Individual Self-Directed Learning Behaviors: A Measure, Model, and Field Experiment Examining How Working Adults Learn.

Individual Self-Directed Learning Behaviors: A measure, model, and field experiment examining how working adults learn.

A dissertation presented

by

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to

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in partial fulfillment of the requirements for the degree of

Doctor of Business Administration

in the subject of

Management

Harvard Business School

Boston, Massachusetts

Month and year of submission of completed dissertation and Dissertation Acceptance Certificate signed

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Abstract

Individual self-directed learning is learning that is in the hands of the learner and requires sustained active engagement. Although self-directed learning has proven to be both powerful and critical to working adults' ability to develop their careers, little is understood about how self-directed learning occurs as employees face performance demands in their day-to-day work. This dissertation presents a behavioral measure, a process model, and a large-scale field experiment to deconstruct self-directed learning into five key learning behaviors of taking on a challenge, attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection. It empirically tests how and when working adults engage in those behaviors while meeting performance demands. Chapter 1 uses a newly developed Learning Behaviors Measure to test the relationship between a key driver of learning - learning orientation – and each of the five learning behaviors. It reveals that learning-oriented individuals are more likely to take on challenge but not more likely to follow through on the behaviors needed to meet that challenge. Chapter 2 expands these five key behaviors into a model of long-term self-directed learning to posit that all five behaviors are required for long-term learning, that there is an optimal order to the behaviors, and that any one individual is unlikely to freely engage in all five behaviors. One particular behavior that seems difficult for learners to maintain in the long-term is reflection. Therefore, Chapter 3 presents a field study that shows that a simple intervention of allowing employees to see past reflections motivates them to reflect in the future.

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Acknowledgements

This dissertation is the result of being handed the rare opportunity to explore my passions. I'd like to say I earned this opportunity and, to some extent, I did, but not more so than countless others who were not handed such a gift. The truly surprising thing is that I wouldn't have even wanted this gift before I met David Talaga. David, you are my partner in life, parenting, and wine and cheese. Before you, I thought cheese was for sandwiches, and before you, I thought that work was for money. You made countless sacrifices in the past six years to help me finish my degree. From commuting to Boston, patiently helping as I challenged you about statistical methods (you were always right), to having to support a woman who, when you married her, was financially independent. I am very grateful. But my gratitude for these sacrifices pales in comparison to how thankful I am that you not only embraced, but taught me to embrace, my passions and my abilities. Without that, truly, my life would have been less well-lived, and this dissertation would not exist. You taught me, by the choices you make and the dedication you have, that work was for challenging myself to contribute to the world. For that, and much more, I love you.

I am also grateful to our imp son, Calvin Talaga. Calvin, thanks for being such an easy baby so I could get this thing done in a reasonable amount of time! Also, thanks for that joy-filled smile that reminds your Dad and me to stop taking everything so seriously, to dance, and be silly. You are the most curious creature I've ever met. We will do our best to nourish that incredible quality and I hope dearly that your curiosity only grows. Remember, I love you more today than yesterday – every day.

In Harvard, I truly found a home. Before I started this doctoral program, I felt out of place in both work and school. I was too demanding, too aggressive, too questioning. At HBS, I was surrounded by faculty and students who demanded the best of themselves and others, and aggressively questioned the world. To Amy Edmondson, whose body of work

continues to inspire me, and whose questions changed the course of my thinking. Each time we meet, I see my work in new ways and I see new opportunities to contribute to the world. Thank you for your belief in me and in this work. To Ethan Bernstein, thank you for teaching me the ropes. You guided me through the crazy world of publication – and who better to learn from! You always had the time to sit down with me and taught me that good research is as much about communicating it as it is about conducting it. I'd also like to thank Laskhmi Ramarajan for all the times she anticipated I needed her help and support. You truly live as a mentor and collaborator. To Ryan Buell, Francesa Gino, Boris Groysberg, Monica Higgins, Ian Larkin, Joshua Margolis, Kathleen McGinn, Chris Myers, Leslie Perlow, Jeff Polzer, Christine Porath, Katie Roloff, Brad Staats, and Dusya Vera, you have each taken the time to give me guidance and helped me be a better scholar. This dissertation owes a great deal to your insights.

I can honestly say I've never more easily made friends than at HBS. My fellow students are responsible for many of the good ideas in this dissertation - and for the absence of many bad ideas. You are also responsible for making the past six years so much fun. I say to David time and again, I just like them all so much. To Andrew Brodsky, my partner in advisee-ship, you are an inspiration as a researcher, a collaborator, and a friend. Thank you for all your support, your pushback, and your being available to figure things out and, when needed, vent our frustrations. To Lizzie Baily, no one has showed such passion for my work and believed in it more than you. When I start to lose confidence, your voice is in my head telling me how interesting and important this work is. And because you are such a stellar scholar, I listen to that voice! Thank you for all your thoughts and insights. Thank you to both you and Matthias for being such dear and good friends. To Rachel Arnett, you rock. I really look to you as a model for being a rigorous researcher who still has a great time doing what she does. You and Alberto are such a rich part of our lives. To Ting Zhang, my

research would not be as inventive, rigorous, or fun without you. Thank you for sharing your ideas, giving support and guidance, and always being a fantastic friend. To Ryann Manning, you, more than anyone, show me how research contributes to the world. I treasure our friendship and loved every conversation over the past six years. To Lisa Kwan, thank you for being lovely. You are a wonderful, thoughtful scholar, but it is your worldview and kindness that I will take with me most as I journey forward. To my brief office-mate Curtis Chan, thank you for your humor, kindness and support. Thank you my COLLECTion of awesome colleagues: Erin Frey, Hayley Blunden, John Cromwell, and Matt Lee. You know more about this work than most and never fail to provide rich and useful feedback. Thank you also to my Management cohort, Pam Park and Everett Spain for our early years together and showing me that the finish line really does exist.

My HBS family extends across the river to the amazing colleagues and friends I've made at the Learning Innovations Laboratory. They have allowed me to keep this research grounded in the real world and have proved to be true friends over the years. Marga Biller, thank you for always being kind, available, and willing to push me to new levels of thinking. You keep me grounded but still believe in me as a scholar and thinker. Thank you also for opening your house to me and being such a wonderful friend. Daniel Wilson, thank you for keeping me around! You really push me to consider things more openly and more deeply. Because of you, I am a better collaborator, facilitator, and researcher. To David Perkins, thank you for modeling how to communicate even the most complex of ideas. Your mastery of impactful simplicity is something I will aspire to throughout my career. Thank you also for your generosity – you are always available to answer questions and help with research ideas. To Sue Borchardt – no one, and I mean no one, pushes me more than you. I just can't get away with anything with you. Thank you so much for the lively conversations and keeping me honest. To Amanda Nourse, thanks for all the great conversations and for keeping LILA

together. To Katie Heikkinen, thanks for showing me how to communicate ideas through clear writing and insightful research. It has contributed to making this dissertation more readable (I hope).

Beyond my HBS family, there is my other family – or more precisely families. Starting with the traditional form of family, thank you to my Dad, Robert Rigolizzo. Dad, your love, support, and unfailing belief in me is with me everyday. You let me drone on about my work, inspire me to use those stats correctly, and have even served as my guinea pig! Thank you for, well, everything. This work, my life, and Calvin's life are richer because of you. Thank you also to Sandy Rigolizzo for your love and support of both my Dad and me, and for being such a great Nonna. I love you both.

To my mom, Eleanor Dill. You are always there for me, to nurture, to understand, and to be proud. Thanks for all your help with Calvin. I don't know that I would have gotten this thing out on time without you. Thank you also to Chuck Dill, who keeps you going interesting places and is always kind and supportive. You are fantastic grandparents and I love you both.

To my brother, Steven Rigolizzo, my sister, Laura Tierney, and my sister, Gina Gilbertson. You have each provided support and love throughout this crazy process. You are the only ones who know what it's like to be us, and I am grateful that we are close after all these years.

To Jordan Tierney, Jace Tierney, Zack Gilberston, and Brook Gilberston. Thank you for sacrificing time with your aunt so she could do this research and finish this dissertation. It may not feel as much of a sacrifice to you as it does to me, but I wasn't able to spend as much time with you over the past six years, and I have truly missed out. I hope you will each have the opportunity to pursue your passions in life and know that you have my love and support every step of the way.

