MAKING EXPERIENCE COUNT:
THE ROLE OF REFLECTION IN INDIVIDUAL LEARNING

Giada Di Stefano
HEC Paris
Department of Strategy and Business Policy
1, rue de la Libération
78351 Jouy-en-Josas, France
Phone: ++33 (0)1 3967-9615
Email: di-stefano@hec.fr

Francesca Gino
Harvard University
Negotiation, Organizations, and Markets Unit
Baker Library, Bloomberg Center 447
Boston, MA 02163, USA
Phone: ++1 617 495-0875
E-mail: fgino@hbs.edu

Gary Pisano
Harvard University
Technology and Operations Management Unit
Morgan Hall 417
Boston, MA 02163, USA
Phone: ++1 617 495-6562
Email: gpisano@hbs.edu

Bradley Staats
University of North Carolina
Kenan-Flagler Business School
CB #3490
Chapel Hill, NC 27599, USA
Phone: ++1 919 962-7343
Email: bstaats@unc.edu

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ABSTRACT

How do organizations learn? In this paper, we build on research on the microfoundations of strategy and learning to study the individual underpinnings of organizational learning. We argue that once an individual has accumulated experience with a task, the benefit of accumulating additional experience is inferior to the benefit of deliberately articulating and codifying the previously accumulated experience. We explain the performance outcomes associated with such deliberate learning efforts using both a cognitive (task understanding) and an emotional (self-efficacy) mechanism. We study the proposed framework by means of a mixed-method approach that combines the reach and relevance of a field experiment with the precision of laboratory experiments. Our results support the proposed theoretical framework and bear important implications from both a theoretical and practical viewpoint.

INTRODUCTION

By three methods we may learn wisdom: First, by reflection, which is noblest; Second, by imitation, which is easiest; and third, by experience, which is the bitterest.
Confucius

In a diverse array of contexts, competitive advantage hinges critically on the skills of individual contributors. From sales representatives and customer support personnel to highly skilled professionals and senior executives, individual skill heavily influences competitive outcomes. It is no wonder then that U.S. corporations are estimated to have invested approximately $70 billion in training in the US[1] and $130 billion worldwide in 2013. While organizational learning is not the "sum total" of individual learning, it is hard to imagine the former without the latter. Not surprisingly, scholars are increasingly turning their attention to the "microfoundations" of organizational learning (Chan, Jia, and Pierce, 2014; Laureiro-Martinez, Brusoni, Canessa, and Zollo, 2015), with Grant (1996: 112) calling for "dispensing with the concept of organizational knowledge in favor of emphasizing the role of individuals in creating and storing knowledge."

[1] For US spending, see http://www.forbes.com/sites/joshbersin/2014/02/04/the-recovery-arrives-corporate-training-spend-skyrockets/#5b6147b4ab74 and https://trainingmag.com/sites/default/files/magazines/2014_11/2014-Industry-Report.pdf. For estimate of global spending, see http://www.forbes.com/sites/joshbersin/2014/02/04/the-recovery-arrives-corporate-training-spend-skyrockets/#5b6147b4ab74.

One of the most obvious sources of individual learning is the accumulation of experience (Argote and Miron-Spektor, 2011). As Gary Becker noted back in 1964, “Many workers increase their productivity by learning new skills and perfecting old ones while on the job.” (Becker, 1964: 8) The very idea of experiential, on-the-job learning goes back to Middle Ages with novice apprentices learning their trade by working along side with master craftsmen (Epstein and Prak, 2008). It should hence come as no surprise then that research on individual learning has mostly focused on the role of cumulative experience (e.g., Huckman and Pisano, 2003; Clark, Huckman, and Staats, 2012; KC, Staats, and Gino, 2013).

However, we also know from previous work that the accumulation of experience is only part of the story. As Zollo and Winter (2002: 340) argue, “relatively passive experiential processes of learning (‘by doing’)” should be studied together with “more deliberate cognitive processes having to do with the articulation and codification of […] knowledge.” Still, despite some efforts at understanding how these more “deliberate” forms of learning can affect progress along the learning curve (Anseel, Lievens, and Schollaert, 2009; Ellis *et al.*, 2014), research in this domain has not yet unveiled how they interplay with more traditional “experiential” forms of learning.

This is particularly crucial in the light of the fact that while experiential and deliberate cognitive approaches to learning can occur sequentially, they are substitutes at any one point in time. A minute spent on accumulating additional experience means a minute not available for articulating and codifying the experience accumulated in the past. Consider for instance a cardiac surgeon in training. She has completed ten operations under the eye of an instructor. It is in everyone’s interest for the cardiac surgeon to get better as fast as possible. Imagine she was given a choice in planning her agenda for the next two weeks. She could spend that time doing ten additional surgeries, or she could take the same amount of time alternating between a few additional surgeries and time spent reflecting on them to better understand what she did right or wrong. Every hour she spends reflecting on how to get better is costly in terms of lost practice time. Conversely, every hour spent practicing consumes time she could have spent reflecting on how to get better. What would be the optimal use of her time?

In this paper, we ask: which learning source provides the highest benefits to future performance? In particular, we compare the extent to which individuals can learn through the accumulation of additional experience versus through the articulation and codification of experience accumulated in the past (what we will refer to as "reflection"). We theorize that, once an individual has accumulated a certain amount of experience with a task, the benefit of accumulating additional experience is inferior to the benefit of articulating and codifying the accumulated experience.

Next, we isolate two separate mechanisms explaining the performance effect of reflection efforts. To this end, we borrow from research in organizational behavior and cognitive psychology (see for instance Anseel, Lievens, and Schollaert, 2009) to argue the performance effects of reflection depend on an individual's increased self-efficacy, i.e., "the belief in one's capabilities to organize and execute the course of action required to manage prospective situations" (Bandura, 1995: 2). Such an emotional mechanism differs from the "cognitive" mechanism that has been implied in most strategy literature on deliberate learning since Polanyi (1962). Scholars in this research stream have suggested that the articulation and codification of experience with a task allow better understanding of the task itself, which should in turn lead to better performance (Zollo and Winter, 2002; Kale and Singh, 2007).

We study these questions using a mixed-method experimental design that combines the reach and relevance of a field experiment with the precision of laboratory experiments. First, we test for the performance effect of reflection efforts through a field experiment that randomly assigned participants to either a reflection or additional experience condition. Our findings show that individuals who are given time to articulate and codify their experience with a task improve their performance significantly more than those who are given the same amount of time to accumulate additional experience with the task.

To identify the mechanisms at the basis of such an effect, we run a laboratory experiment. Our findings confirm that reflection has an effect on both self-efficacy and task understanding. Results of mediation analyses show that, when considered independently, both the cognitive and emotional mechanisms serve as mediators of the relationship between reflection efforts and improved performance. However, when both mechanisms are considered together (i.e., entered in the same regression model), only task understanding significantly mediates the relationship, thus suggesting a fundamental role for the cognitive catalyst of performance improvements.

Finally, we run a last laboratory experiment in the attempt to understand whether the "superiority" of reflection is common wisdom or runs contrary to most people's intuition. Our empirical evidence shows that when given a chance to choose between accumulating additional experience with a task versus articulating and codifying the experience they have already accumulated, individuals largely prefer doing to thinking. The results of this study however also suggest that this is a sub-optimal strategy: participants who chose to reflect outperformed those who chose additional experience.

