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Learning Strategic Representations: Exploring the Effects of Taking a Strategy Course

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Abstract. Despite the popularity of strategy courses and the fact that managers make consequential decisions using ideas they learn in such courses, few studies examine the learning outcomes of taking a strategy course—a research gap most likely the result of the methodological challenges of measuring these outcomes in realistic ways. This paper provides a large-sample study of *what* individuals learn from taking a strategy course and *how* those learning outcomes depend on individual characteristics. We examine how 2,269 master of business administration (MBA) students evaluate real-world video cases before and after taking the MBA core strategy course at a large U.S. business school. We document several changes in their performance, mental representations, and self-perceptions. Among other findings, we show that taking a strategy course improves strategic decision making, increases the depth of mental representations and the attention paid to broader industry and competitive concerns, and boosts students' confidence, while making them more aware of the uncertainty pervading strategic decisions. We also find that the magnitude and significance of these changes are associated with individual characteristics, such as cognitive ability, prior knowledge, and gender.

Keywords: learning strategy • expertise development • mental representations • strategy course • managerial cognition

1. Introduction

1.1. The Unknown Effects of Strategy Courses

More than 100,000 master of business administration (MBA) students graduate each year in the United States alone (Snyder et al. 2019). All take at least one strategy course, which typically covers frameworks and cases aimed at developing competence in strategic decision making (Grant and Baden-Fuller 2018). Such a course is relevant to students (and is their topmost must-have course; Hazenbush 2019) because many MBAs go on to make important strategic decisions. Indeed, MBAs account for 40% of the CEOs of U.S. publicly traded firms (Bertrand and Schoar 2003), 58% of venture capitalists (Zarutskie 2010), and nearly all associates and partners at the leading consulting firms (Rasiel 1999). Although the MBA is the most popular graduate degree, strategy is its most popular subject, and momentous decisions hinge on the ideas taught in strategy courses, not much is known about the effects of such courses on those who take them. This is puzzling as the strategy field is defined in terms of decision-making consequences (Strategic Management 2017), yet the consequences of the main vehicle for communicating strategy knowledge to nonexperts are not well-understood.

We are aware of only three studies that look at the effect of business courses. Priem and Rosenstein (2000) show that having a business education affects managers' causal maps on what drives firm performance. Gary and Wood (2011) show that those who have a more accurate knowledge of operations perform better in a business simulation. And Yang et al. (2020) observe that CEOs who took the strategy course at Harvard Business School from 1983 onward—that is, after Michael Porter redesigned it—are more likely to use formal strategy processes in their current jobs than CEOs who took the earlier version of that course.[1] Hence, out of these three papers studying the effect of business courses, only one studies the effect of the strategy course, and it does so by examining just one outcome using a relatively small sample.

Other behavioral strategy research studies variation in mental representations but not in the context of a course. For instance, the literature applying a learning perspective to strategy formation (see Mintzberg et al. 1998, chapter 7) studies how managers learn on the job to formulate and implement strategies through processes such as trial and error (Bingham and Eisenhardt 2011), self-reflection (e.g., Argyris and Schön 1978), and double-loop learning (Barr et al. 1992) but not through strategy courses.[2] In turn, the literature on managerial cognition (Huff 1990, Hodgkinson and Sparrow 2002) underscores the relevance of executives' cognition on firm behavior by documenting vast cognitive heterogeneity in how managers conceptualize competitors, product features, and market opportunities; see, respectively, Porac et al. (1989), Benner and Tripsas (2012), and Eggers and Kaplan (2009). However, this literature has not studied how strategic thinking is affected by taking a strategy course.

Finally, another literature that could inform our understanding of the effect of learning in the strategy course is the education literature. However, this literature largely focuses on understanding learning in primary and secondary education (e.g., learning to write and solve mathematics problems; Schoenfeld 1992, Harris et al. 2006). Only a small subset of this literature studies higher education, emphasizing outcomes such as students' career trajectories (see, e.g., Haas and Hadjar 2020) and motivation (Wigfield et al. 2019). Unlike most higher education courses, strategy courses rely heavily on the case method to simulate real-world scenarios that typically involve high levels of complexity, uncertainty, and irreversibility (Mintzberg et al. 1976). Moreover, MBA students average five years of prior work experience and represent a different demographic than the populations studied in education research. All of this limits the conclusions that can be drawn from existing education research.

Taken together, prior research suggests that business education should have an effect on how managers think and the decisions they make.[3] However, very little is known about the effects of strategy courses on students' decision-making outcomes and processes. This is most likely because achieving a fuller understanding of the effects of strategy courses is empirically daunting. In particular, observing the effects of learning strategy calls for (a) observing mental representations and decision-making performance, both of which are difficult to measure in realistic ways, and (b) having access to a large sample of students for which there is granular data both before and after taking the course.

1.2. Our Approach and Contribution

This paper provides a large-sample study of the effects of taking a strategy course. Specifically, we explore two research questions: (a) What do individuals learn from a strategy course? (b) How do learning outcomes depend on individual characteristics? We examine how 2,269 MBA students evaluate four real-world firm strategies before and after taking the MBA core strategy course at a large U.S. business school. Our methodology randomizes the order in which the cases are shown to the students, which allows us to measure the effect of the course by comparing how similar students see the same case at the beginning versus the end of the course. Building on ideas about learning and expertise from cognitive psychology, we measure changes to (a) *performance*, which we quantify in terms of accuracy and item count (i.e., the extent to which students' predictions of firm success match reality and how much students can write about their opinions); (b) *mental representations*, which we code (following Csaszar and Laureiro-Martínez 2018) from an open-ended list of pros and cons that students report for each case; and (c) *self-perceptions*, which we measure in terms of the confidence and difficulty that students experience when working on each case. To isolate the effect of taking the course from other characteristics that could also influence the outcomes we measure, our regressions include individual, case, and class fixed-effects in addition to other controls.

We find that taking a strategy course changes individuals in several ways. First, their performance improves: accuracy and item count both increase. Second, their mental representations increase in depth and in attention paid to aspects of business that do not relate to individuals' experience as consumers, but rather to broader industry and competitive concerns. Thus, individuals attend to different aspects of business cases, and they do so in more detail. Third, individuals become more confident in their opinions while, paradoxically becoming more aware of the uncertainty that characterizes strategy decisions. We also observe that several of the changes depend on a few individual characteristics such as cognitive ability, prior knowledge, and gender. Among other results, we find that students with less prior business knowledge and higher cognitive ability undergo greater changes in their mental representations.

More generally, our paper contributes to better understanding the cognitive processes by which managers learn strategy. Previous literature focuses on how managers learn to formulate strategies via a trial-and-error, on-the-job process (Mintzberg et al. 1998). We extend that literature to encompass a different, yet important and pervasive, mode of learning: learning strategy in an MBA course. In particular, we extend prior work by examining how taking a strategy course—perhaps the most common way of learning strategy—changes students and how such change depends on individual characteristics. Our work also contributes to a number of research streams. It contributes to the strategic decision-making literature by showing how the strategy course affects decision quality and individuals' ability to participate in the strategic decision-making process. It contributes to the managerial cognition literature by showing how the learning that happens in the strategy course can affect the cognitive heterogeneity documented by that literature. And it contributes to the top management teams literature by providing a fuller account of how the demographic characteristics studied by that literature affect strategic decision making. Finally, our paper also makes a methodological contribution by demonstrating a fine-grained way to measure changes in strategic representations using a naturalistic decision-making task.

In practical terms, our research provides a way to address the long-standing question of what the value of an MBA education is. Simon (1967) already noted the decoupling of teaching and research in business schools (see also Khurana and Spender 2012). Recently, this unending decoupling has motivated commentators to question the value of an MBA education (see, e.g., Bennis and O'Toole 2005, David et al. 2011, Hubbard 2019) and business schools to engage in "assurance of learning processes" (Cavico and Mujtaba 2010). The critics' main argument is that academic research is not relevant to business, and hence, learning business at an academic institution cannot add value. Our research provides a counterpoint to that logic by showing that students taking a strategy course in an MBA program change in ways that appear to be valuable. Finally, our study suggests ways to increase the value strategy courses deliver.

2. Theoretical Motivation

In this section, we survey research that addresses the effect a strategy course might have on individuals' strategic decision making. We first review management research that is skeptical about the learning effects of strategy courses. We then review the cognitive psychology literature on learning and expertise development, which suggests positive effects and proposes contingencies.

2.1. Skeptical Perspectives

The management literature advances several arguments expressing skepticism about the effect of strategy courses and management theories on strategic decision making. If valid, these arguments imply that strategy courses have no effect on learning and might even have a negative effect.

A first argument is based on the idea that learning how to make good strategic decisions is extremely difficult. The reason is that strategy problems are typically novel, uncertain, and complex, so there is simply not enough data to learn the optimal decision in most situations—a problem magnified by the noise and delay that are characteristic of feedback on strategic decisions (Csaszar 2018). Strategic decision making, therefore, exemplifies the idea of a "wicked problem," one in which learning is virtually impossible (Churchman 1967). This line of thought implies that strategy is too hard to learn, and therefore, no one, not even seasoned practitioners and researchers, might actually understand it well.

A second argument stems from research that finds little support for theories taught in the strategy classroom. For instance, David and Han (2004) conduct a meta-analysis and find little empirical support for the performance advantages claimed by transaction-cost economics. Campbell-Hunt (2000) similarly analyzes empirical research on generic competitive strategies and reports only minimal support for the performance advantages of cost and differentiation strategies. More generally, several researchers and commentators point out a significant disconnect between management theories taught in MBA courses and the real-world, day-to-day jobs of managers and management consultants (Simon 1967, Pfeffer and Fong 2004, Bennis and O'Toole 2005, Stewart 2009).