To my friends – the family you choose. You are simply the best. I keep the Harvard poster Allen drew, that you each contributed to, on my desk. This journey meant less time with you and your children but I could not have felt more love, pride, and encouragement along the way. Patti McCabe, thanks for reminding me that life is a journey and that you decide where it goes. You simultaneously make me see how ridiculous it is that I get to do this at HBS, and how it doesn't surprise you at all. Adrienne Asta, you inspire the world and it is clear, every day, that your father lives through you. I know there is no greater compliment I could give. Sharing this work with you keeps me going when I get insecure or frustrated. Janice Rowland, thanks for always caring about what is going on in every part of my life. Before I left, you told me to be strong, brave, and bold. I do this by looking to you and knowing you are at my side. Denise Weber, thanks for all your wisdom and laughter. You taught me to appreciate people because of, not despite of, their quirks and weirdness. This skill has served me well in academia! (and my marriage) To Allyson Sandak, you got me through some rough times in the past six years. Thank you for always being so kind and generous. I will try to follow in your footsteps as a rock-star professor at Montclair! To Josh Eisinger, I will never forget the newsletters you sent when I was getting my masters. What a wonderful thing to keep me connected and make me feel I wasn't on this journey alone. You are always there to celebrate with me. You are simply a great friend and I treasure you. To Jennifer Fuges, you have taught me courage and grace under pressure. Thanks for believing in me and our all too infrequent, but cherished, conversations. To Scott Elgart, Jim Anderson, and Allen Radway, thank you for all the great conversations and for making me feel you are my friend, independent of your spouses.

I am also indebted to Barbara Ciaramella, who was more than a manager but a true mentor and friend. I still hold in my head your encouragement when I went to pursue graduate work at Harvard. You said, "if not you, Michele, then who?" This phrase gave me perspective in the times I felt overwhelmed or overshadowed by the great scholarship surrounding me. Your guidance prepared me for one of the best journeys of my life.

There are so many ways this dissertation would not have existed if it weren't for my mentor and friend, Teresa Amabile. Teresa, when I walked out of your office seven years ago, I knew my life would change. I had to physically stop and sit down because I was so powerfully affected by our conversation. I know, without you, I would not be at HBS. I know, without you, I would not be given the freedom to pursue my passion. I know, without you, my research would not be as rigorous. I know, without you, my writing would not be as clear. I know, without you my experimental designs and ideas would not be as creative. I know that for the rest of my life it will be a true statement to say, without Teresa, I would not be here today.

Teresa, you taught me so much about being methodical and rigorous. You shared my strong commitment to integrity over results. There was never a day working with you where that integrity felt in jeopardy. You also taught me so much about why we do what we do. We want to know what is true in the world. We want people to feel inspired by their own abilities. We want to know what drives people to be their best selves. You also taught me how much hard work is needed to pursue these questions. Please know, I did not, I do not, take your hard work for advantage. There are few advisors that are as accessible, thorough, helpful, and supportive as you. You not only respond quickly, you do so thoroughly. Even when I got frustrated (which may have happened once or twice), I could always say to myself 'Teresa has my best interests at heart', and it was easy to believe. Thank you Teresa. I had a grand time working with you, and I will not forget the lessons you taught me about research and about life.

Introduction: Learning As Behaviors

This dissertation is based on three interconnected realities about self-directed learning in dynamic business settings. Employees must continually learn to stay competitive. The complex work employees do provides abundant opportunities to learn on a daily basis. The work demands employees face create substantial barriers to taking advantage of those opportunities. Together, these three workplace realities call for a better understanding of how self-directed learning unfolds in workplace settings. Self-directed learning is when employees take responsibility for their own learning by seeking out and taking advantage of the learning opportunities available through complex work (Noe, Clarke, & Klein, 2014). However, little is understood about the behaviors involved in self-directed learning and the degree to which employees actually engage in those behaviors when they are faced with competing work demands.

Therefore, to advance the study of self-directed learning, I contend that we need to consider learning as observable behavior. Learning is considered a largely internal process, and rightfully so. Individual learning occurs within a single mind, and behavior, or more specifically change in behavior, is traditionally viewed as the outcome of learning (Skinner, 1953). In essence, individual self-directed learning occurs in one's head and is manifest in one's behavior. However, based on research in cognitive science, education, and training, I suggest a reversal of this approach. I propose that the outcome of learning is a cognitive change, namely a change in long-term memory and that this change occurs through enactment of specific observable behaviors. Based on a definition of learning as a change in long-term memory, I identify 5 key behaviors of individual self-directed learning: taking on a challenge, attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection. I then draw from Dual Systems Theory (Wason & Evans 1974) to suggest that each behavior is an effort in moving from conscious deliberate action to automated subconscious performance. In other words, each learning behavior is an attempt to move from System 2 deliberate effort to System 1 automated performance

Viewing individual self-directed learning as multiple behaviors that move in a particular sequence enables three ways to advance the study of individual learning. First, it allows for more precise measurement of learning as it occurs. Learning is often measured through outcomes but this is problematic for long-term learning because there are so many named and unnamed factors that can impact the long-term outcome. However, if we can identify the behaviors that culminate in learning outcomes, then individual self-directed learning can be measured through observing whether individuals engage in those behaviors.

In Chapter 1, I introduce the Learning Behaviors Methodology (LBM), which enables the direct observation of learning behaviors as they occur in the act of learning. With this measure, previously-studied antecedents of learning can be more precisely related to each learning behavior, shedding light on how these antecedents differentially impact the process of learning. A key antecedent in the learning and management literature is learning orientation, which has been shown to predict learning and performance in a variety of settings (Payne, Youngcourt, & Beaubien, 2007). In Chapter 1, I examine the impact of learning orientation on each learning behavior and find that it predicts whether working adults take on a challenge, but not whether they follow through on that challenge by engaging in the subsequent behaviors.

Second, viewing learning as a series of behaviors that lead to a change in long-term memory provides a way to deconstruct learning. This deconstruction enables systematic examination of how each behavior contributes to learning and how each behavior does or does not relate to the other behaviors. In Chapter 1, I found that learning orientation is an antecedent to only one learning behavior. This suggests that each behavior may have distinct motivational drivers and challenges the assumption in the literature that often treats learning as a single entity. In Chapter 2, I build on the Chapter 1 findings to introduce the Learning As Behaviors (LABS) model, which examines separate motivational factors for each behavior. The LABS model also asserts that each behavior leads to a distinct learning outcome because each behavior changes long-term memory in a different way. This explains an additional finding from Chapter 1, that the learning behaviors are largely independent. Because the LBM enables direct observation of each behavior as it occurs during learning, I was able to show that, for the most part, engaging in one behavior does not predict engagement in the others. As such, Chapter 2 reveals a new barrier to long-term expertise development: individuals will likely have to engage in at least some behaviors they would rather avoid. However, on the positive side, it means we can more directly target interventions based on the learning outcome desired and the drivers of the behavior(s) that lead to that outcome.

Third, considering learning behaviors as pathways to move from deliberate slow action to rapid automated performance highlights reflection as a specialized learning behavior because reflection is an attempt to move in the exact opposite direction. This is necessary to critically examine both success and failure and understand the why behind automated performance. Reflection requires slowing down and bringing tacit knowledge to conscious awareness, but getting into the habit of reflection is notoriously difficult. In Chapter 3, I present a large-scale field experiment where I tested whether reflection on learning raises awareness of learning opportunities. I also tested a simple intervention for motivating individual reflection. I allowed one group, but not the other, to see their previous reflections. I found that individuals who were able to view their previous reflections wrote significantly more reflections than individuals who were not able to view previous reflections. Shedding light on both the process and outcomes of reflection can help scholars and managers understand what to expect from reflection activities and explore ways to motivate slow, deliberate thought in an increasingly rapid and dynamic business environment.

Chapter 1: The Role of Learning Orientation in Self-Directed Learning Behaviors

The study of individual self-directed learning has largely been ignored outside of controlled academic settings or formal training. Argyris (1976) identified key interpersonal barriers to individual workplace learning by showing how employees are unwilling to admit error or ignorance. However, he did not elucidate the process by which self-directed learning occurs once those barriers are removed. Later, Marsick & Watkins (2001) proposed a model of informal and incidental learning based on a systematic, facilitated process of group problem-solving. They revealed that much of workplace learning occurs outside of formal settings by collaborating and solving problems. However, there is little empirical evidence of how this learning occurs, especially since most studies occur at the group level (Marsick & Yates, 2012). Despite calls for it (Noe et al., 2014), individual level self-directed learning at work has been largely ignored. This may be due, in part, to the lack of a strong measure. Learning outcomes are typically self-reports of learning and in some cases, managerial reports of performance. Thus far, we have lacked a systematic way to study individual self-directed learning as it occurs.

One strong body of research on individual self-directed learning is the work on goal orientation (Beenen, 2014; Colquitt & Simmering, 1998; Dweck, 1986; Kohli, Shervani, & Challagalla, 1998). Goal orientation differentiates between a learning orientation, where someone approaches a difficult task as an opportunity to improve, and two types of performance orientation, where someone approaches a difficult task as a way to either demonstrate what they know (performance-prove) or avoid revealing their inability (performance-avoid) (Dweck, 1986; VandeWalle, 1997). Goal orientation has been used in hundreds of studies in learning and management and learning orientation has been shown to have a small but significant effect on both learning and performance (Payne et al., 2007).

However, it is unclear which learning behavior or behaviors are impacted by learning orientation.

