Surgeon's own accum. failures **(H2a)** × Elite education			−0.094 (0.034)			−0.091 (0.031)
Surgeon's own accum. failures sq **(H2a)** × Elite education			0.004 (0.022)			0.004 (0.010)
Surgeon's own accum. failures **(H2b)** × Certified expertise				−0.090 (0.034)		−0.084 (0.045)
Surgeon's own accum. failures sq **(H2b)** × Certified expertise				0.004 (0.016)		0.004 (0.012)
Surgeon's own accum. failures **(H2c)** × Specialization					−0.397 (0.023)	−0.366 (0.040)
Surgeon's own accum. failures sq **(H2c)** × Specialization					0.027 (0.012)	0.025 (0.020)
Certified expertise		−0.033 (0.880)	−0.040 (0.857)	0.208 (0.453)	−0.031 (0.887)	0.172 (0.540)
Specialization		0.290 (0.262)	0.286 (0.260)	0.321 (0.210)	1.175 (0.036)	1.102 (0.050)
CONTROL VARIABLES (period *t*)						
Surgeon's accum. iso-CABG surgeries	0.001 (0.358)	−0.002 (0.029)	−0.002 (0.026)	−0.002 (0.020)	−0.002 (0.015)	−0.002 (0.010)
Surgeon's accum. others' failures	0.029 (0.024)	0.029 (0.021)	0.027 (0.034)	0.029 (0.020)	0.027 (0.027)	0.026 (0.041)
Surgeon's average surgery complexity	22.012 (0.002)	20.441 (0.006)	20.177 (0.007)	19.855 (0.008)	20.012 (0.007)	19.222 (0.010)
Multiple hospital affiliation dummy	−0.210 (0.343)	−0.164 (0.457)	−0.158 (0.474)	−0.186 (0.403)	−0.171 (0.444)	−0.184 (0.410)
Hospital's accum. iso-CABG surgeries	0.00005 (0.690)	−0.00004 (0.754)	−0.00006 (0.616)	−0.00004 (0.746)	−0.00003 (0.785)	−0.00006 (0.634)
Hospital's accum. inpatient surgeries	0.000001 (0.840)	0.000004 (0.457)	0.000004 (0.375)	0.000003 (0.508)	0.000003 (0.514)	0.000004 (0.467)
Hospital's number of surgeons	−0.074 (0.112)	−0.088 (0.060)	−0.089 (0.057)	−0.085 (0.069)	−0.084 (0.071)	−0.084 (0.073)

TABLE 3 (Continued)

DEPENDENT VARIABLE: Surgeon's patient RASR (period $t + 1$)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Hospital's trauma center dummy	0.066 (0.720)	−0.053 (0.785)	−0.039 (0.843)	−0.060 (0.757)	−0.049 (0.801)	−0.044 (0.820)
Hospital's cardiac ICU dummy	0.073 (0.654)	0.108 (0.532)	0.116 (0.499)	0.096 (0.577)	0.110 (0.524)	0.106 (0.532)
Teaching hospital dummy	0.234 (0.245)	0.298 (0.152)	0.301 (0.151)	0.302 (0.145)	0.284 (0.172)	0.290 (0.167)
Surgeon turnover	−0.369 (0.354)	−0.174 (0.663)	−0.184 (0.645)	−0.175 (0.663)	−0.199 (0.621)	−0.206 (0.608)
Number of hospitals in region	0.120 (0.017)	0.100 (0.060)	0.104 (0.053)	0.096 (0.071)	0.093 (0.077)	0.095 (0.073)
CONSTANT	0.683 (0.364)	1.461 (0.076)	1.475 (0.074)	1.283 (0.121)	0.693 (0.455)	0.630 (0.496)
Period and surgeon-hospital FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2808	2808	2808	2808	2808	2808
Number of clusters	636	636	636	636	636	636

Note: *p*-Values based on robust standard errors clustered by surgeon-hospital are reported in parentheses. *Elite education* is time-invariant, and therefore its single term is dropped due to fixed effects.

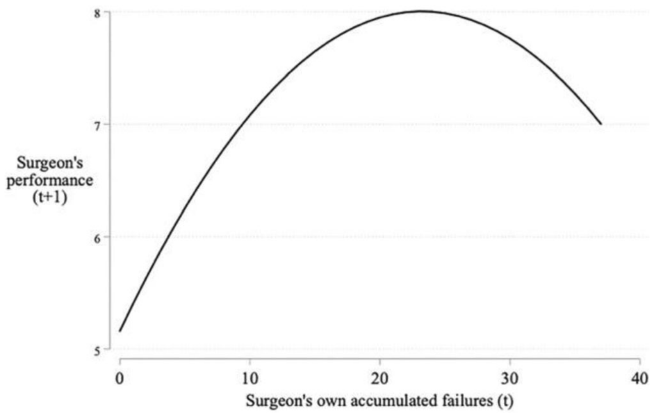

FIGURE 2 Relationship between surgeon's own accumulated failures and surgeon's performance. Surgeon's performance is expressed as logit-transformed expected surgeon's patient risk-adjusted survival rate (RASR).

accumulated others' failures, suggesting that surgeons learned from other surgeons' failures ($p = .02$); (2) *surgeon's average surgery complexity* ($p = .00$), implying that a surgeon learned more from performing complex surgeries than simple ones; and (3) *number of hospitals in region* ($p = .02$), consistent with the possibility of cross-hospital learning or a hospital being situated in a region with higher healthcare quality on average.

To test the inverted-U-shaped relationship predicted in our H1, we included *surgeon's own accumulated failures* and *surgeon's own accumulated failures sq* in Model 2 of Table 3. The coefficient for *surgeon's own accumulated failures* was positive ($p = .00$), and the coefficient for *surgeon's own accumulated failures sq* was negative ($p = .00$), supporting H1. Figure 2 depicts the relationship between a surgeon's performance (the logit-transformed expected *surgeon's patient RASR*) at period $t + 1$ and a *surgeon's own accumulated failures* up to period t. Performance increases until a surgeon experiences a certain number of patient deaths. However, after that point, the surgeon's performance decreases as more patient deaths are experienced, consistent with our theory. Especially, the results support our prediction that these individuals will experience declining performance once they give up learning from their own failures because they will continue behaving in ways that led to failures and not update their existing knowledge although the task environment is changing.