Our research makes a novel contribution to the literature in several ways. First, we contribute to the fast-growing stream of strategy research on microfoundations by unpacking the individual underpinnings of organizational learning. Second, by incorporating both a cognitive and an emotional mechanism for the effect of reflection, we bridge strategy research on the learning process (Zollo and Winter, 2002; Kale and Singh, 2007; Heimeriks, Schijven, and Gates, 2012; Heimeriks, Bingham, and Laamanen, 2014), with organizational behavior research examining learning at the micro level (Anseel, Lievens, and Schollaert, 2009; Schippers, Homan, and van Krippenberg, 2013; Ellis *et al.*, 2014; Schippers, Edmondson, and West, 2014). Finally, we contribute to literature on the role of articulation and codification of experience associated with a task (Kogut and Zander, 1992; Nonaka, 1994; Zollo and Winter, 2002) by providing empirical evidence of the benefits associated with reflection and uncovering the causal mechanisms behind them.

THEORY AND HYPOTHESES

In this paper, we study the microfoundations of organizational learning by looking at the effect of two different sources of learning, namely the accumulation of additional experience (what we will refer to as practice or experiential learning) and the deliberate effort to articulate and codify experience accumulated in the past (what we will refer to as reflection or deliberate learning).

To this end, we mobilize two complementary literatures. On one hand, we rely on strategy research on the learning process (Zollo and Winter, 2002; Kale and Singh, 2007; Heimeriks, Schijven, and Gates, 2012; Heimeriks, Bingham, and Laamanen, 2014). According to this stream of literature, a firm's performance can improve through the articulation (i.e., discussion and reflection) and codification (i.e., abstraction and documentation) of its know-how.

We bridge this firm-level scholarship in strategy to research in organizational behavior and cognitive psychology examining learning at a more micro level (Anseel, Lievens, and Schollaert, 2009; Schippers, Homan, and van Krippenberg, 2013; Ellis *et al.*, 2014; Schippers, Edmondson, and West, 2014). Research in this domain also suggests an important role for articulation and codification efforts. For instance, Schippers, Homan, and van Krippenberg (2013) show that teams engaging in conscious reflection over their functioning, experience a performance increase, especially in the case of relatively low performance. The phenomenon has neurobiological explanations, as the brain's default mode, activated by constructive internal reflection, has been proven crucial for the development of cognitive abilities (Immordino-Yang, Christodoulou, and Singh, 2012). Taken together, this research suggests that performance is positively affected by deliberate learning efforts aimed at articulating and codifying past actions.

We push research in these streams of literature forward by theorizing that deliberate attempts to learn from previous experience generate higher performance outcomes as compared to the accumulation of additional experience alone. We then argue in favor of the existence of both a cognitive and an emotional mechanism behind this effect. We now move to the derivation of our hypotheses.

Deliberate vs. Experiential Learning

Let's go back to the example of the cardiac surgeon. Every minute she spends reflecting on how to get better is costly in terms of lost practice time. Conversely, every minute spent practicing consumes time she could have spent reflecting on how to get better. What would be the optimal choice for her to maximize learning? In other words, which learning source provides the highest benefits in terms of future performance: the accumulation of additional experience or a deliberate attempt to learn from the experience accumulated in the past? Our first hypothesis provides an answer to this question.

Note that deliberate learning becomes possible only if some experience has been accumulated and can then be articulated and codified. This implies that answering this question involves comparing learning generated by the sole accumulation of experience with learning generated by a combination of experience and deliberate efforts at articulation and codification. We expect the combination of different sources of learning to generate higher performance outcomes. That is, once a certain amount of experience has been accumulated, the benefit of accumulating additional experience is inferior to the benefit of coupling the previously accumulated experience with some efforts at articulating and codifying it. Our prediction is based on the existence of different cognitive processes and neurobiological mechanisms behind learning by accumulating experience and learning by articulating and codifying such experience.

First, the process of learning generated by experience and repetition with a task can be thought of as an automatic, unconscious process. By contrast, attempts to learn through deliberate articulation and codification efforts are controlled and conscious by nature. This fundamental difference corresponds to the claims of dual process theory that two different systems of thought underlie intuitive and reflective processing (Kahneman, 2011; Evans and Stanovich, 2013). In particular, System 1 thinking does not require working memory and is typically described as fast, non-conscious, intuitive, automatic, associative, and independent of cognitive ability. It is associated with experience-based decision making and implicit learning; think of the learning processes activated by the surgeon who spends two weeks performing the maximum number of operations. System 2 thinking, by contrast, is defined as a reflective process that requires working memory and is typically described as slow, conscious, controlled, rule-based, and correlated with cognitive ability. System 2 thinking is associated with consequential decision making and explicit learning, as in the case of the learning process activated by the surgeon if she were to spend two weeks alternating between performing operations and analyzing them.

Second, research in neuroscience demonstrates that distinct neuroplastic changes in the brain are associated with the different types of learning (Nyberg, Eriksson, Larsson, and Marklund, 2006). In this context, researchers have used fMRIs[2] to investigate the possible neurobiological mechanisms behind learning and the role of deliberate learning in the development of cognitive abilities (Nyberg, Eriksson, Larsson, and Marklund, 2006; Olsson, Jonsson and Nyberg, 2008; Immordino-Yang, Christodoulou, and Singh, 2012; Saimpont *et al.*, 2013). Results from these studies show that individuals can improve their performance on a task (i.e., motor ability) as a function of actual repetition of the task (i.e., motor training) as well as by simply projecting themselves in the act of

[2] Functional magnetic resonance imaging, or functional MRI (fMRI), is a magnetic resonance imaging used to detect physical changes in the brain resulting from increased neuronal activity.

executing the task (i.e., mental training using motor imagery). Interestingly, evidence on the effectiveness of combining the two types of training is mixed, with Nyberg *et al.* (2006) suggesting that combined motor and mental training results in interference effects, and Olsson *et al.* (2008) finding that mental training coupled with motor training is more effective than motor training alone.

Following the latter, we argue that the combination of experience and articulation/codification is more effective than experience alone. In other words, consider a time T, a sufficiently large fraction of which, called t, has been spent accumulating practice with a task. Learning generated by devoting (T-t) to articulating and codifying the experience cumulated in t will be superior to learning generated by devoting (T-t) to accumulating additional experience. Thus, we hypothesize:

> **Hypothesis 1**: The deliberate attempt at learning from previously accumulated experience generates higher performance outcomes as compared to the accumulation of additional experience.

Unpacking Deliberate Learning

We have hypothesized that individuals will learn more effectively when they are given the chance to articulate and codify the experience they have accumulated in the past. Why might deliberate learning efforts generate such superior improvement in performance outcomes? In particular, does deliberate learning affect our understanding of a task? Can it also impact our disposition toward the task? We argue that two different catalysts explain the performance improvement associated with deliberate learning, namely self-efficacy and task understanding. We think of them as the "emotional" and "cognitive" routes to performance.