A third argument against the value of strategy courses is that the research underlying them can rarely offer the type of prescriptions managers need. For instance, Bettis (1991, p. 315) notes that strategy research "too often offer[s] explanation but not meaningful prescription." Thomas and Tymon (1982) note that, even when research is prescriptive, its prescriptions may be obvious for managers (cf. Priem and Rosenstein 2000). The idea is that the research feeding into strategy courses is often trivial or irrelevant to practitioners or, as Daft and Lewin (1990, p. 1) put it in the inaugural issue of *Organization Science*, it is "incremental, footnote-on-footnote research."

Unlike the previous arguments suggesting negligible effects, the following one posits that strategy courses may be detrimental. Ghoshal (2005, p. 77) postulates that the application of many management theories is detrimental because such theories make "excessive truth claims based on partial analysis and both unrealistic and biased assumptions." Along the same lines, Ghoshal and Moran (1996) argue that the empirical use of transaction-cost economics can be perilous because it guides managers toward deals that destroy trust and other sources of long-term value creation.

2.2. The Learning and Expertise Development Perspective

In contrast to the aforementioned skeptical views, cognitive psychology research on learning and expertise development explores how learning might be possible in tasks that are arguably as complex as making strategic decisions. (For overviews of professional expertise development—including the cases of physicians, magistrates, and software designers—see parts III and IV of Chi et al. (1988) and part V.A of Ericsson et al. (2006).) Such research suggests that learning in these contexts is indeed possible and it should lead to changes not only in performance, but also in mental representations and self-perceptions. These other aspects are also relevant to strategic decision making because managers must explain their decisions (i.e., verbalize their mental representations to persuade others; Gavetti 2012) and managers' motivation—and, hence, their willingness to communicate and continue making strategic decisions—depends on having positive self-perceptions.

However, given the earlier skeptical views and the high levels of complexity and uncertainty that pervade strategic decision making, it is not evident to what extent existing research on learning and expertise translates to learning in strategy courses. In what follows, we elaborate on the possible changes in the three outcomes postulated by this research: namely, (a) performance, (b) mental representations, and (c) self-perceptions. Subsequently, we discuss evidence on how these effects may depend on individual characteristics.

2.2.1. Effects on Performance. Cognitive psychology defines "learning" as a process of knowledge accumulation that changes a mental representation in ways that improve its performance (Langley and Simon 1981). Basic distinctions in the learning literature are the type of task being performed (e.g., simple versus complex) and the aspect of performance being measured. The typical performance measure in this literature is accuracy (Tenison and Anderson 2016).

Learning quickly improves accuracy when the task being learned is simple (Feltovich et al. 2006). For more complex tasks, however, the effect of learning is more nuanced: learning is facilitated when the problems encountered are similar to those previously studied (Novick 1988), when the learners can easily identify the type of problem they face (Ericsson and Charness 1994, p. 732, Patel and Groen 1991, p. 115), and when extraneous demands on working memory are kept to a minimum (e.g., by working in a familiar and consistent environment; Chandler and Sweller 1991).

The effect of learning in contexts in which the solution to a problem is not just a simple decision (such as a yes/no answer or a chess move), the measurement of accuracy is often complemented with a measure of fluency (Ransdell and Levy 1996)—that is, the ease with which the individual can express the solution (e.g., expressing an answer as a yes/no vis-à-vis writing a paragraph-long answer in the same amount of time). Learning produces fluency because it increases the number of useful chunks of knowledge and makes their retrieval more efficient (Bransford et al. 2000). This fluent retrieval of knowledge decreases the demands on working memory (McCutchen 1996), which becomes available for other uses. For instance, those who are fluent with the subject matter of a strategy meeting can use the reclaimed working memory to devise better ways of communicating and persuading the group (Petty and Cacioppo 1984, Fiske and Taylor 2017). Communication and persuasion are particularly relevant in strategy as strategic decisions are typically made by groups (Kaplan 2008, Csaszar and Eggers 2013).

Because the effects of learning on accuracy and fluency are observed in many complex tasks (see, e.g., Ericsson et al. 2006, part V.A), it is reasonable to expect that learning strategy may have similar effects on students. However, such effects could be small or even negligible if some of the conditions that impede learning complex tasks hold (e.g., low task similarity and extraneous demands on working memory).

2.2.2. Effects on Mental Representations. As learners accumulate knowledge, their mental representations can capture more relevant aspects of problems (Vosniadou and Brewer 1987). It follows that those with greater expertise in a given domain can detect patterns that are not recognizable by nonexperts (Bransford et al. 2000). For instance, Grégoire et al. (2010) shows that seasoned entrepreneurs are better at identifying business opportunities.

A simple way of characterizing changes in knowledge is in terms of the breadth and depth of representations (Schwartz et al. 2009). *Breadth* is the unique number of relevant categories that an individual captures in the individual's mental representation. Increased breadth confers the ability to pay attention to more aspects of a problem (Vosniadou and Brewer 1987). *Depth* is the detail with which a specific category is considered; increased depth confers the ability to see more of a problem's details and to perform finer grained analyses (Chase and Simon 1973). Together, breadth and depth may boost the quality of strategy formulation by giving the manager elements to develop a more accurate "theory of value" (Felin and Zenger 2017) or mental representation of the strategic situation (Csaszar 2018). Such a representation may enable managers to see the cognitively distant opportunities that underlie "great strategies" (Gavetti 2012, Gavetti and Porac 2018). Lacking breadth and depth makes managers more likely to make mistakes and act based on social pressure and imitation (Pollock et al. 2008). For instance, Charles Merrill's breadth and depth of representations shaped his unique view of the financial services market and, in turn, enabled Merrill Lynch's strategic success (Gavetti and Menon 2016).

Depth and breadth are aggregate measures of mental representations. Yet one can also assess the content of these representations more directly by measuring the actual categories to which individuals pay attention (Rosch 1975). Research on learning and expertise development establishes that learning domain-specific knowledge increases the number of concepts to which individuals pay attention (Feltovich et al. 2006). For instance, aviation pilots learn how to pay attention to aircraft specifications, meteorological information, and topographic data when making aeronautical decisions (Wiggins and O'Hare 1995). Similarly, strategy courses aim to increase students' awareness of aspects of competition, such as positioning and network effects (Wright et al. 2013). Thus, domain-specific knowledge associated with learning strategy should be closely tied to greater attention to matters beyond what is salient to customers. Taking a strategy course should, therefore, be associated with increased attention paid to aspects of competition that are not directly observable by consumers.

Another characteristic of representations is their degree of uncertainty. Research shows that increased experience with a given problem-solving task generally leads to a higher perception of certainty about the outcome (Barden and Petty 2008). But, in problem domains that are inherently uncertain, experts should perceive such uncertainty, whereas novices may overlook it and bluntly classify the environment into definite categories. In meteorology, an inherently uncertain domain, meteorologists who are certain about their predictions are less accurate than those who are less certain (Stewart et al. 1992, Smallman and Hegarty 2007). Because strategy deals with uncertainty (Rumelt 1984), it is reasonable to expect that learning strategy be accompanied by an increase in perceived uncertainty.

Thus, research suggests that learning strategy should be associated with mental representations that (a) have more breadth and depth and (b) pay more attention to aspects germane to strategy, including an appreciation of the uncertainty inherent in strategy problems.

2.2.3. Effects on Self-Perceptions. A consequence of the improvements described so far is that individuals' self-perception of their capabilities (aka perceived self-efficacy or perceived ability) improves as they learn (Zimmerman 2000). Self-perception can be measured in terms of (a) feelings of confidence and (b) perceived difficulty of the task (see, e.g., Reyes 1984).

Of course, an increase in self-confidence does not in itself imply that learning has occurred. Although much research shows that self-confidence and learning tend to go hand in hand (see Druckman and Bjork 1994, chapter 8), the well-known Dunning–Kruger effect reveals that novices are more prone than experts to overestimate their capabilities (Kruger and Dunning 1999).

Hence, it is reasonable to expect that, as individuals learn strategy, they will feel more confident in their ability to make strategic decisions and also feel that making such decisions becomes easier. That said, the Dunning–Kruger effect suggests that novices may well experience improvements in self-perception that are decoupled from actual learning.

Improved self-perceptions hold some important implications for organizations as individuals' persuasive and goal-setting abilities depend not only on knowledge, but on having positive self-perceptions (Bandura 1993, Fiske and Taylor 2017). For example, Wood and Bandura (1989) show that managers with higher self-perceptions achieve greater organizational performance in a strategy simulation because of their higher aspiration levels (i.e., setting more challenging goals). Along the same lines, Petty et al. (2002) show that high levels of self-confidence increase persuasion when high-quality arguments are presented.

2.2.4. Individual Differences. So far, we describe average effects observed by the literature on learning and expertise development. This literature also describes ways in which learning outcomes may depend on individual characteristics, which we summarize next. Key contingencies studied by this literature are cognitive ability, prior knowledge, and gender. These contingencies also figure prominently in management research, including research on strategic decision making and top management teams (Hambrick and Mason 1984, Finkelstein et al. 2009, Gary and Wood 2011).[4]

Perhaps not surprisingly, cognitive ability (often measured using an IQ test or a standardized test such as the Graduate Management Admission Test (GMAT)) is positively associated with learning. This is one of the most robust results of the learning literature (Garlick 2002). Different mechanisms are proposed to explain it, for example, that cognitive ability increases the speed at which individuals can process and interconnect new information and that more intelligent individuals are better at applying what they know to answer new questions.