In Chapter 1, I introduce the Learning Behaviors Methodology (LBM) for observing learning behaviors as individuals engage in a complex learning task. Integrating research from education, cognitive science, and management, I identify five learning behaviors of taking on a challenge, attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection. This methodology takes place entirely online to ensure that every choice participants make can be tracked. First, learners choose their level of challenge. This directly measures the extent to which participants engage in the first learning behavior of taking on a challenge. Second, participants are given learning materials and the extent to which they pay attention to those materials is measured by the time spent reading, controlling for their reading rate. Throughout the learning materials are hyperlinks to contextual information that will help participants build cognitive connections about the topic. The number of hyperlinks clicked measures the extent to which participants engage in the third learning behavior of forming meaningful connections. Participants are then asked to apply their knowledge in a practical task. The fourth learning behavior of repeated practice with feedback is measured by how many times they choose to practice and the time they spend on processing feedback between those rounds. Finally, participants are given the opportunity to critically reflect on their learning, which is measured by whether they write a reflection and the content of those reflections.

In Chapter 1, I use the LBM to test the impact of learning orientation on each learning behavior and overall performance. I find that learning orientation predicts only the first learning behavior of taking on a challenge. It does not predict whether individuals follow through on that challenge by engaging in subsequent behaviors. This finding reveals learning orientation as an important but limited predictor of learning. One of the key barriers to learning in organizations is that, when faced with mistakes, errors or difficult tasks, individuals do not take on the challenge of learning but rather enact outdated routines, even if they are ineffective (Argyris, 1976; Cyert & March, 1963). Individuals with a learning orientation, however, are more likely to take on learning challenges. Nevertheless, according the findings in Chapter 1, they are no more likely to engage in the subsequent learning behaviors.

With the introduction of the LBM and revealing the merits and limits of learning orientation as a predictor of learning, Chapter 1 makes an important contribution to the study of learning. However, it also raises unanswered questions. First, are all the learning behaviors needed for long-term learning? Second, does the order of those behaviors matter? Finally, if learning origination doesn't predict the other behaviors, what does? Each of these questions is addressed in Chapter 2.

Chapter 2: Mapping Learning Behaviors in the Learning As Behaviors (LABS) Model

Research has shown that developing expertise is hard because it requires learners to sustain "consistent purposeful effort over very long periods of time" (Feltovich, Prietula, & Ericsson, 2006, p. 45). In past research, there is an implicit assumption that barriers to expertise are overcome by exerting more effort (Ericsson, Krampe, & Tesch-Römer, 1993). Chapter 2 challenges that assumption and embraces the possibility that developing expertise involves engaging in multiple learning behaviors, each of which constitutes a different type of effort. Chapter 2 introduces the Learning As Behaviors (LABS) model, along with three novel propositions about individual self-directed learning: 1. each of the five learning behaviors is required for long-term learning, 2. each stage of expertise is dependent on automating the learning outcomes of the previous stage, though learners can regress within and between stages and 3. that any one individual is unlikely to engage in all five behaviors without intervention.

The LABS model builds on the work in Chapter 1 to assert that each of the five behaviors is needed to achieve expertise. Expertise is defined as the ability to perform in novel situations and research has found that experts differ from non-experts because they have access to a vast reservoir of knowledge in their long-term memory (H. A. Simon & Chase, 1973). Therefore, Chapter 2 outlines how each behavior contributes to building that reservoir in long-term memory based on Atkinson & Shiffrin's (1968) well-established model of human memory. Taking on a challenge launches the change. Paying attention to new information leads to short-term recall (Nissen & Bullemer, 1987). Forming meaningful connections leads to longer-term recall (Ausubel, 1960; Mayer, 2002). Repeated practice with feedback enables automated performance (Garavan, Kelley, Rosen, & Rao, 2000; Jolles, Grol, Van Buchem, Rombouts, & Crone, 2010). Finally, the relationship between reflection and long-term memory is not well understood but it likely helps further solidify connections and build meaning to consolidate knowledge for the long-term. Since each behavior uniquely contributes to the formation of long-term memories, each behavior is needed to achieve expertise.

The second proposition of the LABS model is that each stage of expertise is dependent on automating the learning outcomes of the previous stage. This proposition is based on a Dual Systems (Wason & Evans, 1974) view of learning. In Chapter 2, I argue that learning occurs when individuals move from System 2 slow, deliberate action to System 1 automated performance. This is most obvious in practice effects. Over time and with practice, recalling knowledge and performing skills move from taking conscious effort to becoming automated. I argue that each stage of expertise is accomplished when the outcome of that stage becomes automated and no longer taxes working memory (Shipstead, Harrison, & Engle, 2015). This frees up working memory to engage in the subsequent stage. Therefore, there is an optimal order to learning because each stage benefits from the learning or automation of the previous stage.

However, the LABS model also suggests that learners can regress during learning, moving back and forth between stages, but in predictable ways. In Chapter 2, I combine Dual Systems Theory (Wason & Evans, 1974) with Dynamic Skills Theory (Fischer & Bidell, 2006), to argue that though there is an optimal order of learning, in reality learners will have to re-visit prior stages because performance dips are a natural part of the learning process. Essentially, knowledge and skills that become automated don't always stay automated and research has shown that learners can regress during learning depending on the level of support and frequency of the learning activity (Fischer & Paré Blagoev, 2000). Therefore, learning appears dynamic but has forward progression over time.

The final proposition of the LABS model is that any one individual is unlikely to engage in all five behaviors without intervention. This proposition builds on the finding in Chapter 1 that the learning behaviors are, by and large, independent and that engaging in one behavior did not predict engagement in the others. In Chapter 2, I draw on expectancy value theory and identification theory to posit that individuals have different expectations that a given behavior will result in learning as a function of the attributes they identify with. I suggest that individuals with certain individual attributes, such as diligence, focus, curiosity, or persistence, will be drawn to some behaviors and not others. For example, the focused individual may be drawn to paying attention to learning materials while the exploratory individual may be more interested in exploring the context of that information. Individuals are unlikely to identify with all the learning attributes for each behavior. Therefore, they are unlikely to engage in all the requisite behaviors. This reveals a previously undiscovered barrier to expertise. It requires the learner to be confident enough to take on a challenge while valuing others' expertise as a novice; diligently focused enough to acquire information, yet curious and exploratory enough to explore context; and doggedly persistent enough to continually practice, yet critically analytic enough to discover underlying principles. Therefore, beyond concerted time and effort, the long-term learning needed to develop expertise requires individuals to engage in some behaviors they naturally resist.

The LABS model provides a systematic way to study and understand the full process of individual self-directed learning. In the final chapter of this dissertation, I will home in on one specialized learning behavior, that of reflection. Reflection is specialized because, unlike previous learning behaviors that lead to automated performance, reflection moves in the opposite direction. Reflection is the attempt to move information from the more automated subconscious knowledge structures in System 1 thinking to the slow, conscious, and deliberate thinking characteristic of System 2. However, while reflection is critical to individual self-directed learning, little work has been done to understand how and when busy employees reflect.

Chapter 3: Motivating Individual Self-Directed Reflection

Chapter 3 addresses two questions about individual self-directed reflection: 1. how can repeated reflection impact learning from work and 2. what motivates busy employees to repeatedly reflect. I integrate research on selective attention (Jiang & Chun, 2010), cognitive biases (Tversky & Kahneman, 1974), and category learning (Greenough & Black, 1987) to argue that repeated reflection on learning at work can help employees re-categorize work events as learning opportunities. However, getting busy employees to repeatedly reflect is notoriously difficult (Argyris, 1983) . Therefore, I build on work from rediscovery (Zhang, Kim, Brooks, Gino, & Norton, 2014) and narrative building (Pennebaker & Seagal, 1999) to hypothesize that, when individuals can view previous writing, they will be more motivated to continue reflecting.

In a large-scale field experiment, 195 employees were first asked to list all the learning opportunities they noticed at work in the past 2 days. They were then split into three conditions - two Reflection conditions and one Control. In the Reflection conditions, employees were asked to reflect on their learning twice a week for eight weeks. In the Previous Reflection condition, employees were able to view their previous reflections each time they wrote a new reflection. In the One-at-a-Time Reflection condition, employees were not able to see previous reflections. In the Control condition, employees were not asked to reflect. All participants then filled out a post-survey again asking them to list the learning opportunities they noticed in the past 2 days.

Results showed that employees who were able to view their previous reflections wrote significantly more reflections than employees who were not able to view what they previously wrote. Results also indicated that employees who reflected became more aware of learning opportunities than employees who did not, although these differences were not significant. These results suggest that the ability to make connections between past and present experiences motivates individual self-directed reflection. The Reflection Study shows how a simple intervention of viewing past writing can actually encourage busy employees to take the time to engage in the important and often overlooked learning behavior of reflection.

Summary

This dissertation represents a body of work based on the premise that when we consider individual self-directed learning as a motivated behavioral process, we can better measure and study learning, thereby discovering ways in which working adults can learn from the challenging work they do. Chapter 1 introduces the Learning Behaviors Methodology to provide a better way to think about and measure learning and, in particular, the relationship between learning orientation and each of five key learning behaviors. Chapter 2 extends this work to develop the Learning As Behaviors (LABS) model, which considers how learning actually occurs when there is competition for attention and views self-directed learning as a set of differentially motivated behaviors. Finally, Chapter 3 empirically tests how reflection occurs in the workplace, where there is strong competition for attention, and provides both measurable outcomes of reflection and new ways to prompt individuals to repeatedly reflect.