The emotional effect of deliberate learning. The emotional route has been explicitly put forward by the work of Anseel, Lievens, and Schollaert (2009). The researchers show that when individuals are given feedback on their prior performance, they experience a higher self-efficacy and perform better in the future as a result. This idea resonates with a longstanding tradition of works in psychology that emphasize feeling competent and capable as a basic human motivation (White, 1959; Ryan and Deci, 2000). When people experience self-efficacy in an activity, they devote more time and energy to it because they believe that their effort will translate into success (Bandura, 1977; Ryan and Deci, 2000). Self-efficacy is also "an essential motive to learn" (Zimmerman, 2000: 82). For instance, prior research has demonstrated that self-efficacious students select more challenging tasks (Bandura and Schunk, 1981), exert more effort (Schunk and Hanson, 1985; Schunk, Hanson, and Cox, 1987), and have less adverse reactions when faced with difficulties (Bandura, 1997). As a result, self-efficacious students consistently show higher academic achievement as compared to inefficacious ones (Multon, Brown, and Lent, 1991).

Information that shapes one's self-efficacy beliefs comes from various sources (Bandura, 1986, 1997). The main and most reliable source is one's own prior experience with the tasks in question (Bandura, 1986, 1997). Deliberate learning, we suggest, strengthens one's self-efficacy by reducing a person's experience of uncertainty about being capable to complete such tasks competently and effectively. Though it is often the case that one's past experience includes ambiguities and errors, individuals tend to focus on their strengths and positive aspects when evaluating past experiences so that they can maintain a positive view of themselves (e.g., Taylor, 1991). As a result of their decreased uncertainty in their ability to complete the task they have reflected on, individuals will end up performing better on the task at hand.[3] In short, we expect the increase in self-efficacy to mediate the relationship between deliberate learning efforts and performance outcomes. Accordingly, we hypothesize:

> **Hypothesis 2**: Individuals' perceptions of increased self-efficacy will mediate the effect of the deliberate attempt to learn from previously accumulated experience on performance outcomes.

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[3] Here we should recognize that the accumulation of additional experience is also likely to increase self-efficacy. However, in light of our first hypothesis, we expect the combination of experiential and deliberate learning efforts to raise self-efficacy even further than the accumulation of additional experience alone.

The cognitive effect of deliberate learning. An alternative explanation of why deliberate learning generates performance improvements has to do with the effect of learning on the ability to understand the causal relationship between actions and outcomes (Zollo and Winter, 2002). Kale and Singh (2007) were the first to explicitly mention such a mechanism in explaining the performance effects of the deliberate effort to articulate and codify alliance-related know-how. In their paper, the researchers show that when alliance managers articulate actions and decisions in prior alliances (as in deliberate learning), they improve alliance success in the future (the expected performance outcome). As the authors explain, this may be the case because "the articulation process itself can facilitate ex post sense-making of actions and decisions […] as managers talk about or reflect on them. This helps a firm (and its managers) better understand the causal relationships that might exist between those actions and their associated outcomes" (Kale and Singh, 2007: 984). In other words, an improved understanding of the causal relationships between actions and their associated outcomes (our cognitive mechanism) is used to motivate the hypothesized relationship between deliberate learning and performance outcomes. Although such a relationship is now assumed by most research on alliances (see, for instance, Heimeriks, Bingham, and Laamanen, 2014), to the best of our knowledge, no study has explicitly tested the existence of such a cognitive mechanism in the context of alliances or in the broader context of learning process. Our third hypothesis is intended to fill this gap.

Here we suggest that deliberate learning strengthens one's understanding of the task by reducing a person's experience of causal ambiguity, or the perceived uncertainty about the causal relationships that link actions and associated outcomes. In other words, we expect the improved understanding of the task to mediate the relationship between deliberate learning efforts and performance outcomes. Accordingly, we hypothesize:

> **Hypothesis 3**: Individuals' perceptions of increased task understanding will mediate the effect of the deliberate attempt to learn from previously accumulated experience on performance outcomes.

Summary of Hypotheses and Overview of Research Design

In the section above, we have hypothesized that after some experience has been accrued, the benefit of accumulating additional experience is inferior to the benefit of articulating and codifying experience (H1). We have explained this effect using an emotional mechanism (deliberate learning enhances an individual's perceptions of self-efficacy, H2) and a cognitive mechanism (deliberate learning enhances an individual's perceptions of task understanding, H3). Figure 1 provides a graphical representation of our theoretical framework.

– Insert Figure 1 about here –

To test our hypotheses, we collected data from both the laboratory and the field. In Study 1, we test the first hypothesis through a field experiment. In Study 2, we test the full model using a laboratory experiment. Finally, in Study 3, we use a laboratory experiment to uncover individuals' beliefs about the benefits associated with deliberate vs. experiential learning. The use of laboratory and field experiments offers us complementary strengths and weaknesses. The laboratory experiments allow us to identify causality in a controlled setting and precisely measure our proposed mechanism. The field experiment provides a platform to not only identify causality but also establish external validity. Together, this approach allows us to more confidently evaluate our research model.

STUDY 1: THE POWER OF DELIBERATE LEARNING

Methods

In Study 1, we test H1 in the context of an actual organization by means of a field experiment with employees at a large business-process outsourcing firm.

Participants. Our field study was completed at Wipro BPO, an India-based global leader in the business-process outsourcing industry. Wipro provides knowledge-based customer support and back-office services (e.g., data entry and data processing) for its global customer base. We conducted this study using one customer account. The work for this account involved answering technology-related support questions via the telephone for customers of a Western technology company. The call center provides us with an excellent setting to study learning and performance outcomes at the individual level. Successful completion of the work requires technical knowledge on the part of Wipro employees. Questions can cover a wide range of topics; some can be answered easily, while others require a great deal of problem solving. To complete the work, Wipro not only recruits well-qualified agents (college graduates) but also trains them for four weeks on the technical process they will follow once they join the firm (known as "process training"). After technical process training, agents go through two weeks of "on-the-job training" – a combination of classroom training and answering actual calls. At the end of their training, agents transition full-time into their customer service responsibilities.

Design and procedure. Our field study sample was comprised of agents who joined Wipro BPO in the focal account between June and August 2013. Agents joined in batches of 10 to 25, and each batch was assigned to one of two conditions: (1) reflection or (2) practice.[4] The final sample included 101 agents, 56 of whom were assigned to the reflection condition. Participants within each condition represent a similar profile of agents and went through the same overall technical training. The primary difference between the two groups was that agents in the reflection condition spent the

[4] We collected additional data on a third condition, in which we asked participants to spend the last 15 minutes of the day (1) articulating and codifying the experience accumulated in the past (10 minutes) and (2) sharing this knowledge with another participant (five minutes). We included this condition to examine whether sharing (a third step in the learning process put forward by Kale and Singh, 2007) would further increase the benefits of articulation and codification. Results show that this is not the case. For ease of discussion, we hence decided not to report this additional analysis. Results are available from the authors upon request.

last 15 minutes of their day performing the tasks associated with our experimental manipulation instead of spending the same amount of time getting additional practice in their on-the-job training.