Management research also explores the relevance of cognitive ability in strategic decision making though the findings in this stream of work are mixed. For instance, Gary and Wood (2011) find no relationship between cognitive ability and the accuracy of individuals' mental representations. In contrast, LePine (2005) shows that lower levels of cognitive ability produce suboptimal learning in group tasks that are novel and complex.

Another finding in the literature on learning and expertise is that students with less initial knowledge are more likely to learn the most in a course (as long as they are well-qualified to take the course; Ericsson 2006). This is consistent with Bayesian learning: those with the least experience are the ones who update their priors the most when exposed to new information. This logic is confirmed by recent research on entrepreneurship. For example, Lyons and Zhang (2017) show that individuals without prior entrepreneurship experience gain more from formal entrepreneurship programs. Similarly, Chatterji et al. (2019) show that entrepreneurs with prior business knowledge are less affected by formal advice from mentors.

Gender is also found to be associated with learning outcomes. Previous research in the context of science, technology, engineering, and mathematics courses shows that women are more likely to focus on the broader picture over individual details when solving problems (Ro and Loya 2015). Previous research also shows that women often exhibit greater verbal ability than men (Hyde and Linn 1988) but less self-confidence (Beyer 1990, Häussler and Hoffmann 2002), which can impair their careers (Beyer 1990, Häussler and Hoffmann 2002; see also Gibson and Lawrence 2010, Sterling et al. 2020 on the career impacts of the confidence gap).

In sum, unlike the skeptical arguments mentioned earlier, the learning literatures reviewed suggest that taking a strategy course should improve not only performance, but also mental representations and self-perceptions. The main predictions stemming from these literatures are summarized in Table 1. However, the extent of learning is likely to depend on individual characteristics, such as

Table 1. Summary of the Main Expected Effects According to the Learning Perspective

Effects on performance	• Increased accuracy • Increased fluency
Effects on mental representations	• Increased depth • Increased breadth • Increased awareness of strategy concepts • Increased awareness of uncertainty
Effects on self-perception	• Increased confidence • Decreased perceived difficulty

cognitive ability, prior knowledge, and gender. Our empirical analyses elucidate the extent to which the predictions we describe hold true in the context of taking a strategy course.

3. Method

In this section, we describe the methodology used to test for the effects theorized in the prior section. In what follows, we describe our sample, task, measures, and regressions.

3.1. Sample

To evaluate the hypotheses outlined previously, we use data from a classroom exercise: a decision-making task completed as part of the core strategy course in a full-time, two-year MBA program at a large U.S. business school. In this program, students are required to take the core strategy course during their first term while, also take courses on financial accounting, applied microeconomics, and business statistics. The strategy course meets twice each week for a total of 12 sessions, and each session is 2.25 hours long.

The task was completed by 2,269 MBA students taking the course between 2014 and 2019, corresponding to 29 sections of the course.[5] The average age of these students was 27.4, 40.2% of them were women, 36.4% had a business undergraduate degree, 23.4% had an engineering undergraduate degree, 69.9% were native English speakers, and their average GMAT score was 697.3.

Table 2 shows the size of the sections across each year of the sample. Students are assigned to sections by the MBA office, which tries to ensure that the sections are demographically balanced. The composition of sections is, therefore, similar in terms of gender, age, standardized test scores, prior business education, and proportion of international students.

3.2. Data Collection and Task

Our study's empirical design relies on a strategic decision-making task in which participants are shown a video of a real start-up that is attempting to raise money. The students, who take the role of investors, must decide what multiplier they would set for the start-up (i.e., what interest rate they would charge), describe the pros and cons of the start-up's strategy, and answer several control questions. The videos, which were selected from Kickstarter.com, are approximately four minutes long and are similar to start-up pitches to investors. After watching each video, students are given seven minutes to fill out the survey questions.

This task was designed to reflect a common activity of managers working in strategy roles: deciding, based on incomplete information, whether a strategy is good or not and justifying that decision. The task was developed following a series of pilot tests of alternative possible tasks: written business cases, vignettes, and simulations. Using videos of start-ups trying to raise funds has the advantage of being similar to situations managers face in the real world in terms of content (complex problem), form (audiovisual presentation), and purpose (strategy evaluation task) (Csaszar and Laureiro-Martínez 2018). More generally, evaluating pitches is a quintessential strategy task, one that requires building a mental representation of the firm (along with its competitors and consumers) and using it to forecast the firm's future performance under different conditions (Csaszar 2018). Strategy courses help with this task by teaching students (a) to what information to pay attention and (b) how to use that information to predict firm performance.

Evaluating strategies is a core skill of strategists as it allows them to pick among alternative paths of action (e.g., choose between maintaining the status quo or launching a new product or choose between several possible strategic moves). It is also required when *formulating* a strategy as strategy formulation entails searching a space of possible strategies and, thus, evaluating each considered possibility (Csaszar and Levinthal 2016). Evaluating a strategy is a complex cognitive task, one that requires perceiving and making sense of nuanced cues representing social and technical dynamics under conditions of great uncertainty (Pollock et al. 2008, Rindova et al. 2012).

The task occurs twice at the beginning of the course (in the first session) and twice near the end of the course (in session 9 of 12, when students have finished all the

Table 2. Total Number of Individuals in Each Year and Section of the Sample

Year	1	2	3	4	5	6	Total
2014	–	72	70	73	–	–	215
2015	63	66	68	69	64	63	393
2016	83	84	79	81	82	–	409
2017	84	87	81	83	83	–	418
2018	84	84	85	84	82	–	419
2019	83	84	84	85	79	–	415
Total	397	477	467	475	390	63	2,269

Note. In 2014, the exercise was conducted for only three sections; starting in 2016, section 6 was closed.

course content on business-level strategy); thus, we collect students' answers on four start-ups. All students see the same four videos (although in different sequences), which allows us to compare how similar students analyze the same case at the beginning and end of the course.

Table 3 shows the number of students who completed the decision-making task for each of the four cases in each of the four possible sequential positions. In total, we collected 6,724 surveys from 2,269 students (an average of 2.96 per student). The variation in the number of surveys per round is due to several reasons: we do not have exactly four surveys per student because of students missing class, incomplete surveys, surveys that were eliminated because students reported they were already familiar with the company shown in the video, and the fact that in 2014 and 2015 the survey was only administered at the end of the course.

We selected the videos using the following criteria. First, to allow for comparisons across start-up pitches, all four videos described a consumer product and had a high video-production quality. Second, all four start-ups' actual success or failure as a business were determined shortly after the video was filmed. This increases the chances that the video contains information pertinent to the start-up's success or demise. The successful firms are SCIO and SmartHerb (hereafter SH); the unsuccessful are DRIVE and MindRider (MR).[6] To keep the difficulty of the task similar between the two sessions, the two videos used in each session involve one successful and one unsuccessful firm.

To minimize the chances of subjectively deciding whether a start-up was successful or not, we picked pairs of start-ups whose performance was diametrically opposed according to three measures of performance: financial, technological, and commercial success. That is, the successful start-ups raised more money than required, delivered their products on time, and were commercially successful, whereas the failed start-ups were unable to raise sufficient funds, did not deliver their products on time, and failed to remain commercially viable once the product was available.

It is important to note that our research design is a large-sample observational study and not an experiment as all students *must* take the strategy course (and, thus, we do not have a control group). In the robustness checks section, we describe a number of analyses that attempt to rule out alternative hypotheses (i.e., that the learning effects we uncover are not a result of the strategy course but some other changes students undergo). For now, we highlight the face validity of our study: among the courses students are taking, the strategy course is the only one that focuses on teaching how to evaluate whether a firm strategy is more or less likely to succeed.

Table 3. Number of Survey Responses for Each Firm Shown per Round

	Beginning of course		End of course		
Firm	Round 1	Round 2	Round 1	Round 2	Total
DRIVE	256	254	146	530	1,186
MR	162	823	766	384	2,135
SCIO	366	380	609	147	1,502
SH	728	157	315	701	1,901
Total	1,512	1,614	1,836	1,762	6,724

3.3. Measures

Much can be measured from our in-class activity. Two key aspects of our method are how we measure accuracy and how we use the open-ended list of pros and cons to measure mental representations. We define *"accuracy"* as how good the student is at detecting which company is more likely to succeed. This is a binary measure constructed by checking whether students assign the highest interest rate to the firm that fails in each pair. The accuracy variable is one if students correctly assign the higher interest rate to the failed firm and zero if they do not.

We measure students' mental representations—how they think about each of the start-ups—by categorizing the list of pros and cons that each student writes. Our categorization method is the same one used in Csaszar and Laureiro-Martínez (2018).[7] This method categorizes each item (pro or con) into one of 10 categories (see Table 4 for the list of categories and examples of categorized items). The 10 categories correspond to strategy concepts that are relevant to predict firm success and were constructed by applying Weber's (1990) iterative content analysis protocol (for more detail on how this categorization was constructed, see appendix D in Csaszar and Laureiro-Martínez 2018).

Two research assistants were trained in the categorization method; each one categorized all 42,284 survey items—achieving an interrater agreement of 0.78 and a Cohen's κ of 0.75 (Cohen 1960), values that indicate substantial agreement (Landis and Koch 1977, Stemler 2000). One coauthor examined all items on which the research assistants disagreed and resolved the differences. Only 76 items did not properly belong in any of the 10 categories and were eliminated from further analyses. In the robustness checks section, we show that our results are robust to alternative categorizations.