CHAPTER 1: THE ROLE OF LEARNING ORIENTATION IN SELF-DIRECTED LEARNING BEHAVIORS

Abstract

Literature has shown that learning orientation is an important driver of learning outcomes in both academic and organizational settings. However, it is unclear how learning orientation relates to how working adults actually behave while learning, particularly when there is competition for their time. This chapter examines the impact of learning orientation on five key individual learning behaviors of taking on a challenge, attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection. Across three studies, I find that learning orientation consistently significantly predicts whether working adults take on a challenge in a learning task. In the third study, I introduce the Learning Behaviors Methodology, which enables me to directly observe the extent to which working adults engage in the remaining learning behaviors. Study 3 shows that, while learning orientation again predicts taking on a challenge, it does not predict whether individuals follow-through on that challenge by engaging in subsequent learning behaviors. By opening the black box of self-directed learning, this chapter sheds light on the predictive value of learning orientation as a key individual difference but also illuminates the limits of learning orientation as a predictor of learning behaviors. It provides new avenues for research by advancing the measurement of self-directed learning beyond self-reports to quantifiable, observable behaviors.

Introduction

Both business environments and individual careers are increasingly more dynamic and the constant pace of change calls for both exploiting existing knowledge and exploring new areas of knowledge (Benner & Tushman, 2003; March, 1991). Employees can no longer rely on spending their full career with a single organization or even in a single field of knowledge (Noe & Tews, 2010). Whether it is transitioning to a new career, a new role, or taking on a new assignment, employees are continually tasked with learning new things. As such, individual learning, which has largely been studied by education researchers (A. Bandura, 2001; e.g. Dweck, 1986; McCombs, 2009; Yeager & Dweck, 2012) is gaining increased attention in the field of management. Studies include examining the drivers for engaging in formal classroom training (Colquitt & Simmering, 1998), the role of developmental assignments (DeRue & Wellman, 2009), informal problem-solving (Marsick & Yates, 2012) and how learning can occur incidentally as a byproduct of high performance (Marsick & Watkins, 2001).

Cutting across these settings is the need for self-directed learning wherein employees take responsibility for their own learning by seeking out and taking advantage of the learning opportunities available through complex work (Noe et al., 2014). Self-directed learning offers benefits beyond those of accumulated experience or learning-by-doing (Nembhard & Tucker, 2010). It is characterized by learners taking an active role in their learning experiences and asserting control over their learning by way of their ongoing decisions (Gureckis & Markant, 2012). Because individuals, particularly experienced workers, can construe the same challenging work experience as either a threat to their knowledge or a learning opportunity (Dane, 2010; Dweck, 1986), self-directed learning plays a critical role in whether, when, and how working adults engage in learning. However, research on self-directed learning is limited and primarily anecdotal (Noe et al., 2014).

Since self-directed learning is characterized by the decisions individuals make when confronted with a learning opportunity, it can be operationalized by the choice of whether or not to engage in learning behaviors to take advantage of those opportunities. Therefore, self-directed learning can be informed by the long-standing research in education and cognitive science that delineates what behaviors are needed to learn. Learning refers to a cycle of action and reflection by which individuals are given the opportunity to learn (DeRue & Wellman, 2009), pay attention to new information (Nissen & Bullemer, 1987), put that information into context (Ausubel, 2012), practice applying their learning (Ericsson et al., 1993), and critically reflect (Mezirow, 1990). When individuals autonomously choose to engage in these five behaviors of taking on the challenge to learn, attending to learning materials, forming meaningful connections, repeated practice with feedback, and critical reflection, learning is self-directed.

Since employees have increasing control over when, where and how to engage in learning (Sitzmann & Ely, 2011), it is important to understand what drives working adults to direct their own learning. Although there are likely many factors that influence self-directed learning, one important driver investigated in previous research is goal orientation and, in particular, learning goal orientation. Grounded in Dweck's (1986) work on the implicit theory of intelligence, goal orientation captures differences in how people approach tasks as either learning opportunities (i.e., with a learning orientation), or ways to demonstrate what they already know (i.e., with a performance orientation). Learning orientation targets the degree to which working adults pursue learning even when they have competing work demands and, therefore, would appear to be the ideal driver to include when studying the actual behavior of individuals in this circumstance.

Learning orientation is also one of the most widely-used predictors of learning for working adults (Payne et al., 2007). There has been little systematic work on what drives self-directed workplace learning but learning orientation is an exception. It has been shown to predict learning outcomes in a variety of workplace tasks, including improving on past performance (D. A. Moore & Healy, 2008), sales performance (Porath & Bateman, 2006), and scores in training simulations (Ford, Smith, Weissbein, Gully, & Salas, 1998). However, the learning itself has remained somewhat of a black box because few studies actually examine what working adults are doing as they participate in learning complex materials. For this reason, little is known about the relationship between learning orientation and the individual self-directed learning behaviors enacted by working adults.

One reason for this lack of research is that there has not been a way to measure learning behaviors as they occur during a learning task. Therefore, I developed a Learning Behaviors Methodology which tracks the decisions working adults make as they are confronted with a learning opportunity. This methodology first presents individuals with the choice to take on a challenging learning opportunity. It then tracks the extent to which they engage in each of the other learning behaviors as they move through the task. It measures how long they spend with the learning materials (attend to information), whether they make the effort to put those materials in meaningful context, the extent to which they practice applying their learning and attend to feedback, and whether and how they choose to reflect. Finally, it measures their performance to determine how much they learned from their efforts. By individually tracking each decision made during learning complex material, the Learning Behaviors Methodology enables the study of 1. the antecedents to each learning behavior, 2. the relationship among the learning behaviors themselves and 3. the outcomes of the learning. In sum, the Learning Behaviors Methodology allows for direct observation of what working adults actually do while in the act of learning complex material.

Integrating research from cognitive science, education, and management and using the new Learning Behaviors Methodology, this chapter hypothesizes and finds that learning orientation predicts the willingness of working adults to take on challenging assignments but not whether they engage in the subsequent learning behaviors needed to meet that challenge. It also reveals that the learning behaviors themselves are largely independent in that, with a few key exceptions, engaging in one behavior does not predict engagement in the others. By deconstructing individual learning into observable behaviors and describing a way to measure those behaviors, this chapter presents new opportunities to systematically increase learner engagement. If we can more systematically understand what drives each learning behavior, managers and scholars will have a new toolbox at their disposal to keep working adults motivated as they engage in the full process of learning.

Theory and Hypothesis Development

Goal orientation and the workplace

In education, psychology, and management, goal orientation has received attention as a motivating factor in achievement situations, explaining differences in task interest, goal setting (Seijts, Latham, Tasa, & Latham, 2004), seeking feedback (VandeWalle, Ganesan, Challagalla, & Brown, 2000), and trainee motivation (Colquitt & Simmering, 1998). Goal orientation was originally studied to account for differences observed in the classroom between students who seemed to have a positive response when confronted with something they didn't know how to do and students who viewed that situation as threatening (Dweck & Bandura, 1985). Thus, in Dweck's (1986) Implicit Theory of Intelligence, she divided goal orientation into two orientations of learning and performance. She posited and found that learning-oriented students view challenging situations as the opportunity to improve and develop skill while performance-oriented students view these situations as evidence of their innate talent (or lack thereof) (Dweck, 1986; Dweck & Leggett, 1988). These differences were not based on ability; indeed, often, high ability students displayed a performance orientation.

Subsequent research by organizational scholars further differentiated between a performance-prove orientation and a performance-avoid orientation (VandeWalle, 1997). The first represents individuals who seek to demonstrate their ability, while the second applies to individuals who seek to avoid demonstrating incompetence. This difference proved valuable because meta-analysis of goal orientation studies conducted with adult populations shows that only learning orientation is reliably predictive of increased, and performance-avoid orientation is reliably predictive of decreased, learning and performance outcomes. In addition, learning orientation was found to be positively correlated with performance-prove orientation. Importantly, however, this meta-analysis also demonstrated that there is little variance in goal orientation scales and the predictive value of trait goal orientations for learning, task, and job performance is small (Payne et al., 2007).

The small predictive value of goal orientation for distal consequences, such as learning, task and job performance may be due to the fact that goal orientation scales target only one of the behaviors that lead to these outcomes. Specifically, goal orientation scales may predict which individuals are more likely to take on the challenge of learning and, therefore, slightly more likely to learn in the long-term. However, taking on a challenge does not directly lead to actual long-term learning. The motivation of learning-oriented individuals may dip at any point during the learning process. At present, there is little evidence on the specific learning behaviors that are impacted by learning orientation. As called for by Baumeister et al., (2007), research would benefit from direct observation of behavior – in this case, whether learning-oriented individuals are actually more likely to engage in learning behaviors. To answer this call, we first need to specify key behaviors in the individual learning process.