Manipulations. Agents assigned to the practice condition spent the last 15 minutes of their day on their normal training activities – that is, they accumulated additional experience with the tasks associated to their job. Instead, in the reflection condition, trainers adjusted the timing of their trainees during the day to free up the last 15 minutes for the intervention. Starting from the sixth day of training, agents assigned to this condition were given a paper journal and asked to spend the last 15 minutes of their day articulating and codifying the experience they had accumulated during the day. Agents were given time to reflect at the end of each day for a total of 10 days. The exact instructions provided by their Wipro trainer were:

> *Please take the next 15 minutes to reflect on the training day you just completed. Please write about the main key lessons you learned as you were completing your training. Please reflect on and write about at least two key lessons. Please be as specific as possible.*

Measures. Our primary independent variable of interest is reflection, as manipulated in the experimental condition described above. Our dependent variable is participants' performance in the test they took at the end of their process training. This is a test administered directly by Wipro at the end of each process training in order to assess the extent to which trainees have learned the main lessons taught during the training. Scores can range from 0 to 100 and were provided to us directly by the company. Finally, in our analyses, we include a series of controls at the individual level, namely age (years), gender (male=1, female=0), and previous work experience (months). Table 1 reports descriptive statistics and correlations among the variables we collected, while Table 2 reports mean comparisons across participants allocated to the two different experimental conditions. It is worth noting that participants in the different experimental groups did not differ significantly in terms of age and work experience. We do observe a lower number of female participants allocated to the reflection condition as compared to the practice condition. However, gender is poorly correlated with all other variables and does not significantly predict our dependent variable.

– Insert Tables 1 and 2 about here –

Results

To analyze the results from our field experiment, we run an ordinary least squares (OLS) regression in which we estimate the effect of reflection on performance in comparison with practice.[5] Table 3 shows two models: Model 1 includes only control variables; while Model 2 includes reflection while omitting practice, which acts as the baseline case.

– Insert Table 3 about here –

The results from Model 2 show strong support for H1: by being allocated to the reflection (rather than practice) condition, participants improved their score on the final assessment test by 14.843 points (p = .000, CI: 8.484, 21.203), a 23.2% increase with respect to the average score for the entire sample (63.911). We ran an additional test to evaluate whether the positive effect of articulating and codifying the accumulated prior experience lasted over time. To this end, Wipro shared customer satisfaction data, as rated by randomly sampled customers served in the first three months after each agent transitioned into their customer service responsibilities. In particular, our performance measure is a common measure of customer satisfaction in call centers called "top box" – that is, the percentage of randomly sampled callers that mark their satisfaction in the highest category. Compared to participants in the practice condition, participants in the reflection condition improved their likelihood of being in the top-rated category by 19.1%. The effect disappeared after the first month.[6]

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[5] As a robustness test, we also used an alternative logit specification using a dichotomous dependent variable, *passed,* indicating whether our participants passed the final assessment test or not. This pass/fail evaluation was again provided directly by Wipro. Results based on this alternative specification are consistent with those presented in the paper.
[6] Results from this additional analysis are available from the authors upon request.

Discussion

Results from our field experiment provide support for our prediction that the performance outcomes generated by the deliberate attempt to articulate and codify the accumulated prior experience will be greater than those generated by the accumulation of additional experience alone (H1). In addition, our findings show that the beneficial effect of reflection endures over time, as we were still able to observe a significant effect of our manipulation on performance one month after the agents transitioned full-time into their customer service responsibilities.

STUDY 2: THE ROLE OF EMOTIONAL AND COGNITIVE MECHANISMS

Methods

Having found support for our main hypothesis in the field, we designed a second study, which we carried out in the laboratory. The purpose of this study was to test our full model to reach a better understanding of the mechanisms that explain the performance outcomes associated with the deliberate articulation and codification of previously accumulated experience.

Participants. Participants were recruited through Amazon Mechanical Turk (see Buhrmester, Kwang, and Gosling, 2011 for a description), where they were provided with a brief description of the study and elected to participate in exchange for $2. To be eligible for the study, participants were required to be located in the United States and to pass a color-blindness test (necessary to effectively complete the task at the basis of the study). The final sample included 453 participants, consisting of 50.6% women with a mean age of 32.52 (SD_{Age} = 7.94).

Design and procedure. Participants were randomly assigned to one of three between-subjects conditions: reflection, practice, or control. We told participants that they were participating in a task called "Tumor cell count task." In the task, they would be counting the number of tumor cells that appeared within an image. The instructions informed participants that "Although we already have initial counts from one source, we need humans to verify the count of tumor cells within each image. Given the nature of the task, you may not participate if you are colorblind." This task was adapted from the paradigm used by Chandler and Kapelner (2013). We used this task to provide a context that would be challenging and unfamiliar to participants, making it more likely that they would learn across rounds.[7]

After answering demographic questions, including the red-green color blindness test mentioned earlier, we included two attention filters. Participants who failed one or both attention filters were automatically brought to a screen telling them that, given their answers, they could not participate in the study. Their data was not recorded.

Next, participants received the instructions to the tumor cell count task (see Appendix A) and were given the opportunity to see an example of the task they would be completing. When they felt sufficiently prepared, participants could advance to the first part of the task, in which they saw six different images, each representing a blood smear that contained several tumor cells (see Figure 2 for an example). For each image they saw on the screen, participants had to indicate the number of tumor cells that were present in the image.

– Insert Figure 2 about here –

Manipulations. After seeing six images in the first round, participants were randomly assigned to one of three conditions: reflection, practice, or control. In the *reflection* condition, participants were asked to think about and write down the main lessons learned from the task they had just completed. Participants had three minutes to engage in such an effort. The study advanced to the next stage once the three minutes were over. The exact instructions were:

> *Please take the next few minutes to reflect on the task you just completed. Please write down your reflections and be as specific as possible.*

[7] We have conducted a number of pre-tests using different tasks (sum-to-ten games as per Study 3, construction of circuit boards, karaoke exercise) and different incentive systems (pay for performance, flat play). Results across all these studies are consistent with those from the study reported above.

You will have THREE minutes to engage in this reflection. The study will advance to the next stage once the THREE minutes are over.

In the *practice* condition, participants were asked to accumulate additional experience on the task they had just completed. They saw a few images and, for each, they could count the number of tumor cells that were present. Participants had three minutes to practice on the images. The study advanced to the next stage after three minutes. The exact instructions were:

Please take the next few minutes to practice some more on the task you just completed. Below you'll see a few images. For each, you can count the number of tumor cells that are present.
You will have THREE minutes to practice on the images. The study will advance to the next stage once the THREE minutes are over.

In the *control* condition, participants were asked to read a short story shown to them on the screen. They were told that we would ask them a few questions about it after they were done reading it. Participants had three minutes to read the story. The study advanced to the next stage once the three minutes were over. The exact instructions were:

Please take the next few minutes to read the short story below. We'll ask you a few questions about it after you're done reading it.
You will have THREE minutes to read the story. The study will advance to the next stage once the THREE minutes are over.

Measures. After completing the task used as manipulation, participants were told that they would soon be asked to complete the second round of the tumor-cell count task. Before the second round, we asked them to answer a short questionnaire measuring our mediating variables, namely self-efficacy and task understanding. Participants received the questions in random order.