We next describe how our dependent and independent variables are calculated.

3.3.1. Dependent Variables.

To test the effects of the strategy course on accuracy, mental representations, and self-perceptions, we look at the eight dependent variables described next.

Accuracy is a binary assessment of an individual's ability to detect which company is more likely to succeed. It equals one if the individual set a lower multiplier

Table 4. Categories for Classifying the Items on the Pros and Cons Lists and Sample Quotes (from Surveys) for Each Category

	Category	Main topics covered by the category *Sample quotes from surveys*
1.	Industry structure	Five forces, entry barriers, industry rivalry, substitutes, supplier power, buyer power *"Easily replaced by hands-free automobile devices," "The number of substitutes"*
2.	Market size	Market size, market trends, growth potential, expansion opportunities *"Potential use cases," "Large customer segment"*
3.	Imitability and time to market	Preemption, imitability, uniqueness, differentiation, intellectual property, patents *"Other companies could copy technology," "Inimitability"*
4.	Costs	Economies of scale, minimum efficient scale, learning curve *"Cost of production/distribution," "Cost of production/economies of scale"*
5.	Operations	Manufacturing concerns, technological risks, past products, stage of development *"Existence of a prototype," "Feasibility"*
6.	Value to customer	Price, product attributes, usability, usefulness, utility, novelty, design, willingness to pay, network effects *"What would motivate consumers to pay for the product?" "Willingness to pay"*
7.	Nonmarket	Regulation, safety, socioenvironmental concerns *"Safety; is the helmet as safe as other products?" "Liability; potential for lawsuits for distracted drivers"*
8.	Marketing	Marketing, communication, advertising, founder characteristics, team characteristics *"Pitch video looks dated, "Expertise of company"*
9.	Business model	Distribution and sales channels, product synergies *"Success of wide geographic distribution," "Application in phones or other smart devices"*
10.	Funding	Net present value, likelihood of success, exit opportunities *"The needed funding amount of 75k," "How successful I think it will be"*

(i.e., charged a lower interest rate) to the successful firm than to the unsuccessful one and zero otherwise.

Number of items is the total number of items on an individual's list of pros and cons for a firm. For example, two pros and three cons count as five items.

Breadth is the number of unique relevant categories an individual considered when making a decision. For example, if an individual mentions four items relating to industry structure and three relating to the value proposition, then *Breadth* = 2.

Depth is the detail with which categories are considered by an individual and is calculated as the average number of items per category. For instance, if an individual reported five items falling into two categories, then *Depth* = $5/2 = 2.5$.

Non-consumer items is the total number of items that fall into a "*non-consumer*" category. We split the 10 categories into (a) those that are visible to consumers (market size, value to customer, marketing, and socioenvironmental (aka nonmarket concerns)) and (b) those that are typically visible only to strategists (industry structure, imitability and time to market, costs, operations, business model, and funding). Suppose that the student reports two value-to-customer items and one funding item; then *Non-consumer items* equals one. The idea behind this measure is that, as described earlier, learning domain-specific knowledge expands the aspects to which individuals pay attention; just as aviation pilots learn to pay attention to meteorology and topography, strategists learn to pay attention to aspects that are relevant to strategy but invisible to consumers.

Certainty is calculated using the linguistic inquiry and word count program (LIWC; Pennebaker et al. 2015). It is the percentage of words used in a list of pros and cons that appear in the "uncertainty" dictionary.

Confidence and *Difficulty* are answers to survey questions: "How difficult did you find this exercise?" "How confident do you feel about your answer to the 'investment decision' question?" These variables are measured on a Likert scale from 1 = very low to 7 = very high.

3.3.2. Independent and Control Variables. The main independent variable of our study captures the effect of having taken the course. We call this variable *Course* and set it to zero for surveys taken at the beginning of the course and one for surveys taken at the end.

As demographic controls, we either use individual fixed effects or six variables capturing demographic characteristics: the participant's GMAT score, age, gender, whether their native language is English, and their undergraduate degree. The latter is coded as two dummy variables, one for business and the other for engineering. GMAT score and undergraduate degree operationalize, respectively, the constructs of cognitive ability and prior knowledge described in Section 2.2.

3.4. Regressions

Recall that our study addresses two research questions: what do individuals learn from a strategy course, and how do learning outcomes depend on individual characteristics? We study these using two sets of regressions. We address the first question by estimating regressions of the form

$$y = \beta_1 Course + IndFE + CaseFE. \quad (1)$$

Here, y can be any of our eight dependent variables and β_1 is the effect of the course after controlling for individual (*IndFE*) and case (*CaseFE*) fixed effects.

The individual fixed effects not only capture the effects of the demographic controls previously described (e.g., GMAT, age, gender, undergraduate degree) and any time-invariant unobserved heterogeneity across individuals (e.g., initial knowledge about strategy), but also the effect of the section the student is in and the year in which the survey was taken (because each individual is uniquely associated with a section and a year). Hence, such effects as those arising from class dynamics or news influencing a case's prospects in a given year are all controlled for by our regressions' individual fixed effects. At the same time, case fixed effects capture unobserved heterogeneity because of, for example, the case's difficulty or the relevance of what is presented in the video.

In all, estimating the effect of the course using this specification is conservative as the fixed effects control for many unobservables and so leave β_1 as an adequate estimate of the effect of the course. (In the robustness checks section, we discuss the possible effect of mechanisms that might not be captured by these two fixed effects.)

To address our second research question—how learning outcomes depend on individual characteristics—we use a second set of regressions that use, instead of individual fixed effects, the six demographic controls, which enter both alone and interacted with the *Course* variable. This allows us to estimate a "baseline" and an "improvement" effect for each control. For instance, if, in the regression predicting item count (the number of pros and cons), $\beta_{\text{female}} = 0$ and $Course \times \beta_{\text{female}} = 0.3$, we can say that, before the course, there was no relationship between gender and item count, but after taking the course, women wrote more items. The second set of regressions has the following form:

$$y = \beta_1 Course + \beta_{2..7} CONTROLS + \beta_{8..13} Course \times CONTROLS + ClassFE + CaseFE. \quad (2)$$

Here, y can be any of the eight dependent variables, β_1 is the main effect of the course, β_2 through β_7 are main effects of the demographic controls, and β_8 through β_{13} capture how the effect of the course depends on the demographic controls, that is, how different individuals may benefit differently from the course. To capture other sources of unobserved heterogeneity, these regressions include case and class fixed effects (we define a *class* as a section–year, e.g., section 2 in 2017). The class fixed effects capture the heterogeneity associated with, for example, class dynamics, seating arrangements, year, and instructor. Note that class fixed effects are not needed in the first set of regressions because individuals do not change classes, which means that any effects of the class were captured already by the individual fixed effects.

4. Results

Here, we analyze the two sets of regressions to shed light on our two research questions.

4.1. Descriptive Statistics

Before delving into the regression results, it is useful to gain a sense of the data by examining the descriptive statistics and intercorrelations. Table 5 reports descriptive statistics at the beginning and end of the course (left and right halves of the table, respectively). Note that the number of observations (N) is not constant across variables because some individuals leave questions unanswered and, initially, the survey was only administered at the end of the course.

Table 5. Descriptive Statistics for Key Variables in the Analyses

	Beginning of course					End of course				
	N	Mean	Standard deviation	Minimum	Maximum	N	Mean	Standard deviation	Minimum	Maximum
Accuracy	2,674	0.69	0.46	0.00	1.00	3,228	0.68	0.46	0.00	1.00
Item count	3,126	5.97	2.12	1.00	14.00	3,598	6.57	2.32	1.00	14.00
Breadth	3,126	4.09	1.32	1.00	9.00	3,598	4.33	1.37	1.00	9.00
Depth	3,126	1.51	0.48	1.00	6.00	3,598	1.57	0.50	1.00	7.00
Non-cons items	3,126	0.46	0.23	0.00	1.00	3,598	0.51	0.21	0.00	1.00
Certainty	3,126	0.44	0.98	0.00	14.29	3,598	0.35	0.88	0.00	10.00
Confidence	2,851	4.29	1.40	1.00	7.00	3,359	4.88	1.34	1.00	7.00
Difficulty	2,680	3.80	1.40	1.00	7.00	3,146	3.36	1.41	1.00	7.00
Course	3,126	0.00	0.00	0.00	0.00	3,598	1.00	0.00	1.00	1.00
GMAT	3,126	697.72	52.21	475.63	783.73	3,598	697.55	50.47	475.63	798.63
Age	3,126	27.44	2.25	22.00	39.00	3,598	27.46	2.28	22.00	39.00
Female	3,126	0.42	0.49	0.00	1.00	3,598	0.39	0.49	0.00	1.00
Native English	3,126	0.70	0.46	0.00	1.00	3,598	0.69	0.46	0.00	1.00
Business UG	3,126	0.36	0.48	0.00	1.00	3,598	0.37	0.48	0.00	1.00
Engineering UG	3,126	0.22	0.42	0.00	1.00	3,598	0.24	0.43	0.00	1.00