To test H2a, we introduced interactions between *elite education* and the single and squared term of *surgeon's own accumulated failures* in Model 3 of Table 3. We were interested to see how the *inflection point* of the inverted-U relationship in H1 differed based on *elite education*. Unlike conventional methods of moderation hypothesis testing in which interaction terms' coefficients are examined, testing the difference in inverted-U curves' inflection points (e.g., H2a–c) requires computing the inflection points for a given pair of surgeon types based on coefficient estimates and examining whether the two points statistically differs (see Medappa & Srivastava, 2019).[9] Thus, as mentioned in the econometric models section, we tested whether the inflection point for surgeons without elite education ($-\beta_1/2\beta_2$) occurred earlier than that for those with elite education ($-(\beta_1+\beta_3)/2(\beta_2+\beta_4)$) and ran a Wald-type test to check if the two points were statistically different. Figure 3 depicts the results for H2a. Surgeons without

[9]That is, testing H2a–c does not involve directly interpreting the statistical significance of the regression coefficients.

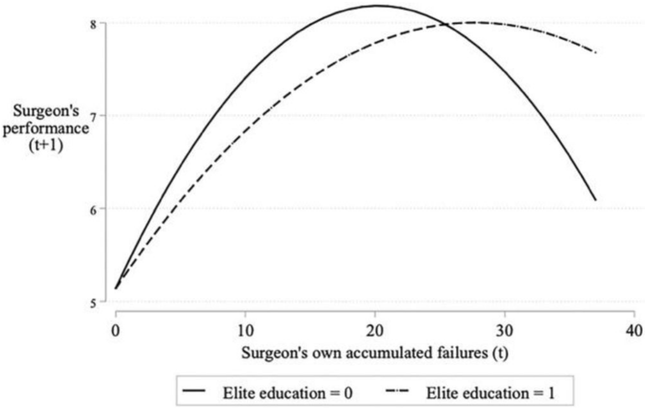

FIGURE 3 Relationship between surgeon's own accumulated failures and surgeon's performance moderated by elite education. Surgeon's performance is expressed as logit-transformed expected surgeon's patient risk-adjusted survival rate (RASR).

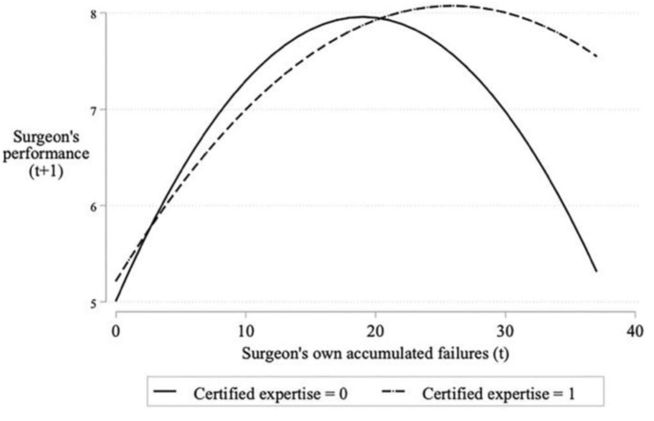

FIGURE 4 Relationship between surgeon's own accumulated failures and surgeon's performance moderated by certified expertise. Surgeon's performance is expressed as logit-transformed expected surgeon's patient risk-adjusted survival rate (RASR).

elite education reached the learning inflection point earlier than those with elite education ($p = .02$), supporting H2a.

Similarly, we tested H2b by including the interactions between *certified expertise* and the single and squared term of *surgeon's own accumulated failures* in Model 4 of Table 3. Figure 4 shows the results for H2b. Surgeons without certified expertise reached the learning inflection point sooner than surgeons with certified expertise ($p = .00$), supporting H2b. Next, we tested H2c by adding the interactions between *specialization* and the single and squared term of *surgeon's own accumulated failures* in Model 5 of Table 3. Figure 5 depicts the results for H2c. Surgeons who did not specialize in patient care reached the learning inflection point earlier than surgeons who specialized in patient care ($p < .00$), supporting H2c. Finally, Model 6 of Table 3 shows the full model with all interaction terms to test Hypotheses 2a–c. Results were in line with Hypotheses 2a–c (H2a, $p = .07$; H2b, $p = .06$; H2c, $p = .00$). In sum, all our hypotheses were supported.

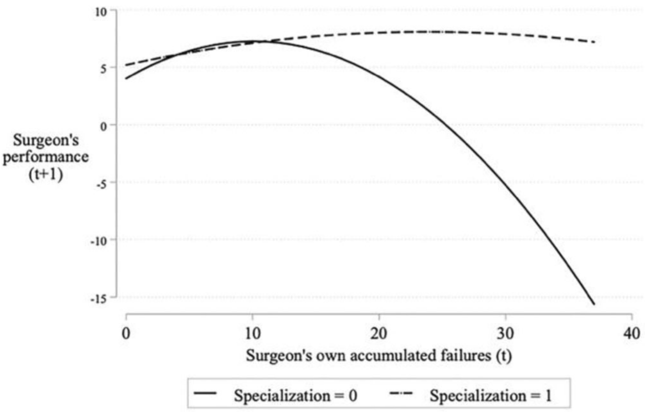

FIGURE 5 Relationship between surgeon's own accumulated failures and surgeon's performance moderated by specialization. Surgeon's performance is expressed as logit-transformed expected surgeon's patient risk-adjusted survival rate (RASR).