We assessed perceived self-efficacy using a four-item measure adapted from Bandura (1990). In particular, we asked participants to rate the extent to which they agreed with four statements (from 1 = Strongly disagree, to 7 = Strongly agree), namely: (1) "Right now, I feel capable"; (2) "Right now, I feel competent"; (3) "Right now, I feel able to make good judgments"; and (4) Right now, I think I can manage to solve difficult problems if I try hard enough." We averaged these items into one measure of self-efficacy (α = .95).

We measured perceived task understanding using three items (1 = strongly disagree, 7 = strongly agree), namely: (1) "I now understand how to perform this task better"; (2) "It is now clearer to me how this task works"; and (3) "I now know how to count accurately in this task." We averaged these items into one measure of task understanding ($\alpha = .93$).

After responding to these questions, participants advanced to a second round of the tumor-cell count task with a series of six different images. As our main dependent measure, we computed participants' performance on the second round of the task in terms of their accuracy (scoring their tumor cell count against the correct count for the same image) for each of the six images in the round. Additionally, we also captured their first-round score (which we use as a control in our analyses). We also computed the difference in these two accuracy scores to identify the (likely) improvement in accuracy observed across rounds. Table 4 reports descriptive statistics by condition of the variables we collected.

– Insert Table 4 about here –

Results

Performance. We conducted an ANOVA using participants' accuracy on the second set of rounds of the tumor cell count task (after our manipulation took place) as the dependent measure and condition as the independent variable, and controlling for accuracy on the first round (before our manipulation occurred). We found a significant effect of condition on the accuracy score in the rounds after the manipulation occurred, F (2, 449) = 3.52, p = .031, $\eta^2_p = .015$. As one may expect, the accuracy score at time 1 predicted the accuracy score at time 2, F (2, 449) = 802, p < .001, η^2_p = .64. Similarly, improvement in accuracy across rounds (comparing the rounds before and after the manipulation occurred) varied by condition, F (2, 450) = 4.15, p = .016, $\eta^2_p = .018$. When examining differences in improved accuracy across conditions, we found that participants in the reflection condition showed greater improvement in their accuracy of counted tumor cells (M = 48.58, SD =

74.07) compared to those in the practice (*M* = 24.76, *SD* = 68.31; *p* = .007) and control (*M* = 29.22, *SD* = 86.12; *p* = .028) conditions. The improvement in accuracy did not differ for participants in the practice condition compared to those in the control condition (*p* = .610).

Self-efficacy. We used participants' perceived self-efficacy in an ANOVA with condition (reflection vs. practice vs. control) as a between-subject factor. As expected, this analysis revealed a main effect for our manipulation, F (2, 450) = 13.11, $p < .001$, $\eta^2_p = .055$. Participants reported feeling more self-efficacious following the manipulation in the reflection condition (*M* = 3.88, *SD* = 1.44) than they did in the practice (*M* = 3.48, *SD* = 1.57; *p* = .018) and control (*M* = 3.02, *SD* = 1.38; $p < .001$) conditions. Perceived self-efficacy also differed for participants in the practice condition compared to those in the control condition (*p* = .007).

Task understanding. Participants' perceived task understanding also varied across conditions, F (2, 450) = 6.89, $p = .001$, $\eta^2_p = .03$. Participants reported greater task understanding following the manipulation in the reflection condition (*M* = 4.03, *SD* = 1.42) than they did in the practice (*M* = 3.50, *SD* = 1.50; *p* = .002) and in the control (*M* = 3.49, *SD* = 1.45; *p* = .001) conditions. Task understanding did not differ for participants in the practice condition and those in the control condition (*p* = .95).

Mediation analyses. Next, we examined whether self-efficacy or task understanding mediated the effect of reflection on performance. We conducted three set of analyses: one with self-efficacy as the only mediator (to test H2); one with task understanding as the only mediator (to test H3); and a final set of analyses self-efficacy and task understanding together as mediator. In each set of analyses, we followed the steps recommended by Baron and Kenny (1986). The first and second criteria specify that the independent variable should significantly affect the dependent variable and the mediators. The prior analyses showed that these two criteria were met, as reflection had a significant effect on both performance, as well as on self-efficacy and task understanding. To assess the third and fourth criteria, we conducted a hierarchical ordinary least squares (OLS) regression analysis (including a dummy variable for the practice condition) predicting performance first from reflection (Step 1), and then from self-efficacy and/or task understanding (Step 2). The third criterion specifies that the mediator should significantly predict the dependent variable while controlling for the independent variable. To complete the test of mediation, the fourth criterion holds that the effect of the independent variable on the dependent variable should decrease after controlling for the mediator. Finally, to test whether the size of the indirect effect of reflection on performance through our proposed mediator differed significantly from zero, we used a bootstrap procedure to construct bias-corrected confidence intervals based on 10,000 random samples with replacement from the full sample (Preacher and Hayes, 2004). Since we are interested in learning, in our analyses below we use improvement in accuracy as the dependent measure. Greater accuracy improvement means greater performance (We note, however, that the results do not change when considering accuracy in the second set of rounds as the dependent measure and controlling for accuracy in the first set of rounds).

Self-efficacy as the only mediator. Self-efficacy mediated the effect of reflection on performance when considered on its own. Having controlled for reflection, self-efficacy significantly predicted accuracy improvement (β = .15, t = 3.11, p = .002). After controlling for self-efficacy, the effect of reflection on performance decreased significantly (from β =.12, t = 2.21, p = .028; to β =.079, t = 1.44, p = .15). The 95% bias-corrected confidence interval excluded zero (2.69, 12.39), indicating a significant indirect effect.

Task understanding as the only mediator. Task understanding also mediated the effect of reflection on performance when considered on its own. Having controlled for reflection, task understanding significantly predicted accuracy improvement (β = .17, t = 3.67, p < .001). After controlling for task-understanding, the effect of reflection on performance decreased significantly (from β =.12, t = 2.21, p = .028; to β =.089, t = 1.66, p = .098). The 95% bias-corrected confidence interval excluded zero (1.71, 10.17), indicating a significant effect.

Self-efficacy and Task-understanding as mediators. When considered together, we found that only task understanding served as the mediator for the relationship between reflection and performance. Having controlled for reflection, task understanding significantly predicted greater accuracy improvement (β = .13, t = 2.42, p = .016), while self-efficacy did not (β =.08, t = 1.46, p = .145). After controlling for both potential mediators, the effect of reflection on performance decreased significantly (from β =.12, t = 2.21, p = .028; to β =.074, t = 1.36, p = .17). The 95% bias-corrected confidence interval excluded zero for task understanding (0.86, 8.93) but included zero for self-efficacy (-0.35, 8.90). Thus, task understanding mediated the effect of reflection on performance.

Results from our analyses provide support to our mediation hypotheses. When considered independently, both task understanding and self-efficacy serve as mediators of the relationship between reflection and performance. However, when both measures are entered in the same regression models, as we did in the analyses reported above, only task understanding is a significant mediator.