Individual learning behaviors

Individual learning has been extensively studied by educators, cognitive scientists, and management scholars as a process of action and reflection that leads to a change in long-term memory because, once knowledge and skills are embedded in long-term memory, they are learned (Corkin, 1984; Ericsson & Kintsch, 1995; H. A. Simon & Chase, 1973). Work in learning theory provides a basis for dividing the process of individual learning into five key behaviors of taking on a challenge, attending to information, forming meaningful connections, repeated practice with feedback, and reflection. Table 1.1 details existing research and theoretical models of individual learning to show that it can be meaningfully categorized into the five key behaviors. This table is specific to research on the cognitive process of learning at the individual level. Therefore, it does not include affective factors or research on self-regulatory processes. In addition, some studies included are not specific to self-directed learning but have strong implications for how self-directed processes, such as directing attention, practicing after failure, and critical reflection contribute to individual learning.

Taking on a challenge is the first learning behavior because while learning opportunities may abound in knowledge work (Skule, 2004), they often go undetected through unwillingness to admit ignorance or error (Argyris, 1976). Adult learning theorists note that self-directed learning in work settings occurs through employees taking on challenges and reflecting on their experiences (Knowles, 1974; A. Y. Kolb & Kolb, 2005; Marsick & Watkins, 2001). In addition, the cognitive psychology research on experts shows that in order to reach the highest levels of performance, individuals must continually push themselves beyond their current capacity (Ericsson et al., 1993). In order to learn, individuals must do something they don't already know how to do, i.e. they must take on a challenge.

The second learning behavior is attending to information. Once engaged, learners must know what to pay attention to and direct attentional resources towards the learning materials or towards models who can demonstrate the requisite knowledge and skills (A.

Bandura, 1977). Attentional resources are limited (Shipstead et al., 2015), and novices are often inefficient because they don't know what information to attend to and which to ignore in the initial stages of learning (Chi, Feltovich, & Glaser, 1981). Attending to the right information enables learners to not just take on a challenge, but begin to follow through on it.

However, newly acquired information is often quickly forgotten (Ebbinghaus, 1913) and research has shown that putting new information into meaningful context overcomes the tendency to quickly forget it (Glaze, 1928; Noble, 1952). Therefore, the third learning behavior is forming meaningful connections. Remembering what has one paid attention to requires giving meaning to the material through association (De Houwer, Thomas, & Baeyens, 2001; Pavlov, 1960). Learners can remember material beyond the short term by either connecting the new material to existing knowledge or making new connections within the new domain (Ausubel, 2012; Mayer, 1998). For example, when employees are onboarded they can relate their new job to their previous one and they can also see how their new job responsibilities connect to the goals of the new organization. In short, building meaning enables learners to retain information in the longer-term.

This retention, in turn, enables learners to apply the information in the form of repeated practice with feedback (Jolles et al. 2010), the fourth learning behavior. Decades of research have shown that consistent practice improves performance (Ackerman, 1988; Schneider & Shiffrin, 1977) and cognitive psychologists have shown that to develop expertise, practical application must take a specific form. It must invite failure and the learner must have access to timely and relevant feedback about success and failure (Ericsson et al., 1993).

These successes and failures provide the fodder for the final learning behavior of critical reflection. Management scholars have long noted that reflection plays a key role in understanding complex materials and systems. During critical reflection, individuals examine their performance in an attempt to understand the underlying principles of the domain (Chi et al., 1981). Research in management theory and adult learning (Mezirow, 1990; 2000; O'Neil & Marsick, 1994; Schön, 1983) shows that the behavior underlying these the abilities to understand complex systems is premise reflection, which is "assessing the grounds [justification] of one's beliefs" (Dewey, 1933, p. 9). Beyond accepting the failures and successes that occurred during practice, this behavior involves analyzing why they occurred in order to generate a new understanding of the domain (Ellis & Davidi, 2005a). This indicates that critical reflection is only possible after learners gain some level of competence. The outcome of critical reflection is long-term because reflection results in a deeper level of understanding of fundamental principles (Mezirow, 1990). This understanding leads to the ability to consistently perform, even in novel situations (H. A. Simon & Chase, 1973).

Table 1.1 Evidence Supporting the Categorization of Five Learning Behaviors

Self-directed Learning Behavior	Source	Domain	Subjects	Model (if applicable)	Findings	Implications for Self-directed Learning Behavior
Take on a Challenge	(Bryan & Harter, 1897)	Mgmt.	Adult workers		Plateaus in learning occur often but were overcome when improvement was rewarded through promotion.	Individuals often operate below maximum capacity, even when they are able.
	(Piaget, 1966)	Dev. Psych.	Children		Learners responded in one of two ways to new information. They either assimilated the new information into existing schemas or accommodated their schemas to the new information.	Individuals only create new connections and schemas when they confront information that does not fit into existing mental models.
	(Ericsson et al., 1993)	Psych.	Students and Adults	Deliberate practice	Learning only occurs when individuals continually seek to improve.	Individuals must continually take on challenges in order to learn.
	(McCauley, Ruderman, & Ohlott, 1994)	Mgmt.	Working adults		Jobs that presented developmental challenges to managers resulted in higher on-the-job learning.	Employees learn more when they are given the opportunity to engage in challenging work.
	(Dragoni, Tesluk, Russell, & Oh, 2009)	Mgmt.	Working adults		Mangers given challenging assignments achieved higher levels of managerial competencies.	Employees perform better over time when they are given the opportunity to engage in challenging work.
	(Locke, Shaw, Saari, & Latham, 1981)	Psych.		Goal-setting theory	Specific challenging goals result in more improved performance than easy, 'do your best' or no goals.	During the learning process, challenge increases learning outcomes.
Attend to Information	(A. Bandura, 1977; N. E. Miller & Dollard, 1941)	Dev. Psych.	Children	Social Cognitive Theory	Imitation of a model enabled the learner to perform the correct response earlier than he otherwise would.	Learning requires knowing what information to pay attention to.

Table 1.1 Evidence Supporting the Categorization of Five Learning Behaviors (continued)

Self-directed Learning Behavior	Source	Domain	Subjects	Model (if applicable)	Findings	Implications for Self-directed Learning Behavior
	(Chi et al., 1981; Hinsley, Hayes, & Simon, 2013; Larkin, McDermott, Simon, & Simon, 1980; D. P. Simon & Simon, 1978)	Cog. Psych.	Students		Novices are ineffective at problem-solving because they do not know which information to attend to and which to ignore.	Novices need to acquire information to increase efficiency in problem-solving.
	(Shipstead et al., 2015)	Cog. Psych.	Adults		The ability to engage attention in a controlled manner was found to be critical to learning.	There is competition for attention resources and what is not attended to is lost.
Form connections	(Ebbinghaus, 1913; Noble, 1952)	Cog. Psych.	Self		Learning word lists without attaching meaning follows a predictable 'forgetting curve'.[1]	Information acquisition is not enough for long-term learning.
	(A. Bandura, Ross, & Ross, 1961)	Dev. Psych.	Children	Social Learning Theory	Learners discerned the meaning of a social interaction (aggressive or non-aggressive) through observation of an adult model.	Meaning of information is actively (often socially) constructed.
	(De Houwer et al., 2001; Levey & Martin, 1975; Pavlov, 1960)		Mammals and Adults	Classical Conditioning	In mammalian learning, the meaning of one object was constructed through associating it with another object.	Meaning of new objects is learned through association with existing knowledge.
	(Chi et al., 1981; Hinsley et al., 2013; Larkin et al., 1980; D. P. Simon & Simon, 1978)	Cog. Psych.	Students and Adults		Novices engaged in inefficient search processes because they are unable to meaningfully classify information	Putting information into meaningful context enables greater efficiency during practical application.