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Table 6. Intercorrelations Among Key Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1. Accuracy														
2. Item Count	−0.01													
3. Breadth	−0.02	0.73***												
4. Depth	−0.00	0.34***	−0.31***											
5. Non-Cons Items	−0.01	0.06***	0.29***	−0.29***										
6. Certainty	0.01	−0.01	0.00	−0.01	−0.00									
7. Confidence	0.08***	0.03**	−0.00	0.04**	0.01	0.01								
8. Difficulty	−0.04**	−0.05***	−0.01	−0.05***	0.04**	0.00	−0.37***							
9. Course	−0.00	0.13***	0.09***	0.07***	0.11***	−0.05***	0.21***	−0.15***						
10. GMAT	0.07***	0.01	0.03**	−0.03*	0.01	0.03**	0.01	0.03*	−0.00					
11. Age	−0.02	−0.02	−0.04***	0.02	0.00	0.00	0.05***	0.01	0.00	−0.06***				
12. Female	−0.08***	0.03*	0.01	0.03*	−0.03*	−0.04**	−0.12***	0.13***	−0.03**	−0.28***	−0.17***			
13. Native English	0.00	0.10***	0.06***	0.05***	−0.06***	0.02	−0.09***	−0.12***	−0.01	−0.25***	−0.18***	0.08***		
14. Business UG	0.02	0.01	0.02^{+}	−0.01	0.01	−0.00	0.01	−0.03*	0.01	0.00	−0.06***	−0.07***	0.06***	
15. Engineering UG	0.01	−0.04**	−0.03*	−0.00	0.02	−0.01	0.06***	0.02	0.02^{+}	0.21***	0.05***	−0.15***	−0.35***	−0.41***

$^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Comparing the mean values at the beginning and end of the course gives us a preliminary feel for the course's effect on the dependent variables. For example, *Item count* increases from 5.97 to 6.57. Yet, given that such differences do not control for confounding effects, change is better analyzed using the regression estimates presented later. Another observation from Table 5 is that the minor changes in the means of the demographic variables (the rows from GMAT onward) are due to the two groups not consisting of exactly the same individuals (because of class absences and the initial years having only one survey). Finally, a careful reader may note that the minimum and maximum GMAT scores have decimal numbers and that the minimum is unusually low. These artifacts result from converting scores on the Graduate Record Examinations (GRE) (which a minority of students take) into GMAT scores.[8]

Table 6 reports the intercorrelations for the independent and dependent variables. Given the absence of any extreme correlations, the table suggests that multicollinearity concerns are negligible (Mansfield and Helms 1982). A few variables are moderately correlated. For instance, *Breadth* and *Depth* are correlated with *Item count* (correlations of 0.73 and 0.34, respectively) because both depth and breadth depend on how much an individual writes. *Breadth* and *Depth* have a negative correlation of −0.31, which reflects a natural trade-off between the two. Finally, *Confidence* and *Difficulty* exhibit a negative correlation of −0.37, which makes sense when one considers that confidence goes hand in hand with finding a task easy.

4.2. Research Question 1: Overall Effect of the Course

The results from the first set of regression analyses with individual and case fixed effects (Equation (1)) are presented in Table 7. The effect of the course is in the theorized direction for all eight dependent variables. All effects are statistically significant at the 5% level except for breadth, which is only significant at the 10% level. Moreover, the magnitudes of the effects are relevant. For example, Model 1 shows that the effect of the course on accuracy is 0.07, which is certainly meaningful; after all, the ability to increase the proportion of good investments by 7% (say, from 60% to 67%) would be coveted by any investor.

Table 7. Regression Results for Each Dependent Variable from Regressions that Incorporate Individual and Case Fixed-Effects

	Performance		Mental representations				Self-perceptions	
	Accuracy (1)	Item count (2)	Breadth (3)	Depth (4)	Non-cons items (5)	Certainty (6)	Confidence (7)	Difficulty (8)
Course	0.07***	0.28***	0.07^{+}	0.05***	0.04***	−0.09**	0.71***	−0.46***
	(0.02)	(0.07)	(0.04)	(0.01)	(0.01)	(0.03)	(0.05)	(0.05)
Individual fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Case fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,902	6,724	6,724	6,724	6,724	6,724	6,210	5,826
R^2	0.73	0.73	0.60	0.45	0.50	0.38	0.59	0.72

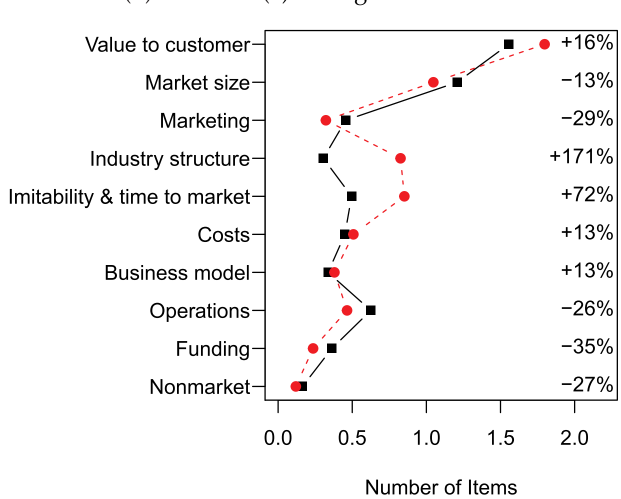
Note. Standard errors clustered by class in parentheses.
$^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

A read of the rest of Table 7 reveals that the course appears to have a positive and significant effect on almost all the dependent variables. Model 2 shows that the *Number of items* on students' lists of pros and cons increases by 0.28 (from the initial average of 5.97 reported in Table 5). This confirms our prediction that taking a strategy course increases fluency (ease of expression). Being fluent at describing strategies is a valuable skill for managers as it increases their ability to develop strategic plans, convincing others about their merits (e.g., investors, colleagues, and superiors), and coordinating the implementation of these plans.

Model 3 shows that the course increases individuals' *Breadth* by 0.07 categories (from an average of 4.09 although this effect is not statistically significant). Because breadth is but a coarse measure of students' mental representations, it is useful to interrogate the data further by analyzing how students "see" the different start-ups before and after the course.

Figure 1 illustrates how students' attention to the different categories changed through the course. Each point in this figure represents the number of items that the average student mentions for each category. For instance, at the beginning of the course, on average, about 1.5 items are devoted to issues related to value to the customer, whereas at the end of the course, it is about 1.7 (a 16% increase). A first observation from this figure is that not all categories increase equally. Categories corresponding to central concepts of the course (*Industry structure* and *Imitability & time to market*) increase the most (171% and 72%, respectively). A second observation is that not everything increases. In particular, students pay less attention to *Operations*, *Funding*, and *Nonmarket* issues. This is consistent with the content emphasized by strategy courses as well as the idea that attention is a limited resource (Ocasio 1997); hence, learning strategy cannot increase attention over all aspects. For instance, the decreased attention to *Operations* is consistent with the observation in Yang et al. (2020) that exposure to a strategy course that emphasizes Porterian frameworks causes MBA graduates to deemphasize implementation considerations.

Figure 1. (Color online) Comparison of Item Counts for Each Firm Before (■) and After (●) Taking the Course



Note. All differences are statistically significant at the 5% level.

Returning to the results in Table 7, Model 4 presents the change in individuals' depth of representations. Taking the course is associated with a 0.05 increase in *Depth* (i.e., a 3% increase over the average depth in the first session).

Model 5 shows that the strategy course increases the number of non-consumer items that individuals consider by 0.04 items (an 8% increase over the first session's average). This corroborates the expected changes described in detail in the context of Figure 1, indicating that the course teaches students to examine strategic decisions from vantage points beyond those available to a consumer.

According to Model 6, the level of certainty students express in their lists of pros and cons declines post-course by 0.09 (from a baseline of 0.44; recall that these numbers represent the percentage of words that appear in the LIWC certainty dictionary). This finding supports the idea that the course makes students more aware of the uncertainty surrounding strategic decisions, which is consistent with the view that strategy is fundamentally about dealing with uncertainty (Rumelt 1984).

Models 7 and 8 in Table 7 depict the changes in individuals' self-perceptions after taking the strategy course. Recall that we measure self-perceptions in survey questions that ask students how confident they are in their answers and how difficult they found the task. These models reveal that, by the end of the course, students become more confident in their answers and more at ease with the task. Specifically, Model 7 shows that the strategy course boosts students' confidence by 0.71 points (from an average of 4.29 on a 7-point Likert scale) and Model 8 shows that perceived task difficulty declines by 0.46 points (from an average of 3.80 on a 7-point Likert scale).

Overall, the regressions whose results are reported in Table 7 strongly support nearly all the changes hypothesized in the theoretical motivation section and summarized in Table 1. These results address the paper's first research question: what are the consequences of taking a strategy course? Next, we analyze the second set of regressions (which still contain case fixed effects but, instead of individual fixed effects, contain demographic controls and class fixed effects as described in Equation (2)). Analyzing these regressions addresses our second research question: how do the course's learning outcomes depend on individual characteristics?

4.3. Research Question 2: Effect of Individual Characteristics

Whereas the prior regressions (Table 7) capture the course's overall effect (i.e., a before–after change in each dependent variable), Table 8 captures its effect in combination with the demographic controls, offering insight into how learning outcomes vary for different types of students.

Each regression in this new table assesses (a) the main effects of the course and the controls and (b) the interactions between the course and the controls. We see that, in some cases, the *Course* main effect is not significant, but some of its interactions are, indicating that the course only benefits students with certain characteristics. These regressions include *Class* and *Case* as fixed effects. We group the discussion of the models in terms of the three types of outcomes we theorize: performance, mental representations, and self-perceptions.