Discussion

In Study 2, we randomly assigned participants to one of three experimental conditions, namely reflection, practice, and control. First, we observe that participants in the reflection condition outperformed those in the other conditions. This result provides further support for H1, according to which the performance outcomes generated by the deliberate attempt to articulate and codify the accumulated prior experience are greater than those generated by the accumulation of additional experience alone.[8]

Second, we observe that when considered independently, both task understanding and self-efficacy serve as mediators of the relationship between reflection and performance. This supports our mediation hypotheses, according to which the higher performance outcomes associated with deliberate learning are explained by both an emotional (H2) and a cognitive (H3) mechanism. However, we find that when both measures of perceived self-efficacy and perceived task understanding are entered in the same regression models, only task understanding significantly mediates the relationship between reflection and performance. This final result suggests that when both the emotional and the cognitive mechanisms are considered, only the latter mediates the effect of the deliberate attempt at learning from previously accumulated experience on performance outcomes, thus ultimately supporting H3 at the expense of H2.

We speculate that this may be the case as the effect of the emotional mechanism may partially depend on the valence of prior experience. Individuals could have a harder time boosting their self-efficacy when prior experience has been mostly negative. Failure elicits negative emotional responses that have been compared to the feeling of grief and have been suggested to interfere with the ability to learn from the events surrounding the failure (Sheperd, 2003). This may explain why the positive effect of deliberate learning on self-efficacy is weaker in the case of negative prior experience. The same should not hold true for the cognitive mechanism. Even if my prior experience with a task has been negative, the act of articulating and codifying it should still increase

[8] We run a specific test to measure the extent to which participants engaged in deliberation rather than providing impulsive answers. When measuring self-efficacy and task understanding, we also provided participants with three questions from the Cognitive Reflection Test (Frederick, 2005). Since the test included three questions, the final score for this measure was a number between 0 and 3, with higher scores indicating greater levels of deliberation. Results from this additional analysis show that reflection improves deliberation, while practice does not. Participants' score on the CRT was higher in the reflection condition (M = 2.05, SD = 1.12) than in the practice (M = 1.71, SD = 1.23; p = .017) and control (M = 1.77, SD = 1.24; p = .045) conditions, with no significant difference between the latter two (p = .69).

the extent to which I understand the task. Despite being emotionally daunting, learning from failures is actually possible (Cannon and Edmondson, 2001; Edmondson, 2011). We hope that future research will better clarify whether the valence of prior experience explains the finding that the cognitive mechanism prevails over the emotional one when the effect of both is examined at the same time.

STUDY 3: MISTAKEN BELIEFS ABOUT THE BENEFITS OF DELIBERATE VS. EXPERIENTIAL LEARNING

Methods

In our last study, we examine people's beliefs regarding the benefits of reflection versus practice. We do so by giving participants a choice regarding how to allocate their time after gaining some experience on a task and before working on it more. Participants could choose between gaining additional experience on the task in question or by articulating and codifying the experience they accumulated so far.

Participants. We recruited 256 adults (56.3% male, M_{age}=31.67, *SD*=8.46) on Amazon Mechanical Turk (see Buhrmester, Kwang, and Gosling, 2011 for a description) to participate in an online study in exchange for $1 and the potential to earn an additional bonus based on performance. Specifically, 10 percent of the participants (chosen randomly) received a bonus based on their performance in the study.

Design and procedure. Participants first received welcoming instructions and were then asked two questions used as attention checks. Participants who failed one of the attention checks were redirected to a page telling them they could not participate in the study. Participants who answered both attention-check questions correctly moved on to a screen with instructions. We told these participants that they would complete a brainteaser under time pressure. The brainteaser was a series of five "sum-to-ten game" grids (initially developed by Mazar, Amir, and Ariely, 2008). Each grid was a 3 x 4-cell matrix of numbers (see Figure 3 for an example). We gave participants 20 seconds to find the two numbers in the grid that summed to 10. Participants would earn $1 for each correct brainteaser solved in 20 seconds or less (if they were among the 10 percent selected at the end of the study).

– Insert Figure 3 about here –

Participants first completed a practice round to gain familiarity with the task. They then completed the first round of the brainteaser (i.e., a set of five different grids). After each grid, they were told whether the answer they selected was correct or not.

Manipulations. We introduced our choice variable after the first round of the brainteaser. Participants received the following instructions:

> *We'll soon be asking you to engage in a second round of the MATH BRAIN TEASER (i.e., five more math puzzles). Before you start round 2, you can choose how to spend the next 3 minutes. You have two choices:*
> *1) You can spend 3 minutes thinking and writing about the strategies you used in the first round;*
> *2) You can spend 3 minutes practicing on another set of math puzzles (the same type of math puzzles as the ones you solved in the first round).*
> *Please choose how you want to spend the next 3 minutes, to best prepare for round 2 of the MATH BRAIN TEASER.*

Participants indicated their choice. Next, depending on their choice, they were redirected to one of two different screens. Participants who chose to engage in deliberate learning received the following instructions:

> *Please take the next few minutes to reflect on the task you just completed. Please write about what strategies if any you used as you were working on the task. Also please write about what you think one can do to be effective in solving the math problems included in this task. Please be as specific as possible.*
> *You will have THREE minutes to engage in this reflection. The study will advance to the next stage once the THREE minutes are over.*

Participants who chose to engage in experiential learning received the following instructions:

> *Please take the next few minutes to practice some more on the task you just completed. Below you'll see a few puzzles that you can try to solve. (You can keep track of your performance on a piece of paper if you'd like.)*
> *You will have THREE minutes to practice on the puzzles. The study will advance to the next stage once the THREE minutes are over.*

After the three minutes spent on either of the two conditions, all participants completed two other rounds of math puzzles, each comprising five different grids. The grids from the three rounds were all different.

Measures. After completing the third round, participants completed a short questionnaire with a few demographic questions. We measured our dependent variable by looking at participants' performance in the two rounds of the brainteaser that followed our manipulation. Table 5 reports descriptive statistics by condition of the variables we collected.

– Insert Table 5 about here –

Results

Eighty-two percent of the participants (210 out of 256) chose to gain additional experience on the task; only 18 percent (46 out of 256) chose to spend time articulating and codifying the experience they accumulated in the first round, $X^2(1) = 105.6$, $p < .001$. Despite these preferences, reflection resulted in higher levels of performance over rounds 2 and 3 of the brainteaser. To show this, we ran an ANOVA using participants' performance on the second and third rounds of the brain teaser as the dependent variable, and choice (i.e., whether people decided to engage in reflection or practice) as the independent variable, controlling for performance on the first round (before the choice occurred). We found a significant effect of our manipulation on performance in the second and third rounds, $F\,(1, 253) = 5.24$, $p = .023$, $\eta^2_p = .02$. Participants correctly solved more grids in the second and third round when they decided to articulate and codify the experience accumulated in the first round ($M = 5.33$, $SD = 2.31$) rather than to gain additional experience ($M = 4.37$, $SD = 2.39$). As one might expect, performance in round 1 predicted performance over time 2 and 3, $F\,(1, 253) = 56.39$, $p < .001$, $\eta^2_p = .18$. We also conducted independent samples t-tests and found no significant difference in performance in time 1 between those who later chose reflection vs. practice ($p = .37$).