[1] Replicated in (Murre & Dros, 2015)

Table 1.1 Evidence Supporting the Categorization of Five Learning Behaviors (continued)

Self-directed Learning Behavior	Source	Domain	Subjects	Model (if applicable)	Findings	Implications for Self-directed Learning Behavior
	(Giambra, Camp, & Grodsky, 1992; R. McGrath, 2001)	Mgmt.	Working adults		Project groups reported higher learning when they engaged in exploratory behaviors.	Effectiveness of learning relies on exploratory behaviors
Repeated practice with feedback	(Ackerman, 1988; Fisk & Schneider, 1984; Schneider & Shiffrin, 1977)	Psych.	Working adults/ Undergrads		Consistent practice increases performance speed and accuracy and reduces attentional demands.	Repeated practice with feedback increases skill efficiency.
	(Karpicke & Blunt, 2011)	Cog. Psych.	Students		Students who repeatedly practiced retrieving both right and wrong answers had better performance and conceptual understanding than students who practiced only wrong answers or students who engaged in conceptual mapping.	Repeated practice with feedback increases skill and conceptual understanding.
	(Dweck, 1986)	Dev. Psych.	Students	Implicit Theory of Intelligence	Students who viewed failure as feedback learned more than students who viewed failure as evidence of inability.	Learning from practice is dependent on learners' response to failure.
	(Ericsson et al., 1993)	Psych.	Music undergrads	Deliberate practice	Individual differences in performance can be accounted for by differential amounts of practice.	Practice improves performance.
	(Kluger & DeNisi, 1996)	Psych.	Meta-analysis	Feedback Information Theory	Feedback that is helpful, useful, and future-oriented boosts performance.	The optimal feedback for learning and performance depends on the context of the material

Table 1.1 Evidence Supporting the Categorization of Five Learning Behaviors (continued)

Self-directed Learning Behavior	Source	Domain	Subjects	Model (if applicable)	Findings	Implications for Self-directed Learning Behavior
	(Kluger & DeNisi, 1998)	Psych.	Review	Feedback Information Theory	Information feedback reveals discrepancies between standards of task performance and the outcomes of practice	Feedback that contains information about performance increases learning from practice.
	(DeRue & Wellman, 2009)	Psych	Working adults		Access to feedback can offset the diminishing learning returns from developmental challenges	Access to feedback increases learning from challenging work experiences.
Reflect	(Mezirow, 1990; Schön, 1983; Zollo & Winter, 2002)			Dynamic Capabilities	Achieving expertise requires articulating and codifying the underlying principles of the knowledge domain	Critical reflection reveals the underlying causes of events.
	(Ellis & Davidi, 2005b)	Psych.	Soldiers		After-event reviews of both successes and failures increased task performance compared with reviews of failure only.	Critical reflection on past performance reveals patterns that increase future performance.
	(Ellis, Mendel, & Nir, 2006)	Psych.	Soldiers and Students		Accurate evaluation of one's task performance increased performance on subsequent tasks.	Critical reflection on past performance reveals patterns that increase future performance.
	(Anseel, Lievens, & Schollaert, 2009)				Reflection on performance in practice task enhances task performance	Reflection after feedback is superior to reflection alone.

Learning orientation and taking on a challenge

Learning orientation seems particularly well-suited to capturing whether individuals will engage in the first learning behavior of taking on a challenge. Management scholars have long recognized that there are strong interpersonal barriers to this behavior in organizational settings. Argyris (1976) found that managers often miss or purposefully disregard learning opportunities due to an unwillingness to admit mistakes or ignorance. Errors, which could have triggered important learning about organizational systems, went both undetected and uncorrected. Edmondson (1999) later found these same tendencies to be a key obstacle to team learning and performance. At the individual level, however, the barriers to taking on learning challenges are likely more intrapersonal.

In fact, research on goal orientation originated from research on individual differences. While goal orientation was initially studied as dichotomous (individuals had either a learning or performance orientation), further research showed that working adults could hold both long-term improvement and short-term performance as valuable (Button, Mathieu, & Zajac, 1996). Therefore, in his development of the goal orientation scale for the workplace domain, Vandewalle (1997) differentiated between a performance-prove orientation, wherein employees seek assignments that demonstrate their ability, and performance-avoid orientation wherein employees avoid challenging assignments to escape appearing incompetent. He showed that learning orientation was positively associated and performance-avoid orientation was negatively correlated with a preference for challenge, a desire to work hard, and the desire to seek feedback. Performance-prove orientation, on the other hand, was not significantly associated with these self-reported inclinations. This distinction bore out in a meta-analysis showed that while a performance-prove orientation was not predictive of learning or performance, a performance-avoid orientation was consistently negatively correlated with both (Payne et al., 2007). Further, learning orientation is often positively correlated with performance-prove but consistently negatively correlated with performance-avoid orientations.

Therefore, seeking challenges seems to be at the heart of learning orientation in this body of work. This may be especially true for working adults, who no longer have the support of an academic setting where learning is the primary goal. In schools, students of all goal orientations have less choice to take on the challenges of their assignments, but in workplaces, adults have competing demands for performance, and the choice of whether to engage in a learning challenge. Therefore, learning orientation should positively predict taking on a challenge and performance-avoid orientation should negatively predict taking on the challenge of learning. In line with previous research, I don't expect that performance-prove orientation will be predictive.

H1: Learning orientation will positively predict the learning behavior of taking on a challenge

H2: Performance-avoid will negatively predict the learning behavior of taking on a challenge

Learning orientation and subsequent individual learning behaviors

The competition for time likely plays a critical role in the degree to which employees follow-up on the challenge. Research on implementation intentions demonstrates that even when individuals fully intend to complete a task, they often don't follow through on it (Gollwitzer & Sheeran, 2006). When employees are time-constrained and there is a cost to learning, they may be less likely to engage in the remaining learning behaviors, even if they took on the challenge. In particular, the time employees have to dedicate to learning may be limited and learning often plays a secondary role (at best) to performing. While individuals with a learning orientation may be drawn to challenging assignments, they may be less likely to engage in subsequent learning behaviors if doing so takes time away from their ability to perform other work-relevant tasks.

A key difference between the learning behavior of taking on a challenge and the remaining behaviors is that making the choice to take on a challenge only consumes potential time or resources. Each of the remaining learning behaviors consumes actual time and resources. Attending to information means paying attention to the learning – actually engaging with the content – at the expense of other stimuli (Pashler, Johnston, & Ruthruff, 2001), such as email, routine work tasks, or presentations. Forming meaningful connections means taking the time to go beyond what learning materials are at hand and seeking ways to make sense of the information in meaningful ways (Mayer, 2002). Practice is only valuable if it is repeated, but doing so means trying again and again which can be both frustrating and again, extremely time consuming (Ericsson et al., 1993). Finally, critical reflection takes deep cognitive effort as learners take the time to review past successes and failures to discover underlying patterns (Mezirow, 1990).

Therefore, to understand self-directed workplace learning, it is critical to test the relationship between learning orientation and each of the learning behaviors in an environment where workers experience a cost to their learning. While learning-oriented individuals may fully intend to follow-through on the behaviors needed to meet that challenge, they may not take the time to do so if it means that they could be spending that time on a different performance task.

From the perspective of expectancy-value theory (Vroom, 1964), while learning-oriented individuals may have a high expectation that they will be able to achieve the desired learning outcome, that expectation may decrease once the competition between learning and performing becomes salient. Expectancy value theory asserts that behavior is a function of the expectancy of a successful outcome and the value to the individual of achieving that outcome (Vroom, 1964). In workplace settings, both the expectation of success and the value of learning are vulnerable to performance demands. Specifically, the time and effort it takes to perform well may preclude employees from engaging in learning behaviors, thereby lowering their expectations of being able to achieve the learning outcome. In addition, the value of that learning, which may seem high early on, may decrease as performance demands become more pressing. Learning is a longer-term investment and its value may seem less salient when pitted against short-term work responsibilities. Therefore, learners may seek the learning challenge but quickly become overwhelmed when they realize the actual work involved, especially when that work comes at the expense of performance-related tasks.

H3: When individuals are given the option to engage in all five learning behaviors, learning orientation will only predict the learning behavior of taking on a challenge.

Study 1: Learning Orientation in a Management Task

Study 1 investigated Hypotheses 1 and 2 by testing the extent to which learning orientation positively predicts and performance-avoid negatively predicts the choice to take on a challenging task, As argued above, in order to truly test self-directed learning, it is important that individuals perceive learning behaviors as taking away from other work-relevant tasks and that they have a genuine choice about the extent to which they engage in the learning behaviors. Therefore, I tested these hypotheses with working adults recruited from Amazon Mechanical Turk. The task was designed such that it was clear that taking on the challenging task would take more time than the easy task. In Amazon Mechanical Turk, workers are paid based on task completion. Therefore, taking on the challenging task came at a perceived cost because it would take time away from other tasks that could earn them money. To further mimic a typical work environment for professionals, I gave participants the choice to read an easy or difficult article on a management topic[2].

Participants

The participants were 106 working adults recruited on Amazon Mechanical Turk. Participants had to work at least 20 hours per week to qualify for this task. They were 49 percent (52) male. Sixty-five percent (69) worked full-time and 35 percent (37) part-time. Participants ranged in age from 21 to 63, with a mean age of 35 (SD = 10). Eighty-six percent (91) were White, eight percent (9) were African-American, and the remaining five percent were Hispanic (3), Asian (3), Native American (2), or Other (1). Sixty-eight percent (72) had at least a college degree. Participation was voluntary and participants were told that they would be paid for completing the exercise, regardless of the choice they made.

Procedure

Having given their consent, participants were asked to fill out a pre-survey containing measures for demographics, goal orientation, and personality. They were then given the choice of which article to read. Prior to engaging in the survey, it was made clear that payment was not contingent on any of their choices during the task or on their overall performance.

The study first displayed the two "covers" of an article on management theory (Figure 1.1). Participants were asked to choose which article they would like to read. The articles were presented in a way that made one seem more time-consuming but more information-rich than the other.

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[2] Studies 1 and 2 also included measures for some of the other learning behaviors in a pilot form.