4.3.1. Performance. Model 1′ in Table 8 shows the effect of the strategy course on individuals' accuracy. The model shows that accuracy improves by 10% after taking the course, which is similar to the 7% estimated in the context of Table 7. The demographic controls that are statistically significant show that engineers have, on average, a 4% higher accuracy and women 4% lower accuracy. Note that these are main effects, so these effects are independent of the effect of the course; that is, they affect accuracy at both the beginning and end of the course. We conjecture that a reason for the higher accuracy of engineers is higher problem-solving ability, which is consistent with the positive correlation between *GMAT* and the engineering undergraduate dummy (*Engineering UG*) observed in Table 6. Women's lower accuracy may reflect a lower exposure to strategy content in ways that are not captured by our controls. This is consistent with the negative correlations observed between *Female* and both *Age* and *Business UG* (as reported in Table 6).

Examining the interactions between the course and the demographic controls provides insight on how individual characteristics affect what people learn in the course. Model 1′ shows that the interaction between *Course* and *GMAT* is positively related to *Accuracy*, suggesting that individuals with higher GMAT scores benefit more from the course. This makes sense if we interpret GMAT score as a proxy for cognitive ability (Frey and Detterman

Table 8. Regression Results for Each Dependent Variable When Demographic Controls and Class Fixed Effects Replace Individual Fixed Effects

	Performance		Mental representations				Self-perceptions	
	Accuracy (1′)	Item count (2′)	Breadth (3′)	Depth (4′)	Non-cons items (5′)	Certainty (6′)	Confidence (7′)	Difficulty (8′)
Course	0.10***	−0.05	−0.04	0.02	0.03*	−0.16*	0.52***	−0.52***
	(0.03)	(0.12)	(0.08)	(0.03)	(0.01)	(0.06)	(0.09)	(0.08)
GMAT (*z*-score)	0.01	0.06	0.05$^+$	−0.01	−0.004	0.01	−0.08**	0.04$^+$
	(0.01)	(0.04)	(0.03)	(0.01)	(0.004)	(0.02)	(0.03)	(0.02)
Age (0-centered)	−0.002	−0.01	−0.02*	0.004	−0.003$^+$	0.01	0.02$^+$	−0.01
	(0.003)	(0.01)	(0.01)	(0.004)	(0.002)	(0.01)	(0.01)	(0.01)
Female	−0.04*	0.09	0.01	0.03	−0.03***	−0.13**	−0.36***	0.45***
	(0.02)	(0.08)	(0.05)	(0.02)	(0.01)	(0.04)	(0.05)	(0.06)
Native English	0.03	0.41***	0.13*	0.07***	−0.04***	0.03	−0.34***	−0.42***
	(0.02)	(0.08)	(0.05)	(0.02)	(0.01)	(0.04)	(0.06)	(0.05)
Business UG	0.01	−0.11	0.02	−0.04*	0.02**	−0.01	0.03	−0.11$^+$
	(0.02)	(0.10)	(0.06)	(0.02)	(0.01)	(0.04)	(0.05)	(0.06)
Engineering UG	0.04*	−0.34**	−0.12*	−0.02	0.02	−0.05	0.13*	−0.13$^+$
	(0.02)	(0.11)	(0.05)	(0.02)	(0.01)	(0.05)	(0.06)	(0.07)
Course × GMAT (*z*-score)	0.04*	0.12*	0.05	0.01	0.01	0.04	0.02	0.04
	(0.02)	(0.05)	(0.04)	(0.01)	(0.01)	(0.02)	(0.04)	(0.04)
Course × Age (0-centered)	−0.01	0.04	0.02	0.01	0.003	−0.01	−0.02$^+$	0.03$^+$
	(0.01)	(0.02)	(0.01)	(0.01)	(0.002)	(0.01)	(0.01)	(0.02)
Course × Female	−0.04$^+$	0.30*	0.16*	0.01	0.03**	0.11*	0.01	−0.05
	(0.02)	(0.12)	(0.07)	(0.02)	(0.01)	(0.05)	(0.07)	(0.09)
Course × Native English	−0.01	0.22$^+$	0.10	−0.01	0.02$^+$	0.04	0.22**	0.03
	(0.03)	(0.12)	(0.07)	(0.03)	(0.01)	(0.05)	(0.08)	(0.07)
Course × Business UG	−0.01	0.04	−0.07	0.04$^+$	−0.03**	0.01	0.09	0.10
	(0.03)	(0.13)	(0.08)	(0.02)	(0.01)	(0.05)	(0.07)	(0.08)
Course × Engineering UG	−0.07$^+$	0.38*	0.07	0.06*	−0.03$^+$	0.02	0.04	0.02
	(0.04)	(0.15)	(0.08)	(0.03)	(0.01)	(0.06)	(0.08)	(0.09)
Class fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Case fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,902	6,724	6,724	6,724	6,724	6,724	6,210	5,826
R^2	0.07	0.12	0.08	0.03	0.08	0.03	0.10	0.08

Note. Standard errors clustered by class in parentheses.
$^+p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

2004), which, in turn, affects performance for many tasks, including learning (Kuncel et al. 2004, Schmidt and Hunter 2004). The positive effect of GMAT score contrasts with previous results finding no relationship between it and the ability to make good decisions in the context of strategy (Gary and Wood 2011, Csaszar and Laureiro-Martínez 2018). That difference may be due to our study's much larger sample size.[9]

Model 2′ depicts the effect of the course on *Item count*. Compared with the effect in the previous set of regressions (Model 2 in Table 7), the main effect of the course here is not significant, suggesting that learning about strategy only alters item count for some. The demographic controls show that native English speakers write 0.41 more items on average. This result suggests that native speakers have an advantage in strategy jobs given that fluency, as described earlier, is a valuable skill for managers. We also observe that having an undergraduate engineering degree is negatively associated with *Item count*, which we conjecture is due to less familiarity with strategy concepts.

The interactions between the course and the demographic controls show that *Engineering UG*, *GMAT*, and *Female* play a statistically significant role in the extent to which individuals produce longer lists of pros and cons. As shown by the interaction between *Course* and *Engineering UG*, the course has an equalizing effect as the effect of the interaction (+0.38 items) more than eliminates the main effect of the engineering undergraduate degree (−0.34 items). The interactions also show that GMAT score plays a significant role in an individual's ability to list more pros and cons, an outcome consistent with the effect of the GMAT interaction in Model 1′. Women increase the *Number of items* they write after taking the course—a finding aligned with the research finding that women, on average, have greater verbal abilities than men (Hyde and Linn 1988).

4.3.2. Mental Representations. Model 3′ shows the effect of the course on individuals' breadth. As with *Item count*, the main effect of the course in this model is not significant, indicating that the strategy course may only affect breadth for some individuals. The demographic controls show that *Age*, *Native English*, and *Engineering UG* affect breadth. These patterns are similar to those observed in Model 2′ (with the exception of *Age*, which previously was not significant). We conjecture that this similarity reflects common underlying mechanisms: verbal ability and previous familiarity with strategy concepts. The negative association of *Age* with *Breadth* represents the fact that the older MBA students have less exposure to strategy (this is consistent with the negative correlation between *Age* and *Business UG* in Table 6).

Examining the interactions between the course and demographic controls shows that women increase their breadth when taking the course (by +0.16 categories; this is the only statistically significant interaction), consistent with research showing that women tend to focus more on the broader picture over individual details when problem solving (Ro and Loya 2015).

Model 4′ presents the change in individuals' depth of representations. As in Model 3′, the main effect of the course is not significant, and the controls show that *Native English* is beneficial. Unlike the previous regressions, these show that business undergraduates have less depth (−0.04 items per category on average). This could mean that they are more efficient at describing what they see, and rather than going around in circles, they get straight to the point.

The interactions in Model 4′ show a positive association between *Engineering UG* and *Depth*. That is, after taking the course, engineers have more things to say within the categories they use. This effect is aligned with engineers' improvement on *Item count* described in Model 2′.

Model 5′ depicts the change in the number of non-consumer items listed in the pros and cons. The model's main effect shows that individuals' attention to non-consumer items increases by 3% after the course. The control variables show that *Female* and *Native English* are negatively associated with the number of non-consumer items considered, whereas *Business UG* exhibits a positive association. The latter result is consistent with our conceptualization of non-consumer items: business undergraduates are more likely to know about them (e.g., from a previous strategy course). The other significant main effects suggest that women and native speakers—who the previous results suggest have greater verbal abilities—focus on things with which they are more familiar (i.e., consumer items rather than non-consumer items).

The interactions in Model 5′ exhibit significant relationships for *Female* and *Business UG*. The positive coefficient for *Female* may imply that the course improves women's awareness of non-consumer items. The negative coefficient for the *Business UG* interaction is somewhat puzzling. It could mean that business undergraduates become more selective in what non-consumer concepts to use (e.g., avoid unnecessary jargon).

Model 6′ shows how individuals' level of certainty (as expressed in the text of the pros and cons) changes when taking the course. The *Course* main effect in this model shows that, after taking the course, individuals use more uncertain language. As explained earlier, this is consistent with the view that strategy involves dealing with uncertainty (Rumelt 1984), and the strategy course makes students more aware of that. Women are overall less certain than men, consistent with research showing that women tend to use more tentative language (for a meta-analysis, see Leaper and Robnett 2011). A look at the interactions in Model 6′ shows that the course makes the initial differences between men and women almost disappear (i.e., *Female*'s main effect was −0.13, whereas its interaction was +0.11).

4.3.3. Self-Perceptions. Model 7′ depicts the effect of the course on individuals' confidence levels, and Model 8′ depicts its effect on perceptions of difficulty. Because the results of both models are similar, we interpret them together. We find that the course, overall, makes students more confident and that they find the task less difficult, consistent with our earlier set of results (Table 7). The largest effect sizes in both models' main effects are associated with *Native English* and *Female*: native speakers are less confident about their answers yet find the task less difficult; women are less confident and find the task more difficult.