4.2 | Qualitative evidence corroborating the empirical results

We found high consistency between our empirical results and our qualitative data. For example, related to the increase in opportunities to learn as failures accumulate, one surgeon told us:

> Having more of an experience base allows you to see a pattern where a person with less experience, or fewer mistakes, or fewer complications might have a hard time seeing a pattern.

Similarly, another surgeon highlighted the learning opportunities generated by each additional failure experience:

> We may look the same, but inside, ischemic heart muscle, it has all these different coronaries with different blockages and stuff. … And also the myocardium's different. … So we discuss the physiology, the history of the operation, how it was performed, the pathophysiology and the pathology, what happened (each time a surgery does not go well).

This was consistent with how a leading cardiac surgeon, Stephen Westaby (2017) described the diversity of learning opportunities gained by each surgery in his autobiography *Open Heart*:

> There I found that every heart is different. Some are fat, some are lean. Some are thick, some are thin. Some are fast, some are slow. (p. 5)

Our interviews also revealed surgeons' motivation to learn from their own failures, especially from their earlier ones, despite feeling negative emotions from the failure. For example, describing his early failure, one physician explained:

> If a person dies or goes to the ICU… it does wear on you because it's a person dying because of the mistake you've made. Then you have to talk to their family and cope

> with their reactions. So there's always that component of guilt and sadness. I think you need a day or two to process it emotionally. Then, you start thinking about what you could have done or like at least know what would have helped in those situations so that you don't make similar mistakes in the future.

However, as negative emotions accumulated due to repeated failures, due to experiences such as the following one that one of our interviewees had, "(*At the hospital I used to work for*,) *someone would come up and say*, '*Man, you killed that patient*,' *and I took it so hard*," it seemed that some surgeons could fall into the state of helplessness. For example, one surgeon told us:

> (After repeated failures) I would feel so frustrated. I would seriously doubt whether I deserve to be a surgeon. A few negative events could be learning opportunities but if it happens more than that, I don't think I qualify.

This sort of helplessness seemed to eventually lead surgeons to cease learning from their failures. At the same time, we also found evidence of surgeons blaming their failures on other factors as they accumulated failures. For example, a surgeon explained:

> (Once I had an error), and the error kind of centered around a very dramatic bleeding episode that took place immediately after an operation. There was some wiggle room as to whether it was a surgical technique problem … my ego made me look at all the other possible options and kind of cling to those to kind of protect my ego.

Similarly, another physician explained:

> You play golf? It's like repeatedly slicing a ball into the woods, the water, or another fairway and coming back to the golf cart saying that you've used the wrong golf club or ball. Even if it's your fault you start blaming failures on other things because you think you've done enough. That is why people's golf stops improving. The same goes for surgery if you get into that mindset.

It is important to note that qualitative data does not allow for testing of causality. Especially, the process of gathering our own interview data had its unique limitations that may have made it susceptible to biases such as social desirability bias, self-selection bias, attribution bias, and recall bias. For example, our limited existing connections with cardiothoracic surgeons, their constrained time availability due to demanding schedules, and their general reluctance to discuss their failures (i.e., patients' deaths) could have contributed to such biases, should they have arisen. Nevertheless, alleviating these concerns, we found that our informants, despite being interviewed independently, displayed surprisingly consistent perspectives that aligned with our proposed mechanisms.

4.3 | Robustness checks

First, we confirmed H1's inverted-U relationship using procedures proposed by Lind and Mehlum (2010) (see also Haans et al., 2016). The slope of the curve was positive at the lower bound ($p = .00$) and negative at the upper bound ($p = .00$) of *surgeon's own accumulated* *failures*. In addition, the inflection point and the 95% confidence interval of the point were within the data range of *surgeon's own accumulated failures*. We also conducted a sensitivity analysis by excluding surgeon-hospital dyads with extreme *surgeon's accumulated own failures* values (1st and 99th percentile cut-offs) and found robust results. Furthermore, we retested H1 using an Arellano-Bond linear dynamic panel model that controlled for the lagged dependent variable, to control for the possibility that surgeons' past performance predicted their future performance. Results were robust.

Next, we reexamined our hypotheses after limiting our sample to surgeons in hospitals without thoracic residency programs during the focal period. While all surgeons confirmed that they were responsible for the patient deaths reported to the HCAI, a resident might have performed a surgery instead of an attending surgeon as part of training. To rule this out, we identified hospitals offering thoracic residency from the Accreditation Council for Graduate Medical Education website and excluded those observations. All the hypotheses were supported in this alternative test (H1, $p = .00$; H2a, $p = .04$; H2b, $p = .00$; H2c, $p = .00$) (see Appendix G for the results).

Finally, we followed Bennett and Snyder's (2017) recommendation to investigate whether our results were primarily driven by mechanical relationships between variables that can cause regression coefficients to deviate from zero even in random data. To assess this, we conducted a placebo test using randomly generated variables created based on the characteristics of our actual data. Notably, our data exhibit some mechanical effects, likely attributable to correlations among input variables in the model (see Bennett & Snyder, 2017). Nevertheless, these effects were not substantial enough to suggest that our original findings were primarily driven by them. Specifically, the coefficients of our original results exhibited magnitudes that were beyond the ± 2 standard error of those predicted by the placebo models, implying that we have extracted meaningful information from the original models (see Appendix H for more details on the placebo test).

5 | ADDITIONAL ANALYSES

5.1 | Examination of learning from *others'* failures to test mechanisms driving H1

While we cannot directly measure surgeons' motivation using our data, examining learning from *other* surgeon's failures can provide insights for validating our proposed mechanisms. Specifically, experiencing others' failures would increase a surgeon's *opportunity to learn* (through vicarious learning), but would not affect the surgeon's *motivation to learn* (since others' failures are unlikely to evoke negative emotions or attribution biases). Based on this logic, we test the single and squared term effects of *surgeon's accumulated others' failures* on a *surgeon's patient RASR*. We expect the single-term coefficient to be positive and statistically meaningful but the squared term's coefficient to be statistically insignificant. Appendix I presents the results of this test.