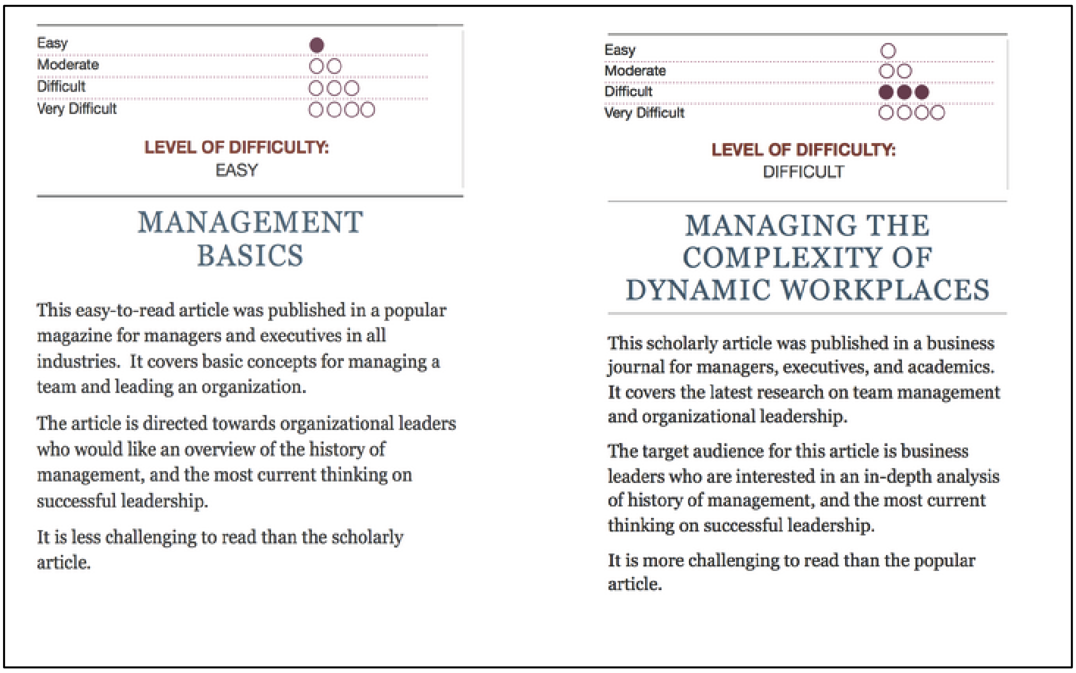

Figure 1.1 Study 1 Article Choice

Measures

The *Big Five personality domains* were measured using Gosling, Rentfrow, and Swann's (2003) abbreviated scale. Although there were no a priori expectations about the relationship between personality and engagement in learning behaviors, this measure was included to control for individual variability if, in fact, a relationship did exist between personality and taking on a challenge.

Goal orientation was measured using Vandewalle's (1997) scale, a commonly used measure of goal orientation in workplace domains. Vandewalle's scale distinguishes between learning, performance-prove, and performance-avoid orientations making it an ideal choice for testing Hypotheses 1 and 2.

Taking on a challenge was measured by whether participants chose to read the easier or more difficult article. A measure check was included which openly asked participants why they chose the challenging task.

Measure checks

Checks for taking on a challenge confirmed that participants engaged in this behavior for the expected reasons (Table 1.2). They chose the more difficult article primarily because they saw value in doing so, even at the cost of finishing faster and moving on to a different task.

Table 1.2 Reported reasons for Taking on the challenging task.

Question	Reason	%
Why did you choose the challenging article?		
	Challenge	38
	More interesting	20
	Contained more information	18
	Could learn more	8
	Already have some knowledge	8
	Other	8
	Total (N = 40)	100
Why did you choose the easier article?		
	Easier	70
	Understand basics first	17
	Time limited	5
	More interesting	3
	Other	5
	Total (N = 66)	100

Results

Summary statistics and point-biserial correlations for Study 1 are provided in Table 1.3.

Table 1.3 Study 1 Correlations and Descriptive Statistics (n=106)

Variable	Mean	SD	1	2	3
1. Learning orientation	4.9	0.7			
2. Performance-prove orientation	4.3	1.0	0.33^{***}		
3. Performance-avoid orientation	3.2	1.2	-0.32^{***}	0.29^{***}	
4. Take on challenge	0.38	0.5	0.21^{*}	-0.14	-0.24^{*}

* p < .05; ** p < .01; *** p < .001

There was a significant relationship between learning-goal orientation and taking on a challenge ($r(106) = .21$, $p = .04$) supporting Hypothesis 1. Taking on the challenging task was also significantly negatively correlated with performance-avoid orientation ($r(106) = -.24$, $p = .01$), showing support for Hypothesis 2. Taking on a challenge was not significantly correlated with performance-prove orientation. The correlations for the taking on a challenge task are point-biserial correlations because one variable is dichotomous. Since the learning orientation were left-skewed confidence intervals were confirmed in a bootstrapping analysis and the results held as significant. Participants who reported higher learning-goal orientation tended to choose the more difficult article and those who reported higher performance-avoid orientation tended to choose the easier one. No personality measures significantly predicted taking on a challenge, though openness to experience was marginally correlated with that behavior ($r(106)= .17$, $p=.08$).

Discussion

Study 1 provided support for Hypotheses 1 and 2. It demonstrated that learning orientation is positively predictive and performance-avoid orientation is negatively predictive of the first learning behavior—taking on a challenge. However, a number of open questions remain. Study 1 administered the learning orientation survey directly prior to individuals making the choice of taking on a challenge. While there were other demographic and attention questions included, Study 1 cannot rule out possible priming effects of asking about an individual's desire to seek challenges minutes before asking them to choose a challenging or easy task. Also, although Study 1 took advantage of Amazon Mechanical Turk as a new organizational form, it used a traditional management task, that of reading an article on managing others. However, Amazon Mechanical Turk workers are not in a traditional management job. Therefore, it would be prudent to test these findings with an entirely different task that was more suited to that working population. Finally, Study 1 explored only learning orientation as a possible antecedent to taking on a challenge. This was done to limit the number of variables in the study and minimize the possibility of finding a significant result by chance. However, it meant that other possible antecedents to taking on a challenge were not examined. Study 2 addresses each of these concerns.

Study 2: Learning Behaviors in an Imaging Task

Study 2 extended the findings of Study 1 in four ways. First, it replicated the measure of taking on a challenge using a fundamentally different type of task. Second, it administered the pre-survey one week prior to the task, minimizing any priming effects. Third, it explored additional possible antecedents for taking on a challenge. Finally, it increased external validity by asking Amazon Mechanical Turk workers to complete work they are typically asked to do.

The pre-survey included two additional scales to measure need for cognition and curiosity. Need for cognition captures "the need to understand and make reasonable the experiential world" (Cohen, Stotland, & Wolfe, 1955, p. 291). It targets the desire to engage in thinking and those who view thinking as engaging or enjoyable may be more likely to embrace learning challenges. Curiosity is explicitly defined as the motivation to engage in exploratory behaviors (Voss & Keller, 2013) and it can be separated into stimulation-seeking or information-seeking behaviors (Gottlieb, Oudeyer, Lopes, & Baranes, 2013). Research has shown that adults are more likely than adolescents to seek out information rather than stimulation (Giambra et al., 1992) and that they seek more information than adolescents when they perceive that information to be valuable. Therefore, adults with information-seeking curiosity may be more likely to take on challenging learning tasks.

Since this chapter is directed at studying how employees act when they have competing performance demands, I wanted to make full use of the Amazon Mechanical Turk marketplace as a new type of organization. Amazon Mechanical Turk was developed to pay people to do tasks that were difficult for computers to do efficiently, but could be done remotely and electronically by humans. Amazon Mechanical Turk offers workers the opportunity to complete Human Intelligence Tasks (HITs). One particularly common task is identifying images because humans are much faster and more accurate at doing so than computers. There is, in fact, an entire job category specific to image recognition. Therefore, I gave participants the choice of taking on a difficult or easy image recognition task.

Participants

Three hundred participants were invited to complete a pre-survey, which included measures for demographics, attention filters, learning orientation, need for cognition, and curiosity. Of the 282 participants who successfully completed the pre-survey, 214 completed the task one week later. Like Study 1, this study was targeted to working adults. Consequently, 22 participants were dropped because they did not meet the qualification for working at least 20 hours per week. Two others were dropped due to technical glitches that rendered them unable to complete the task and four were dropped because they had completed the same task in our pilot testing. The final 186 participants were 55 percent male, ranging in age from 21 to 69, with an average age of 33. Once again, participants were told they would be paid the same amount for completing the task, regardless of their choices.

Measures

The measures for demographics and goal-orientation were identical to Study 1. Two additional scales, need for cognition and curiosity, were included.

Need for cognition. Need for cognition was measured using Cacioppo & Petty,'s (1982) scale.

Curiosity. Curiosity was measured using Litman & Spielberger's, (2003) scale.

Taking on a challenge was measured by whether participants chose the easy or difficult imaging task.

Procedure

Study 2 was conducted like Study 1, but with some strategic changes. First, to minimize any priming effects of the scales, participants were asked to complete the pre-survey one week ahead of time. Second, to replicate the original findings in a fundamentally different type of task, participants were given the choice to choose the level of challenge for an image-recognition learning task rather than a task of reading an article on management theory.