The interactions between the strategy course and the control variables in Model 7′ suggest that, after the course, native speakers become more confident, whereas there is no change in women's confidence levels. Finally, Model 8′ shows no statistically significant interactions between the course and the demographic controls.

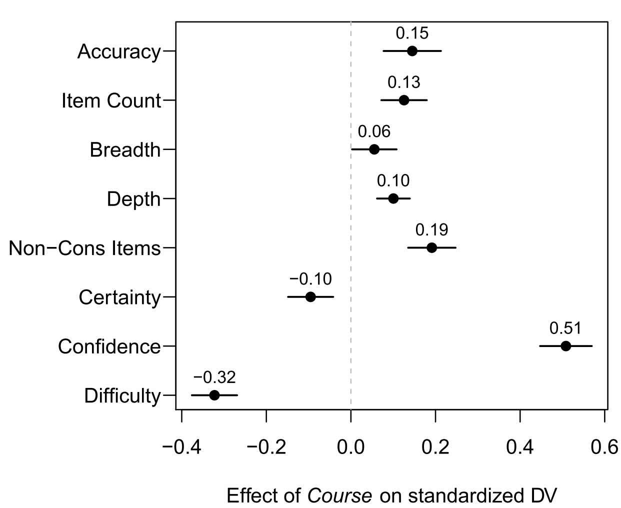
4.4. Comparing Effect Sizes

One complication of the analyses so far is that the dependent variables have different scales (e.g., accuracy ranges from 0 to 1, breadth from 0 to 10, and confidence and difficulty from 1 to 7). Hence, it is difficult to compare the effect of taking the course across different dependent variables. We overcome this problem by rerunning our first, more stringent models (Table 7) on standardized dependent variables; that is, we transform each dependent variable so that its mean is zero and its standard deviation is one.

Figure 2 plots the estimated effect of taking the course on each of the standardized dependent variables. For example, the figure shows that *Accuracy* increases by 0.15 standard deviation from the beginning to the end of the course. The bars around each estimated effect are the confidence bands corresponding to significance at the 5% level. Hence this graph confirms that all effects are significant except for *Breadth*, which is borderline significant because it (barely) touches the dashed line at zero. Figure 2 also shows that the course had the greatest effect on self-perceptions: confidence increased by 0.51 standard deviation and perceived difficulty decreased by 0.32 standard deviation. (It is natural to suspect that this disparity in effect sizes reflects the human inclination to be overconfident, but the question cannot be answered with these data.)

Another observation from Figure 2 is that the effect sizes are relevant. For example, the 0.15 increase in accuracy corresponds to a rise of 6% (= $\Phi(0.15) - \Phi(0)$) in the percentile position or ranking of an average performer. Most effects are around this ballpark figure. (The absolute magnitudes of all the effects, except for *Confidence* and *Difficulty*, are between 0.06 and 0.19, which translates into percentile changes ranging between 2% and 8% for the average performer.) Hence, this figure clearly indicates that the strategy course has, on average, meaningful effects on students.

Figure 2. Estimate of the Effect of Taking the Course (*Course* = 1) on Each Standardized Dependent Variable



Note. The bars denote 90% confidence intervals.

4.5. Robustness Checks

To validate the robustness of our findings, we ran a number of additional tests. The checks included (a) using alternative categorizations of the pros and cons, (b) adopting a different measure of accuracy, and (c) ascertaining the extent to which the results may be driven by a "practice" effect and/or by learning occurring outside the strategy course. These tests confirmed all the results presented so far.

First, we check for the influence of our categorization (which affects the *Depth*, *Breadth*, and *Non-consumer* measures) by rerunning our analyses with alternative categorizations using (a) only the items on which both research assistants agreed, (b) the categorizations of each research assistant separately, and (c) the categorization performed by a machine learning algorithm,[10] which was trained on the research assistants' categorization of the first 20% of the sample. The results were robust to all these changes.

Second, instead of measuring accuracy with our binary measure (i.e., based on assigning the higher interest rate to the start-up that failed), we measured students' ability to predict how much money each firm would raise from Kickstarter (in one of the questions, the survey mentions how much money the firm is requesting and asks students to predict how much money the firm will raise). Formally, this measure of accuracy is defined as the absolute *difference* between the predicted and raised amounts. The effect of the course on this new measure was robust (i.e., statistically significant and in the same direction as the main results).

Third, to check for whether performance improves simply by repeatedly participating in the activity, we looked at (a) the effect of the survey being administered after the first versus second video within each session and (b) the performance of students who missed the first class (and, hence, did not respond to the first two surveys). Neither analysis revealed a practice effect.

Finally, we considered whether the observed improvements may be due to other experiences occurring concurrently with the course (e.g., the student's other courses and extracurricular activities). We believe such an explanation is unlikely because students' other courses do not address the strategy ideas needed to predict and understand what drives firm performance; in particular, courses in accounting, statistics, and microeconomics do not cover the content captured by our categorization (see the appendix for the list of topics covered by strategy and the other courses). Moreover, we ran a similar exercise with undergraduates (who experience a different set of concurrent courses and activities), and our findings were qualitatively similar to those described here (albeit with a much smaller sample). Of course, we cannot randomize students' other courses and activities, and so we cannot completely refute the alternative hypothesis that the changes are driven by the whole MBA experience rather than primarily by the strategy course. However, the fact that the results on our eight dependent variables confirm our predictions, the strength of our results (in terms of both statistical significance and magnitude), the face validity of the exercise (which tests what the strategy course is designed to teach—to predict firm performance), and the robustness checks all suggest that the course is the main driver of the observed changes.

5. Discussion

Strategy research is mostly silent about the consequences of strategy courses. Such a gap is perplexing given the visibility of such courses and the field's focus on measuring performance consequences. A cynic could say the omission was due to the risk of finding that these courses have no added value. We believe that the delay was due to the multiple conceptual and empirical challenges to be overcome before the effects of a strategy course could be measured. These challenges include borrowing from the learning literature to find out at what to look (performance, mental representations, and self-perceptions), discovering how to measure decision-making outcomes using a realistic task, and collecting a sample that is large and rich enough to detect the types of effects we present.

We address this gap by conducting a large-sample study to examine what individuals learn from a strategy course and how what they learn depends on their individual characteristics. We find that a strategy course changes individuals in several key respects: (a) they become more able to discriminate between good and bad strategies (i.e., their accuracy increases); (b) their mental representations expand in terms of depth, awareness of uncertainty, and attention to aspects of competition that are not directly noticeable to consumers; and (c) their self-perceptions of confidence and difficulty increase and decrease, respectively.

We also show that the course's learning outcomes are largely dependent on an individual's cognitive ability and prior business knowledge. Individuals with higher cognitive ability experience greater performance improvement by the end of the course. Meanwhile, those with less prior business knowledge—women and engineers—experience the largest changes in both performance and representations. In that sense, the strategy course helps level the field. However, in terms of self-perceptions, women remain less confident and find the course more difficult than men do. In what follows, we elaborate on the broader contributions of our study, discuss some practical implications, and highlight opportunities for future work.

5.1. Theoretical Contributions

Our paper contributes to the strategy and organizations literatures by examining how individuals learn strategy when taking a strategy course. Using a large sample, we point to changes in eight learning outcomes and show how they depend on individual characteristics. Learning strategy in the classroom not only is widespread, but also operates very differently than on-the-job learning. Whereas the latter depends on a slow trial-and-error process, the outcome of which is dependent on many random conditions, classroom learning is faster and can be designed to teach specific competencies. Thus, our work sheds light on a pervasive yet understudied way of learning strategy.

A first theoretical contribution is to improve our understanding of how individuals learn strategy. Research on this topic primarily studies managers' on-the-job learning (Mintzberg et al. 1998); very little research investigates what students learn in the strategy classroom. The few exceptions of which we are aware suggest that learning does take place in this setting but do not say much about changes along different outcomes (performance, mental representations, and self-perceptions) and who learns what. For example, Yang et al. (2020) suggest that the type of strategy process favored by CEOs depends on the type of strategy course they took. Priem and Rosenstein (2000) show that, compared with other individuals, MBA graduates' mental maps more accurately resemble academic theories. Gary and Wood (2011) show that those with more accurate mental maps perform better in a business simulation.

A second theoretical contribution is to elaborate the relationship between mental representations and decision-making quality. In strategy, a common assumption (rooted in Simon's (1957) conception of bounded rationality) is that managers make decisions based on their mental representations: simple models of the situations they face. Much is known about such representations. For instance, the literature on managerial cognition documents wide diversity in how managers represent almost every aspect of their businesses (Porac et al. 1989, Benner and Tripsas 2012), and many formal models theorize about the effects of different characteristics of representations (Martignoni et al. 2016, Csaszar and Ostler 2020). Yet few scholars study empirically how these representations end up affecting the quality of strategic decisions (for details, see Csaszar 2018). Our paper narrows that gap by showing that the strategy course we study changed students' representations and improved their ability to discriminate between good and bad strategies.

Another theoretical contribution of our research is to shed new light on the determinants of managers' cognitive heterogeneity. This contribution stems from our methodology, which not only measures the before–after change for an average student, but also examines how the strategy course affects different types of students differently. Our results show that cognitive ability, prior knowledge, and gender are strongly associated with the magnitude of the different learning outcomes. Thus, our work suggests that the strategy course may explain part of the vast cognitive heterogeneity observed by the managerial cognition literature (see Rindova et al. 2012 for an overview). Part of the heterogeneity may stem from whether individuals have taken a strategy course and, for those who took one, from the different ways in which the course affects different individuals. Our work can also help the top management teams literature by providing a fuller account of how the demographic characteristics studied by that literature end up affecting the strategic decision-making process. For instance, the main effects in Table 8 can be used to guide hypotheses about the quality of decisions or the self-confidence of top management teams employing different types of individuals.