Model 1 in Appendix I first shows the results of the regression that tests the effect of *surgeon's accumulated others' failures* on *surgeon's patient RASR*, while controlling for our original independent variables and covariates. As predicted, the results showed that surgeons learned from others' failures ($p = .02$). Likewise, in Model 2, the squared term of *surgeon's accumulated others' failures* was statistically insignificant ($p = .47$), whereas the single term remained positive ($p = .08$), in line with our prediction.

5.2 | Were surgeons restricted from performing (certain) surgeries upon experiencing failures?

We can imagine surgeons being restricted from performing further surgeries altogether if they are responsible for an increasing number of patient deaths, which in turn, could bias our data. To examine this possibility, we tested whether *surgeon's patient RASR* at a hospital at period t predicted *surgeon's number of isolated CABG surgeries* at a hospital at period $t+1$, using a Poisson model with the same control variables and specifications as our original models (see Model 1 in Appendix J for results). The coefficient of *surgeon's patient RASR* was positive but statistically insignificant ($p = .14$), suggesting no statistically meaningful relationship between the number of failures in the focal period and the number of surgeries surgeons performed in the next period.

However, it is possible that worse-performing surgeons are precluded from performing *high-risk surgeries*, which would also bias our results if those surgeons experienced fewer failures due to only performing lower-risk surgeries. We examined this possibility by testing whether *surgeon's patient RASR* at a hospital at period t positively predicted surgeons' patient *expected mortality rate* (the variable that reflects surgery complexity) at period $t+1$. The coefficient of *surgeon's patient RASR* was positive, but statistically insignificant ($p = .36$) (see Model 2 in Appendix J). Overall, these results suggest that individuals who experienced more failures were *not* kept from performing additional surgeries or assigned to simpler surgeries in the next period.

5.3 | Did surgeons with higher ability to learn perform more complex surgeries than others?

It is also possible that surgeons who received elite education, had certified expertise, and specialized in patient care performed more complex surgeries than other surgeons. Because performing complex surgeries could offer more learning opportunities (e.g., Stan & Vermeulen, 2013), different learning opportunities instead of different levels of perceived ability to learn could have driven the results for H2a–c. Thus, to rule out this alternative explanation, we ran t-tests to investigate whether surgeons who *did* versus *did not* have elite education, certified expertise, and specialization had statistically different patient *expected mortality rates* for their surgeries in each period. Results, presented in Appendix K, show that there was no systematic difference in the mean patient expected mortality rates between the two types of surgeons.

5.4 | Does surgeons' motivation to learn from their own failures decrease as they become more senior?

Finally, an alternative explanation for the decrease in motivation to learn from their own failures is that surgeons feel greater security as they become more senior. Because senior surgeons have relatively established professional status, they may not feel as pressured as junior surgeons to prove themselves and improve their performance by learning from their failures. This would be a qualitatively different mechanism through which the motivation to learn from failures decreases compared to the ones we argued for. Contrary to this argument, the correlation between *surgeon's own accumulated failures* and a surgeon's professional tenure in our sample was low ($r = .20$), suggesting that surgeons who had accumulated many failures were not necessarily the ones who were more senior. Results for H1 were also robust to limiting our sample to junior surgeons with five or fewer years of professional tenure, who would not be subject to this alternative explanation.

6 | DISCUSSION AND CONCLUSION

This article set out to better understand how individuals learn from their own failures, an important microfoundational process that influences organizational learning and firm performance. Despite increasing attention to this process (Avgerinos et al., 2020; Diwas et al., 2013; Eskreis-Winkler & Fishbach, 2019; Lapré & Cravey, 2022; Wilhelm et al., 2019), existing theories and findings have been inconsistent: some studies theorized and documented positive effects of individuals' own failures on learning, whereas others theorized and found negative effects of such experiences on learning. In a recent review on this topic, Dahlin et al. (2018) emphasized that researchers should jointly consider the interplay among three mechanisms—the opportunity, motivation, and ability to learn—to better understand how individuals learn from failures. Responding to this call for sharper theoretical frameworks on failure learning, we developed and tested a theoretical model on individual failure learning that mutually considers the effects of the opportunity, motivation, and perceived ability to learn from failures.

We theorized that the relationship between an individual's own accumulated failures and learning will form an inverted-U shape—driven by opposing forces between an individual's opportunity and motivation to learn as failures accumulate—and that this relationship will be moderated by the individual's perceived ability to learn. Using extensive panel data on 307 cardiothoracic surgeons who performed isolated CABG surgeries in California across 16 years, we found support for our hypotheses. To the best of our knowledge, ours is the first paper in this literature to document a non-monotonic relationship between an individual's own accumulated failures and learning, and we believe this result has important implications.

To begin with, future studies examining individual-level failure learning should be aware of the possibility that the net effect of failures can differ in certain ranges and consider an inverted-U relationship between individuals' own failures and learning as a baseline theoretical prediction, especially in contexts where failures occur repeatedly and hold significance for individuals (e.g., Avgerinos et al., 2020; Diwas et al., 2013; Lapré & Cravey, 2022; Wilhelm et al., 2019). In fact, the mixed findings observed in prior studies within this domain might be due to specific samples. According to our theory, if the sample was one where individuals had very few or too many accumulated failures, the results may show limited or no learning from an additional failure (e.g., Diwas et al., 2013). Conversely, in samples where individuals have moderate levels of accumulated failures, the results are likely to demonstrate substantial learning (e.g., Lapré & Cravey, 2022).

In our study, on average, individuals continued to learn from their own failures, albeit at progressively slower rates, until they reached significantly high levels of accumulated failures (approximately 3.5 standard deviations above the mean value of accumulated failures). However, beyond this threshold, and particularly when the surgeons reached extreme levels of accumulated failures, their performance steeply declined, suggesting that their learning efforts effectively ceased after reaching this point. It is critical to note that the above explanation pertains to *average effects* in our context. When considering individual characteristics, we observed a significant drop in the threshold. For instance, for surgeons who were not specializing in patient care, the threshold even dropped to one standard deviation above the mean of accumulated failures (see Figure 5).