Discussion

We decided to run Study 3 in order to get a sense of whether the "superiority" of deliberate learning is common wisdom or runs contrary to most people's intuition. Results from our experiment show that the overwhelming majority of participants decided to gain additional experience rather than taking the time to articulate and codify what they learned from prior experience. Their preference for "experiential learning" over "deliberate learning" was supposedly based on the premise that gaining additional experience would have given rise to superior performance improvement as compared to engaging in a deliberate articulation and codification effort. In other words, individuals chose to do because they expected this would enable them to perform better in subsequent rounds. However, our results show just the opposite: this strategy was counterproductive, as participants scored higher in the following round when they decided to reflect upon the experience accumulated in the past instead of collecting additional experience.

DISCUSSION AND CONCLUSIONS

How do humans learn? In particular, which learning source provides the highest benefits to future performance? Should individuals seek to accumulate additional experience or should they focus on trying to articulate and codify the experience accumulated in the past?

These questions are fundamental strategy questions. The competitive advantage of firms, as well as more generally nations, critically depends on the skills of individual contributors. Hence the centrality of individual learning to the competitiveness of any organizational form.

In our daily battle against the clock, taking time to step back and engage in a deliberate effort to learn from one's prior experience would seem to be a luxurious pursuit.[9] Though some

[9] Data show that between 1973 and 2000, "the average American worker added an additional 199 hours to his or her annual schedule—or nearly five additional weeks of work per year (assuming a 40-hour workweek)" (Schor, 2003: 7). In the meanwhile, between 1969 and 2000, "the overall index of labor productivity per hour increased about 80 percent,

organizations increasingly rely on deliberate learning tools, as in the case of after-action reviews and post-mortems (Catmull, 2014), there has been little effort to encourage individuals to take the time to think about the past, rather than to do more and more. Articulating and codifying prior experience does entail the high opportunity cost of one's time, yet we argue and show that thinking after completing tasks is no idle pursuit: It can powerfully enhance the learning process, and it does so more than the accumulation of additional experience on the same task.

Performance outcomes, we find, can be augmented if one deliberately focuses on learning from experience accumulated in the past. Results from our studies consistently show a significant increase in the ability to successfully complete a task when individuals are given the chance to couple some initial experience with a deliberate effort to articulate and codify the key lessons learned from such experience. In explaining the performance outcomes associated with reflection, we show that deliberate learning efforts affect how one approaches the same task afterwards both cognitively and emotionally. In particular, results from our studies show that greater perceived self-efficacy (emotional mechanism) and task understanding (cognitive mechanism) mediate the performance outcomes of reflection. We also find that when both mechanisms are considered at the same time, only task understanding significantly mediates the relationship, thus suggesting a fundamental role for the cognitive catalyst of performance improvements. Although reflection does build confidence in one's ability to deal with a task, it is the improved understanding of the task to drive the actual performance increases.

We believe our research contributes to extant literature along three dimensions. First, we contribute to the fast-growing stream of strategy research on microfoundations, by examining the microfoundations of organizational learning (Chan, Jia, and Pierce, 2014, Laureiro-Martinez,

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from 65.5 to 116.6" (Schor, 2003: 10). As a result, productivity and time efficiency have become significant concerns in modern Western societies, with time being perceived as "the ultimate scarcity" (e.g., Gross, 1987)—a valuable resource to guard and protect (Gleick, 2000; Zauberman and Lynch, 2005).

Brusoni, Canessa, and Zollo, 2015). In this respect, we show that individuals who engage in deliberate learning efforts experience higher performance improvements as compared to individuals who have simply accumulated additional experience. Second, we bridge strategy research on the learning process (Zollo and Winter, 2002; Kale and Singh, 2007; Heimeriks, Schijven, and Gates, 2012; Heimeriks, Bingham, and Laamanen, 2014) with organizational behavior research examining learning at the micro level (Anseel, Lievens, and Schollaert, 2009; Schippers, Homan, and van Krippenberg, 2013; Ellis *et al.*, 2014; Schippers, Edmondson, and West, 2014). In this respect, we show that the performance outcomes of deliberate learning are generated by both the cognitive mechanism (task understanding) put forward by the former, and the emotional mechanism (self-efficacy) put forward by the latter. Interestingly, our results seem to suggest a prevalence of the cognitive over the emotional explanation. Finally, we contribute to the literature on the role of articulation and codification of experience associated with a task (Kogut and Zander, 1992; Nonaka, 1994; Zollo and Winter, 2002) by providing empirical evidence of the benefits associated with deliberate learning efforts and uncovering the causal mechanisms behind them.

Our results also have important practical implications. In our field study, we showed that taking time away from training and reallocating that time to deliberate learning efforts improved individual performance. Companies often use tools such as learning journals as a way to encourage deliberate learning in training and regular operations. Our personal experience is that individuals of all ages may not treat these exercises with much seriousness; however, our findings suggest that they should. We highlight that it may be possible to train and learn "smarter," not "harder." Additional work is needed to clarify how deliberate learning can be incorporated more broadly into both training and regular operations.

Despite our efforts, our results are subject to several limitations. First, despite the fact that we combine the use of laboratory experiments with a field study, additional research is needed to explore these findings across a broader array of contexts and tasks. Second, our research focused on individual learning, with participants being removed from social interactions. Understanding how social interaction may aid or detract from the performance outcomes of deliberate learning is worth additional study. Third, the finding that task understanding prevails over self-efficacy in explaining the relationship between deliberate learning and performance improvements suggests the need for additional studies to better uncover the mechanisms through which reflection operates.

We believe our research opens a number of avenues for future investigation. First, future work could better map the effect of time in the attempt to understand the extent to which different sources of learning produce improvements that last and whether there are differences among them. Future research could also examine potential boundary conditions for the effects we uncovered by focusing on individual differences that moderate the effectiveness of deliberate learning efforts. One may argue that deliberate learning is most beneficial for people with low self-esteem who do not have a lot of task experience, as it may point to important aspects of their prior performance that they would not naturally think about. However, the opposite may also occur if individuals with low self-esteem have a hard time finding strengths in their prior performance. Another possible extension would be to see how the effects we document in this paper interact with group dynamics, as in the case of formal after-action reviews (Goh, Goodman, and Weingart, 2013). More generally, future research could extend the study of deliberate learning to better understand how it can impact other variables. For instance, the notion that reflection favors progress along the learning curve may inform research on employee motivation and the role of work progress as one of its key drivers (Amabile and Kramer, 2011).

Together, our results reveal deliberation to be a powerful mechanism behind learning, confirming the words of American philosopher, psychologist, and educational reformer John Dewey (1933:78): "We do not learn from experience. We learn from reflecting on experience."