One last contribution of our work is methodological: we provide a fine-grained way—using a naturalistic decision-making task—to measure the learning of strategy. We suspect that our methodology may be fruitfully used by others to address the questions of what strategic expertise is and how it can be reliably developed.

5.2. Practical Implications

Our study has implications for students and teachers of strategy and administrators of business schools. First, it emphasizes some of the benefits of learning strategy (e.g., improvements in accuracy, depth, fluency, and confidence) and can, therefore, inform debates about the value of a business school education (see, e.g., Connolly 2003). As shown in the context of Figure 2, the magnitude of these effects is quite relevant. For instance, the observed 7% boost in accuracy levels would very quickly compound in jobs that repeatedly require picking among possible investments or strategic alternatives (such as jobs in venture capital, mergers and acquisitions, and general management).[11]

These findings run against skeptical views of business school education, such as viewing business schools as signaling and networking mechanisms (see, e.g., Stewart 2009, Rubin and Dierdorff 2013). In contrast, our work suggests that the strategy course has a substantial effect on the quality of the decisions managers make. Our work also suggests that taking a strategy course may affect students' careers as the improvements we document in performance, mental representations, and self-perceptions should help students when applying to strategy jobs and, once in a job, to participate more confidently and persuasively in the strategy process (Kaplan 2008). Because the benefits of the strategy course are different for different types of students, there is reason to believe that strategy courses affect the mix of candidates applying to and working in strategy positions.[12]

Second, our study suggests ways to improve learning for specific groups. For instance, one could think of interventions to mitigate women's lower self-perceptions (e.g., using more cases with women protagonists and showing interviews of women strategists). Because high levels of self-confidence increase persuasion (Petty et al. 2002) and managers with higher self-perceptions can achieve higher organizational performance (Wood and Bandura 1989), developing course content designed to boost women's self-perceptions will not only narrow the gender confidence gap, but may also decrease some of the challenges that women may face in gaining consensus and leading organizations.

More generally, our method for measuring learning in the strategy course may be more objective and meaningful than the current methods, such as testing for explicit knowledge and evaluating student participation (e.g., through quizzes and case assignments). We believe that measuring students' performance, mental representations, and self-perceptions more closely matches the job demands of being a strategist. Thus, this way of measuring learning may support initiatives meant to demonstrate that learning does take place in the business school. An example of this is the Association to Advance Collegiate Schools of Business (2021, p. 41) Assurance of Learning process, which tries to "demonstrate that learners achieve learning competencies."

Finally, we note that the main feedback strategy instructors use to adapt their courses may be students' evaluations. Yet these evaluations are noisy, biased, and delayed and often reflect a teacher's popularity rather than students' learning (Emery et al. 2003). The adage "if you cannot measure it, you cannot improve it" seems applicable to strategy courses. Measuring the actual learning that happens in them along the lines of what we have done here could ameliorate the situation.

5.3. Limitations and Future Work

As with other empirical studies, ours has limitations that future work could address. An important class of limitations stems from our empirical setting—a strategy core course that all MBA students take at the same time and along with a fixed set of other courses. Future research could use a laboratory experiment to better determine the causal effect of learning strategy content. Whereas a laboratory experiment would have limits in terms of external validity, it would allow for a statistical comparison between control and treatment groups, further decreasing the concern that other concurrent courses or experiences might have contributed to the changes we document. Such a research design could also examine the effect of different content (e.g., different cases and frameworks) and teaching methodologies (e.g., case- versus lecture-based). Alternatively, future research could use a sample that includes a variety of strategy courses and programs. This could allow us to look at the effect of taking strategy in parallel with different courses and, hence, to statistically control for the effect of the other courses.

Future work could examine how learning outcomes are contingent on other relevant individual characteristics (e.g., personality and work experience) and other types of students (e.g., undergraduates and executives). Other work could also examine how strategy courses affect different stages of the strategic decision-making process; for instance, the ability to formulate or implement a strategy (not merely evaluate one). Yang et al. (2020) suggest that some strategy courses may improve formulation but harm implementation. A practical and relevant question is whether that trade-off is avoidable and, more generally, how to best design strategy courses to develop specific competencies.

5.4. Conclusion

We began this paper by remarking that, despite the ubiquity of strategy courses, not much is known about their effects on students. Both skeptical and positive views of such courses seemed plausible. Our empirical exercise supports the latter view, offering hope that our efforts as instructors are not wasted. Teaching strategy can enrich students' lives by increasing their ability to make good strategic decisions, to think more thoroughly about strategy problems, and to feel more comfortable doing so.

Examining how what we teach affects students' performance amounts, in essence, to using the methods of strategy research to study one of our fundamental tasks as strategy scholars: educating future strategists. Keeping ourselves under the microscope should enhance both our powers of self-reflection and the value created by the field of strategy.

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Appendix: List of Course Topics

Table A.1 includes the main topics covered by the strategy course and the other courses students take concurrently. The lists of topics were extracted from course syllabi for fall 2019.

Table A.1. Concurrent MBA Courses and their Topics

MBA course	Main topics
Corporate strategy	What is strategy, industry structure and profitability, business level strategy and positioning, business level strategy and cost leadership, industry value chain, network effects, corporate scope and diversification, geographic scope and globalization, incentives and pay-for-performance, decision structures
Financial accounting	Purpose and financial statements, bookkeeping and the accounting cycle, revenue recognition, accounts receivable, COGS and inventory, depreciation and property, plant and equipment depreciation, long-lived assets, intangible assets and PP&E, liabilities, cash flow statement, ratios
Microeconomics	Economic costs, cost curves, pricing and monopoly power, antitrust laws, supply curves, market equilibria, efficiency, taxes, price ceilings and floors, trade quotas and tariffs, risk preferences and insurance, asymmetric information, adverse selection, price discrimination, game theory
Business statistics	Introduction to probability models, random variables, normal distributions, sampling distributions, introduction to inference, confidence intervals and hypothesis tests, applications of hypothesis testing, covariance, correlation, simple linear regression, multiple regression, multicollinearity, modeling relationships using dummy variables, statistical modeling

Endnotes

[1] The Yang et al. (2020) conclusion is drawn from a survey of 185 past students of the course, 67 of whom took it before 1983. To the best of our knowledge, this is the only other study on the effect of a strategy course.

[2] The organizational learning literature (Argote 2013) also studies learning; however, it does so at the organizational level (by studying, e.g., how cumulative output drives firm productivity; Darr et al. 1995), and hence, it has not approached the question of what is the effect of strategy courses.

[3] This view is also supported by recent experimental work in entrepreneurship showing that valuable skills, such as personnel management (Chatterji et al. 2019) and scientific thinking (Camuffo et al. 2020), can be taught.

[4] For instance, Westphal and Milton (2000) investigate how the level of influence directors are able to exert on boards is contingent on their gender and prior knowledge (operationalized as educational background).

[5] The 29 sections were taught by four instructors (who taught 17, 7, 3, and 2 sections each). The course syllabus was identical across instructors, and the content (including cases, readings, and main takeaways) was coordinated across instructors. Any remaining teaching differences between instructors are captured in our analyses by the section fixed effects.

[6] Archived versions of the videos are available at the following URLs. SCIO: https://web.archive.org/web/20150325093447/https://www.kickstarter.com/projects/903107259/scio-your-sixth-sense-a-pocket-molecular-sensor-fo, SH: https://web.archive.org/web/20140228113144/https://www.kickstarter.com/projects/mattiaslepp/smart-herb-garden-by-click-and-grow, DRIVE: https://web.archive.org/web/20170421090703/https://www.kickstarter.com/projects/1881989977/drive-safe-connected-driving/, and MR: https://web.archive.org/web/20160408222712/https://www.kickstarter.com/projects/1168534473/mindrider-a-new-mind-mapping-helmet-system.

[7] Apart from this measurement similarity, our paper differs from theirs in three main respects. First, we study the effect of taking the strategy course (i.e., a before–after difference), whereas they study the effect of using groups versus individuals; that is, we analyze a panel of individuals, whereas they compare a cross-section of individuals versus of groups. Second, we look at multiple dependent variables (i.e., the eight columns of Table 1), whereas their focus is only on accuracy. Finally, we use a much larger sample (2,269 students watching four videos versus 358 students watching two videos).

[8] We converted GRE into GMAT scores using the formulas provided by the Educational Testing Service (see pp. 3–4 of https://www.ets.org/s/gre/pdf/background_and_technical_information.pdf).

[9] One should also keep in mind that the relation between cognitive ability and performance is complex and that gains because of higher cognitive ability may level off after thresholds that depend on the particular task (Sternberg and Wagner 1993).

[10] See fasttext (available at https://fasttext.cc).

[11] As an illustration of this compounding effect, imagine two managers with accuracies of 60% and 67%, respectively. Each manager is in charge of an identical firm and has to make 10 sequential decisions. If the initial value of the firms is \$100 million and a good decision increases the value of the firm by 25%, whereas a failed one decreases its value by 25%, then the expected value of the firms after the 10 decisions is \$162 million and \$226 million, respectively (this can be computed using the expected value of the binomial tree: $\sum_{i=1}^{10} \binom{10}{i} p^i (1-p)^{10-i} 1.25^i 0.75^{10-i}$).

[12] We thank an anonymous reviewer for suggesting these differential effects on students' careers.

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