Notably, the thresholds at which individuals "give up" on learning from their failures may vary depending on the empirical context and the individuals experiencing the failures. In our study, we specifically examined a context where failures were high stakes and significantly impacted the surgeons' emotions, motivations, and behaviors. Thus, it is reasonable (and relieving) to find that the average threshold at which individuals cease learning occurred at very high levels since surgeons would seek to avoid failures as much as possible. However, it is important to recognize that in other contexts, this pattern may not hold, and the threshold may appear at lower levels of accumulated failures. Taken together, we recommend that future researchers not only consider the potential inverted-U relationship between individuals' accumulated failures and learning, but also examine the variance in the relationship stemming from the contextual and individual level factors.

In our study, we observed heterogeneity in the degree to which individuals learned from their failures as a consequence of varying levels of individuals' perceived ability to learn. Specifically, surgeons with elite education, certified expertise, and specialization in patient care exhibited a longer persistence in learning from their own failures compared to their counterparts. Our theory posited that these individuals possess higher perceived ability to learn than their counterparts, resulting in stronger motivation to learn and, consequently, reduced vulnerability to negative emotions and attribution biases associated with repeated failures. Importantly, in other contexts, other individual characteristics may reflect an individual's perceived ability to learn from their own failures. Therefore, researchers examining other empirical settings should adapt their predictions and measures to account for any differences from our context.

A more nuanced implication of our study's results is that not all experiences necessarily lead to learning, and they can even be detrimental to learning. The experiential learning literature has often viewed experience as a beneficial source of learning (see Argote et al., 2021 for a review). However, this may not hold for all types of experiences, especially ones that can elicit negative emotions or attribution biases such as failures. In fact, research has shown that even some positive experiences could deteriorate learning (Schumacher et al., 2020). We believe it is crucial for researchers in this domain to consider not only the opportunities for learning that experiences bring, but also other consequences that they lead to, such as changes in the motivation to learn.

We believe our results also have important implications for learning at the organizational level. Organizations are aggregates of individuals; hence, learning by individuals will affect organizational learning. What may seem like a variance in learning rates across organizations could be driven by different learning rates of individuals. Thus, understanding how to improve individuals' learning would be useful for improving organizational performance. Our results suggest that individuals' motivation to learn is an important mechanism for learning from failures and that individuals who have qualifications or past experiences associated with higher perceived ability to learn will have higher motivation to learn, and thus persist longer in learning. While our study focused only on individual learning from their own failures to understand this baseline relationship more deeply, future studies could extend this study to examine how multiple individual-level learning processes aggregate to affect organizational outcomes.

Naturally, our results have implications for organization design and strategic human capital management, especially in the areas of hiring and training. Future research could further investigate the organizational factors that can help individuals be more resilient to the negative effects of failures. While it is understandable that organizations prioritize attributes of job applicants that signal their potential for success within the organization, our findings suggest that it is equally important for hiring organizations to consider attributes that make individuals more resilient to failures, especially in settings where repeated failures that carry significance are inevitable (e.g., R&D labs, start-ups, etc.). Our results also imply that training will be important for employees to learn more from their failures. The literature on self-efficacy has demonstrated that self-efficacy can be trained (Davis et al., 2000; Eden & Aviram, 1993). Relatedly, it has been found that organizational culture that emphasizes positive employee morale and growth mindsets can encourage individuals to frame errors as learning opportunities (Dahl & Werr, 2021).

Our findings come with some caveats. First, failures occur in different forms across different contexts. In our context, failures are high stakes that involve patient deaths. Hence, the negative emotions triggered by these failures or the likelihood of attribution biases are likely to be larger than when the stakes are not as high. For example, some studies have examined near-misses or errors (Dillon & Tinsley, 2008; Madsen et al., 2016; Ramanujam & Goodman, 2011) or less severe failures such as product recalls (Haunschild & Rhee, 2004). Although we predict that the processes we theorized in our paper will occur similarly in most failure-related situations (albeit to different degrees), more research is needed to examine the learning outcomes of experiencing different types of failures. Second, our context involved situations where repeated failures were sometimes beyond the control of the individual. In such contexts, individuals may be more inclined to attribute their failures to external causes as more failures accumulate. Additionally, our setting allowed individuals with relatively high levels of accumulated failures to remain in the organization despite their failures. Thus, it would be valuable to see future studies examining the relationship in other contexts where termination from the organization is more likely.

Third, our study could have benefitted from using more fine-grained, surgery-level data, since it would have enabled us to examine individual learning patterns in greater granularity. For instance, with access to this level of data, we could not only have better identified the threshold at which surgeons might cease learning from failures, but we could have also explored potential variations in the effects of failures on individual learning, such as the impact of failures that were highly anticipated versus unexpected, which may potentially have different magnitudes of impact on the learner. Unfortunately, the HCAI did not publicly offer such data, and as a result, these topics remain as future research agendas. Nevertheless, one important advantage of our data is that it included a substantially larger number of failures compared to prior studies (e.g., approximately four times the amount in Diwas et al. (2013) who studied a similar topic but using surgery-level data), allowing us to capture the effects of accumulated failures at higher ranges.

Fourth, as we explained in our robustness check section, a portion of the results regarding the effects of failures on individual learning may have been influenced by mechanical effects. Encouragingly, a placebo test that we conducted, following the approach outlined in Bennett and Snyder's (2017) research on the empirics of learning from failures, indicated that the mechanically induced effects were not substantial enough to suggest that our findings were primarily driven by such effects. In addition, we have included a comprehensive set of control variables that are both theoretically relevant and available to us in our models. Bennett and Snyder (2017) explain that such control variables can weaken or mitigate any mechanically induced effects (p. 4). Nevertheless, we caution readers to exercise prudence when interpreting our results.