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Table 1.
Descriptive statistics and correlations, Study 1

Variable	Mean	SD	Min	Max	1	2	3	4	5	6
1. Performance	64	18	17	95	1.00					
2. Reflection	1	0	0	1	0.48	1.00				
3. Practice	0	0	0	1	-0.48	-1.00	1.00			
4. Age	25	4	19	34	-0.14	-0.13	0.13	1.00		
5. Gender	1	0	0	1	-0.14	-0.16	0.16	0,05	1.00	
6. Work experience	30	31	0	122	0.13	0.06	-0.06	0.65	0.09	1.00

Table 2.
Univariate Tests across Conditions, Study 1

	Reflection (n=56)		Practice (n=45)		T-test	
	Mean	S.D.	Mean	S.D.	t	Sig
			Control Variables			
Age	24.768	0.483	25.787	0.560	1.385	0.169
Gender	0.752	0.060	0.872	0.049	1.769	0.080
Work experience	31.245	4.483	26.930	4.053	-0.702	0.484
			Dependent Variable			
Performance	71.536	1.308	54.422	3.088	-5.474	0.000

Table 3.
Results from OLS Regressions, Study 1

	Model 1		**Model 2**	
	coef	**p-value**	**coef**	**p-value**
	Control Variables			
Age	-1.797	0.003	-1.212	0.000
Gender	-6.780	0.106	-3.646	0.030
Work experience	0.221	0.003	0.158	0.344
	Dependent Variable			
Reflection			14.843	0.020
_cons	108.024	0.000	84.468	0.000
F	4.539	0.005	9.489	0.000
N	101		101	
Adjusted R2	0.096		0.253	

Table 4.
Means (and standard deviations) by condition, Study 2

Condition	Accuracy score, round 1*	Accuracy score, round 2*	Accuracy improvement	Perceived self-efficacy	Perceived task understanding
Control	127.37	98.14	29.22	3.02	3.49
	(126.16)	(106.37)	(86.12)	(1.38)	(1.45)
Practice	117.21	92.46	24.76	3.48	3.50
	(116.97)	(115.33)	(68.31)	(1.57)	(1.50)
Reflection	135.75	87.16	48.58	3.88	4.03
	(135.51)	(114.78)	(74.07)	(1.44)	(1.42)

* Lower values indicate greater accuracy.

Table 5.
Means (and standard deviations) by condition, Study 3

Condition	Performance, Round 1	Performance, Rounds 2 and 3
Practice	2.22	4.37
	(1.59)	(2.39)
Reflection	2.02	5.33
	(1.28)	(2.31)

Figure 1.
Our theoretical framework

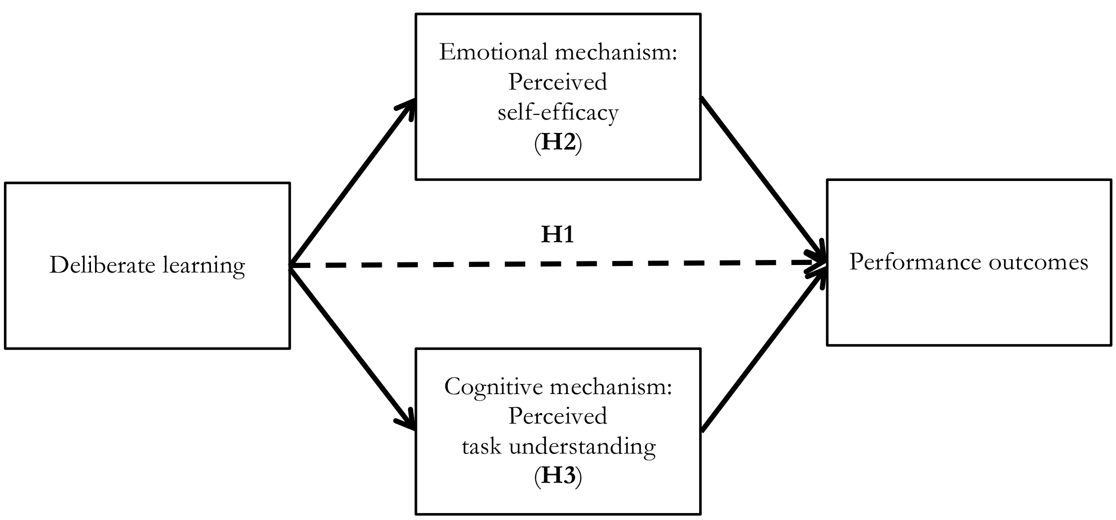


Figure 2.
Example of image participants saw, Study 2

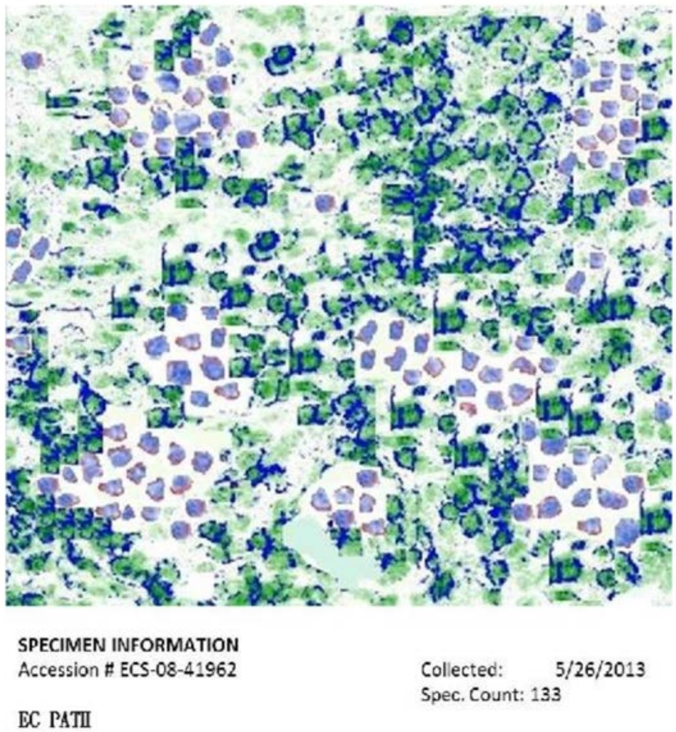


Figure 3.
An example of the type of grid participants were asked to solve, Study 3

8.18	9.01	3.97
5.2	4.56	9.12
0.28	2.92	6.59
1.12	6.93	9.72

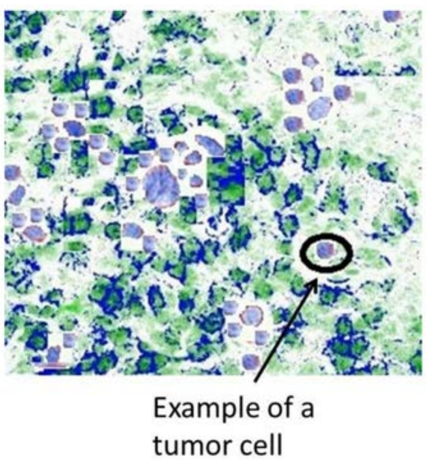
Appendix A
Instructions for the Tumor Cell Count Task (Study 2)

When you begin each image, the magnification will be set to the lowest resolution. This gives you an overview of all points on the image, but you may need to zoom in and out in order to come up with an accurate count of the number of tumor cells. Please look at the image below. The tumor cells appear in a lavender color with faint traces of red around them. The images circled in red are tumor cells.

Your task is to count the number of tumor cells on each page. Please be sure that you have counted all of the tumor cells before you submit the count. After you complete your first image, you'll have an opportunity to count the tumor cells on additional images as part of this HIT.

Thank you for your time and effort. Advances in the field of cancer and treatment prevention rely on the selfless contributions of countless individuals such as yourself.

As you can see below, the tumor cells have a light purplish blue color and are sometimes outlined in red.



The image below is representative of the type of images you will see. Again, the tumor cells have a light purplish blue color and are sometimes outlined in red.