Finally, due to data limitations, we could not directly measure or manipulate our theoretical mechanisms. We considered running lab experiments, but manipulating the effects of failures, especially ones that significantly matter to the subject and those that repeat over time, did not seem feasible nor realistic in such environment. To offset this limitation, we complemented our empirical results with qualitative data and conducted an array of additional analyses to rule in our theorized mechanisms and rule out alternative mechanisms. Notwithstanding, we encourage future studies to investigate the mechanisms using contexts and methods that allow stronger identification.

Overall, our research contributes to the literature on individual failure learning and organizational learning. We especially hope that our paper renews existing perspectives on the relationship between individuals' own failures and learning, presenting exciting opportunities for better understanding the micro-processes of organizational learning and, ultimately, their effects on firm performance. Our findings can also inform organization design and strategic human capital management practices, emphasizing the significance of considering individual attributes that foster resilience to failures. We anticipate that our work will inspire further research in this area and contribute to the broader understanding of learning processes within organizations.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Argote, L. (2013). *Organizational learning: Creating, retaining and transferring knowledge* (2nd ed.). Springer Science & Business Media.

Argote, L., Beckman, S. L., & Epple, D. (1990). The persistence and transfer of learning in industrial settings. *Management Science*, *36*(2), 140–154.

Argote, L., Lee, S., & Park, J. (2021). Organizational learning processes and outcomes: Major findings and future research directions. *Management Science*, *67*(9), 5301–5967.

Argote, L., & Miron-Spektor, E. (2011). Organizational learning: From experience to knowledge. *Organization Science*, *22*(5), 1123–1137.

Audia, P. G., & Brion, S. (2007). Reluctant to change: Self-enhancing responses to diverging performance measures. *Organizational Behavior and Human Decision Processes*, *102*(2), 255–269.

Avgerinos, E., Gokpinar, B., & Fragkos, I. (2020). The effect of failure on performance over time: The case of cardiac surgery operations. *Journal of Operations Management*, *66*(4), 441–463.

Bakaeen, F. (2017). CABG: A continuing evolution. *Cleveland Clinic Journal of Medicine*, *84*(12 Suppl 4), e15–e19.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.

Bennett, V. M., & Snyder, J. (2017). The empirics of learning from failure. *Strategy Science*, *2*(1), 1–12.

Berner, E. S., & Graber, M. L. (2008). Overconfidence as a cause of diagnostic error in medicine. *The American Journal of Medicine*, *121*(5), S2–S23.

Bogdanovic, J., Perry, J., Guggenheim, M., & Manser, T. (2015). Adaptive coordination in surgical teams: An interview study. *BMC Health Services Research*, *15*, 1–12.

Burke, M. A., Fournier, G. M., & Prasad, K. (2007). The diffusion of a medical innovation: Is success in the stars? *Southern Economic Journal*, *73*(3), 588–603.

Cannon, M. D., & Edmondson, A. C. (2005). Failing to learn and learning to fail (intelligently): How great organizations put failure to work to innovate and improve. *Long Range Planning*, *38*(3), 299–319.

Cook, D. A., & Artino, A. R., Jr. (2016). Motivation to learn: An overview of contemporary theories. *Medical Education*, *50*(10), 997–1014.

Dahl, J., & Werr, A. (2021). Sharing errors where everyone is perfect: Culture, emotional dynamics, and error sharing in two consulting firms. *Academy of Management Discoveries*, *7*(4), 509–529.

Dahlin, K. B., Chuang, Y.-T., & Roulet, T. J. (2018). Opportunity, motivation, and ability to learn from failures and errors: Review, synthesis, and ways to move forward. *Academy of Management Annals*, *12*(1), 252–277.

Davis, W. D., Fedor, D. B., Parsons, C. K., & Herold, D. M. (2000). The development of self-efficacy during aviation training. *Journal of Organizational Behavior*, *21*(8), 857–871.

Deichmann, D., & Ende, J. V. D. (2014). Rising from failure and learning from success: The role of past experience in radical initiative taking. *Organization Science*, *25*(3), 670–690.

Desai, V. M. (2015). Learning through the distribution of failures within an organization: Evidence from heart bypass surgery performance. *Academy of Management Journal*, *58*(4), 1032–1050.

Desai, V. M. (2020). Can busy organizations learn to get better? Distinguishing between the competing effects of constrained capacity on the organizational learning process. *Organization Science*, *31*(1), 67–84.

Dillon, R. L., & Tinsley, C. H. (2008). How near-misses influence decision making under risk: A missed opportunity for learning. *Management Science*, *54*(8), 1425–1440.

Diwas, K. C., Staats, B. R., & Gino, F. (2013). Learning from my success and from others' failure: Evidence from minimally invasive cardiac surgery. *Management Science*, *59*(11), 2435–2449.

Dutton, J. M., & Thomas, A. (1984). Treating progress functions as a managerial opportunity. *Academy of Management Review*, *9*(2), 235–247.

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, *53*(1), 109–132.

Eden, D., & Aviram, A. (1993). Self-efficacy training to speed reemployment: Helping people to help themselves. *Journal of Applied Psychology*, *78*(3), 352–360.

Edmondson, A. C. (2004). Learning from mistakes is easier said than done: Group and organizational influences on the detection and correction of human error. *The Journal of Applied Behavioral Science*, *40*(1), 66–90.

Eggers, J., & Song, L. (2015). Dealing with failure: Serial entrepreneurs and the costs of changing industries between ventures. *Academy of Management Journal*, *58*(6), 1785–1803.

ElBardissi, A. W., Aranki, S. F., Sheng, S., O'Brien, S. M., Greenberg, C. C., & Gammie, J. S. (2012). Trends in isolated coronary artery bypass grafting: An analysis of the Society of Thoracic Surgeons adult cardiac surgery database. *The Journal of Thoracic and Cardiovascular Surgery*, *143*(2), 273–281.

Ellis, S., & Davidi, I. (2005). After-event reviews: Drawing lessons from successful and failed experience. *Journal of Applied Psychology*, *90*(5), 857–871.

Ellis, S., Mendel, R., & Nir, M. (2006). Learning from successful and failed experience: The moderating role of kind of after-event review. *Journal of Applied Psychology*, *91*(3), 669–680.

Eskreis-Winkler, L., & Fishbach, A. (2019). Not learning from failure—The greatest failure of all. *Psychological Science*, *30*(12), 1733–1744.

Gaba, V., Lee, S., Meyer-Doyle, P., & Zhao-Ding, A. (2023). Prior experience of managers and maladaptive responses to performance feedback: Evidence from mutual funds. *Organization Science*, *34*(2), 894–915.

Greenwood, B. N., Agarwal, R., Agarwal, R., & Gopal, A. (2019). The role of individual and organizational expertise in the adoption of new practices. *Organization Science*, *30*(1), 191–213.

Haans, R. F., Pieters, C., & He, Z. L. (2016). Thinking about U: Theorizing and testing U-and inverted U-shaped relationships in strategy research. *Strategic Management Journal*, *37*(7), 1177–1195.

Hastie, R. (1984). Causes and effects of causal attribution. *Journal of Personality and Social Psychology*, *46*(1), 44–56.

Haunschild, P. R., & Rhee, M. (2004). The role of volition in organizational learning: The case of automotive product recalls. *Management Science*, *50*(11), 1545–1560.

Head, S. J., Börgermann, J., Osnabrugge, R. L., Kieser, T. M., Falk, V., Taggart, D. P., Puskas, J. D., Gummert, J. F., & Kappetein, A. P. (2013). Coronary artery bypass grafting: Part 2—Optimizing outcomes and future prospects. *European Heart Journal*, *34*(37), 2873–2886.

Huckman, R. S., & Pisano, G. P. (2006). The firm specificity of individual performance: Evidence from cardiac surgery. *Management Science*, *52*(4), 473–488.

Huesch, M. D. (2009). Learning by doing, scale effects, or neither? Cardiac surgeons after residency. *Health Services Research*, *44*(6), 1960–1982.

Jordan, A. H., & Audia, P. G. (2012). Self-enhancement and learning from performance feedback. *Academy of Management Review*, *37*(2), 211–231.

Khanna, R., Guler, I., & Nerkar, A. (2016). Fail often, fail big, and fail fast? Learning from small failures and R&D performance in the pharmaceutical industry. *Academy of Management Journal*, *59*(2), 436–459.

Kim, D. H. (1998). The link between individual and organizational learning. In D. A. Klein (Ed.), *The strategic management of intellectual capital* (pp. 41–62). Butterworth-Heinemann.

Kimmaliardjuk, D. M., Toeg, H., Glineur, D., Sohmer, B., & Ruel, M. (2015). Operative mortality with coronary artery bypass graft: Where do we stand in 2015? *Current Opinion in Cardiology*, *30*(6), 611–618.

Kolb, D. A. (2015). *Experiential learning: Experience as the source of learning and development* (2nd ed.). Pearson Education.

Lai, A. Y. (2021). The incomplete, outdated, incorrect, and unknown: Mitigating threats of knowledge errors in high-performance primary care. *Academy of Management Discoveries*, *7*(4), 581–602.

Lapré, M. A., & Cravey, C. (2022). When success is rare and competitive: Learning from others' success and my failure at the speed of formula one. *Management Science*, *68*(12), 8741–8756.

Lapré, M. A., Mukherjee, A. S., & Van Wassenhove, L. N. (2000). Behind the learning curve: Linking learning activities to waste reduction. *Management Science*, *46*(5), 597–611.

Lapré, M. A., & Tsikriktsis, N. (2006). Organizational learning curves for customer dissatisfaction: Heterogeneity across airlines. *Management Science*, *52*(3), 352–366.

Lee, S. (2019). Learning-by-moving: Can reconfiguring spatial proximity between organizational members promote individual-level exploration? *Organization Science*, *30*(3), 467–488.

Lee, S., Park, J., & Kilic, A. (2021). Bridging two worlds: Application of organizational theory to cardiac surgery. *The Annals of Thoracic Surgery*, *114*(3), 1055–1063.

Levitt, B., & March, J. G. (1988). Organizational learning. *Annual Review of Sociology*, *14*(1), 319–338.

Lind, J. T., & Mehlum, H. (2010). With or without U? The appropriate test for a U-shaped relationship. *Oxford Bulletin of Economics and Statistics*, *72*(1), 109–118.

Locke, E. A., & Latham, G. P. (1990). *A theory of goal setting & task performance*. Prentice-Hall.

Locke, E. A., & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American Psychologist*, *57*(9), 705–717.

Locke, E. A., & Latham, G. P. (2006). New directions in goal-setting theory. *Current Directions in Psychological Science*, *15*(5), 265–268.

Louis, M. R., & Sutton, R. I. (1991). Switching cognitive gears: From habits of mind to active thinking. *Human Relations*, *44*(1), 55–76.

Madsen, P., Dillon, R. L., & Tinsley, C. H. (2016). Airline safety improvement through experience with near-misses: A cautionary tale. *Risk Analysis*, *36*(5), 1054–1066.

Maslach, D. (2016). Change and persistence with failed technological innovation. *Strategic Management Journal*, *37*(4), 714–723.

Medappa, P. K., & Srivastava, S. C. (2019). Does superposition influence the success of FLOSS projects? An examination of open-source software development by organizations and individuals. *Information Systems Research*, *30*(3), 764–786.

Pajares, F. (2008). Motivational role of self-efficacy beliefs in self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and application* (pp. 111–139). Routledge.

Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of Applied Econometrics*, *11*(6), 619–632.

Park, B., Lehman, D. W., & Ramanujam, R. (2022). Driven to distraction: The unintended consequences of organizational learning from failure caused by human error. *Organization Science*, *34*(1), 283–302.

Ramanujam, R., & Goodman, P. S. (2011). The link between organizational errors and adverse consequences: The role of error-correcting and error-amplifying feedback processes. In D. A. Hofmann & M. Frese (Eds.), *Errors in organizations* (pp. 245–272). Routledge.

Reagans, R., Argote, L., & Brooks, D. (2005). Individual experience and experience working together: Predicting learning rates from knowing who knows what and knowing how to work together. *Management Science*, *51*(6), 869–881.

Reason, J. (1990). *Human error*. Cambridge University Press.

Roulet, T. J. (2020). *The power of being divisive: Understanding negative social evaluations*. Stanford University Press.

Rybowiak, V., Garst, H., Frese, M., & Batinic, B. (1999). Error orientation questionnaire (EOQ): Reliability, validity, and different language equivalence. *Journal of Organizational Behavior*, *20*(4), 527–547.

Schumacher, C., Keck, S., & Tang, W. (2020). Biased interpretation of performance feedback: The role of CEO overconfidence. *Strategic Management Journal*, *41*(6), 1139–1165.

Schunk, D. H. (1991). Self-efficacy and academic motivation. *Educational Psychologist*, *26*(3–4), 207–231.

Seckler, C., Fischer, S., & Rosing, K. (2021). Who adopts an error management orientation? Discovering the role of humility. *Academy of Management Discoveries*, *7*(4), 461–481.

Sellke, F. W., Chu, L. M., & Cohn, W. E. (2010). Current state of surgical myocardial revascularization. *Circulation Journal*, *74*(6), 1031–1037.

Seo, M.-G., Barrett, L. F., & Bartunek, J. M. (2004). The role of affective experience in work motivation. *Academy of Management Review*, *29*(3), 423–439.

Shepherd, D. A., & Cardon, M. S. (2009). Negative emotional reactions to project failure and the self-compassion to learn from the experience. *Journal of Management Studies*, *46*(6), 923–949.

Shepherd, D. A., Haynie, J. M., & Patzelt, H. (2013). Project failures arising from corporate entrepreneurship: Impact of multiple project failures on employees' accumulated emotions, learning, and motivation. *Journal of Product Innovation Management*, *30*(5), 880–895.

Shepherd, D. A., Patzelt, H., & Wolfe, M. (2011). Moving forward from project failure: Negative emotions, affective commitment, and learning from the experience. *Academy of Management Journal*, *54*(6), 1229–1259.

Shepherd, L., LaDonna, K. A., Cristancho, S. M., & Chahine, S. (2019). How medical error shapes physicians' perceptions of learning: An exploratory study. *Academic Medicine*, *94*(8), 1157–1163.

Sitkin, S. B. (1992). Learning through failure: The strategy of small losses. *Research in Organizational Behavior*, *14*, 231–266.

Stan, M., & Vermeulen, F. (2013). Selection at the gate: Difficult cases, spillovers, and organizational learning. *Organization Science*, *24*(3), 796–812.

Staw, B. M. (1981). The escalation of commitment to a course of action. *Academy of Management Review*, *6*(4), 577–587.

Staw, B. M., Sandelands, L. E., & Dutton, J. E. (1981). Threat rigidity effects in organizational behavior: A multilevel analysis. *Administrative Science Quarterly*, *26*(4), 501–524.

Taylor, S. E. (1991). Asymmetrical effects of positive and negative events: The mobilization-minimization hypothesis. *Psychological Bulletin*, *110*(1), 67–85.

Tørring, B., Gittell, J. H., Laursen, M., Rasmussen, B. S., & Sørensen, E. E. (2019). Communication and relationship dynamics in surgical teams in the operating room: An ethnographic study. *BMC Health Services Research*, *19*, 1–16.
Vogus, T. J., Ramanujam, R., Novikov, Z., Venkataramani, V., & Tangirala, S. (2020). Adverse events and burnout: The moderating effects of workgroup identification and safety climate. *Medical Care*, *58*(7), 594–600.
Walkey, F. H., McClure, J., Meyer, L. H., & Weir, K. F. (2013). Low expectations equal no expectations: Aspirations, motivation, and achievement in secondary school. *Contemporary Educational Psychology*, *38*(4), 306–315.
Weiner, B. (1974). *Achievement motivation and attribution theory*. General Learning Press.
Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychological Review*, *92*(4), 548–573.
Weiner, B. (2000). Intrapersonal and interpersonal theories of motivation from an attribution perspective. *Educational Psychology Review*, *12*(1), 17–30.
Westaby, S. (2017). *Open heart: A cardiac surgeon's stories of life and death on the operating table*. Basic Books.
Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology*, *25*(1), 68–81.
Wilhelm, H., Richter, A. W., & Semrau, T. (2019). Employee learning from failure: A team-as-resource perspective. *Organization Science*, *30*(4), 694–714.
Wong, P. T., & Weiner, B. (1981). When people ask "why" questions, and the heuristics of attributional search. *Journal of Personality and Social Psychology*, *40*(4), 650–663.
Zakay, D., Ellis, S., & Shevalsky, M. (2004). Outcome value and early warning indications as determinants of willingness to learn from experience. *Experimental Psychology*, *51*(2), 150–157.
Zhao, B. (2011). Learning from errors: The role of context, emotion, and personality. *Journal of Organizational Behavior*, *32*(3), 435–463.
Zimmerman, B., & Schunk, D. (2006). Competence and control beliefs: Distinguishing the means and ends. In P. A. Alexander & P. H. Winne (Eds.), *Handbook of educational psychology* (pp. 349–367). Lawrence Erlbaum Associates Publishers.
Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology*, *25*(1), 82–91.
Zimmerman, B. J., Bandura, A., & Martinez-Pons, M. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting. *American Educational Research Journal*, *29*(3), 663–676.

SUPPORTING INFORMATION

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