Participants were told:

The following exercise is an image recognition task. There is no prior knowledge required to complete it but there are 2 levels of challenge. At the end of each challenge, you will be given a task to apply your knowledge.

Level 1: Easy. *This level includes minimal information and the task will be less challenging.*

Level 2: Challenging. *This level includes all the information in the easy level plus additional information. The task will be more challenging.*

Results

Study 2 replicated the findings in Study 1. Learning orientation once again significantly predicted taking on the challenging task ($r=.27$, $p<.001$) and performance avoid significantly negatively predicted taking on the challenging task ($r=-.15$, $p<.05$) providing further support for Hypotheses 1 and 2. Once again, the correlations for taking on a challenge are point-biserial correlations because one variable is dichotomous and confidence intervals were confirmed in a bootstrapping analysis. Summary Statistics are available in Table 1.4.

Table 1.4 Study 2 Summary Statistics and Correlations

Variable	Mean	SD	1	2	3	4	5
1. Learning orientation	4.6	0.8					
2. Performance-prove	4.0	0.8	0.23^{**}				
3. Performance-avoid	3.1	1.1	0.59^{***}	0.13			
4. Need for cognition	4.3	0.9	0.76^{***}	-0.01			
5. Curiosity	4.8	0.7	0.78^{***}	0.15^{*}	-0.45^{***}	0.82^{***}	
6. Take on challenge	.26	0.4	0.27^{***}	0.01	-0.15^{*}	0.25^{***}	0.34^{***}

* p<.05, **p<.01 ***p<.001

Study 2 included the additional individual-difference measures of need for cognition and curiosity. Unexpectedly, these scales were significantly correlated with each other as well as goal-orientation, and the correlations were quite high. Need for cognition was strongly correlated with curiosity ($r(186)=.82$, $p<.001$), and learning-goal orientation was strongly correlated with both curiosity ($r(186) = .78$, $p= < .001$) and need for cognition ($r(186) = .76$, $p < .001$). In addition, Cronbach's alpha for the three scales considered together was .91, well beyond the standard threshold for internal consistency. Therefore, I performed a principle component factor analysis to determine if a single factor explained the variance across the three parameters. Analysis of the model revealed excellent fit, with a single factor accounting for 86% (eigenvalue = 2.6) of the variance ($p<.0001$).. When combined these scales are highly significantly predictive of taking on a challenge ($r=.31$, $p<.001$). This is not surprising since they all seem to be capturing the same latent variable.

Discussion

Study 2 replicated the findings from Study 1 that learning orientation positively predicts and performance-avoid orientation negatively predicts the learning behavior of taking on a challenge. It also found this relationship held even when the survey was administered one week prior and the task was fundamentally different.

In addition, Study 2 demonstrated that the individual-difference measures of need for cognition (Cacioppo & Petty, 1982), curiosity (Litman & Spielberger, 2003), and learning orientation (VandeWalle, 1997) seem to be capturing a single underlying construct and this construct predicts whether individuals take on learning challenges. When developed, the Need for Cognition scale showed discriminant validity against the related concepts of cognitive style and field dependence (Cacioppo & Petty, 1982). Likewise, the Curiosity scale was divergent from trait anxiety and sensation-seeking measures (Litman & Spielberger, 2003). However, the high correlation among these scales suggests that, although discriminant validity was established against other related concepts, the three scales tap into an individual difference in the desire to challenge oneself to learn new things.

Previous research has shown some relationships between pairs of these three scales. In a meta-analytic review, Cacioppo (2010) showed that need for cognition is related to curiosity and the need for challenge. Day et al. (2007) found a significant but only moderate ($r = .25$) correlation between need for cognition and learning orientation. DeShon and Gillespie (2005) argue that need for cognition is a sub-goal of growth, which is related to learning orientation. However, to my knowledge, this is the first study to include all three scales together and, by doing so, it reveals their close relationship.

Studies 1 and 2 demonstrated a consistent relationship between learning orientation and the choice to take on a challenging task. However, they did not address the relationship between learning orientation and subsequent learning behaviors.

One of the reasons there has been little research on each of the individual learning behaviors is that we lack a measure of these behaviors beyond self-reports. However, particularly at the individual level, self-reports of learning are problematic in two ways. First, learning is a socially desirable activity, and the desire to view oneself in positive ways may lead to over-reporting (Tesser & Paulhus, 1983). Second, since learning is often pitted against performance in the workplace (March, 1991), working adults may tend to think of themselves as either learning or not learning. Therefore, they may assume that if they engage in one of the behaviors, they are engaging in the others. For these reasons, the extent to which individuals engage in each of the five learning behaviors during an actual learning task remains unclear. Therefore, examining individual-level learning required a new, more direct, measure.

The Learning Behaviors Methodology

The Learning Behaviors Methodology (LBM) enables direct observation of whether and to what extent individuals engage in each learning behavior during a learning task. It was built from the technology and approach used in Studies 1 and 2. First, it measures *taking on a challenging task* by the level of challenge participants choose. Rather than using a binary difficult or easy task, the LBM asks learners to choose their level of challenge on a scale of 1 to 5, allowing for a finer distinction of the degree to which individuals engage in this first learning behavior. The LBM then tests whether individuals actually exert the effort to follow-through on that challenge, by directly measuring engagement in each of the four subsequent learning behaviors. Regardless of the level of challenge chosen, all participants are given the same task, so that their engagement in subsequent behaviors will not differ based on the nature of the task.

Second, the LBM tracks the extent to which participants *attend to information* by tracking the time they spend on the learning materials presented to them, controlling for individual differences in reading rate. There is no incentive for taking the time to attend to these materials or penalty for skipping through them. Individuals must choose to spend the time to give attention to the learning materials. Third, embedded in these materials are optional hyperlinks to contextual information about the topic and the LBM tracks which hyperlinks are read and for how long. Again, participants are not incentivized or penalized for their choice of whether or not to explore this information and *form meaningful connections*. Fourth, when participants complete the learning materials, they are asked to apply their knowledge in a practical task. Once they try the full task at least once, participants are given the option to try again as many times as they wish or quit at any time. The LBM tracks whether they *repeatedly practice* and how many times, as well as the time they spend reviewing *feedback*. Finally, at the end, participants are given the option to write a reflection on their learning, measuring whether and to what extent they engage in *critical reflection*.

The LBM tracks engagement in the learning behaviors both as independent acts and as part of a larger learning task, enabling empirical testing of the relationship between learning orientation and each learning behavior, as well as the relationships among the learning behaviors themselves. The LBM measures the resources individuals are willing to allocate towards meeting a learning goal and as noted by Sun et al. (2014), "the resources allocated to one's goal reflects the extent an individual is willing to invest their finite valuable resources; thus, resources allocated represents a more direct measure of motivation as compared with performance, which confounds ability, task difficulty, and other constructs." In short, the LBM tracks what working adults are actually willing to do in order to learn.

Study 3: Learning Orientation and Learning Behaviors

Study 3 tested Hypothesis 3 that, when all five learning behaviors are measured, learning orientation would only predict the extent to which working adults would engage in a learning task by taking on a challenge. The scales for curiosity and need for cognition were so highly correlated with learning orientation, they provided redundant information. Therefore, only goal orientation was used in this study.

The goal orientation data was collected one day prior to the experiment. Results from Study 1 and Study 2 showed that learning orientation remained predictive whether collected directly prior to the experiment or one week ahead of time, but that fewer people participated in the experiment when there was such a long delay. Therefore, in order to minimize any priming but still get strong participation rates, Study 3 administered the pre-survey one day prior to the experiment.

Using the LBM, Study 3 presented participants with all five learning behaviors. For the purposes of experimental control, all participants were given the same learning and performance tasks, regardless of their chosen level of challenge. However, it is possible that merely choosing a given level of challenge could impact the degree to which participants would engage in the subsequent behaviors. In the LBM, for the purpose of creating wide variance in participant behavior, the practice and performance tasks were made quite difficult. Therefore, those who chose the easy level of challenge may have been surprised by that difficulty, affecting the number of times they practiced and their reflection on that practice.

For this reason, Study 3 was divided into three conditions. The first condition, the Challenge Only condition, only asked participants to choose their level of challenge, similar to Studies 1 and 2. The second condition, the Challenge Absent condition, did not give participants the choice of level of challenge, but presented each of the four remaining behaviors of attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection. The third condition, the All Five condition, gave participants the opportunity to engage in all five behaviors. These conditions allowed me to test if the self-perception of taking on a challenge impacted subsequent behavior choice and performance (see Table 1.5).

Table 1.5: Study 3 Behaviors included in each condition

Learning Behavior	**Challenge Only**	**Challenge Absent**	**All Five**
Taking on a Challenge	X		X
Attend to Information		X	X
Build Meaningful Context		X	X
Repeated Practice		X	X
Critical Reflection		X	X

Participants

Study 3 was once again conducted with Amazon Mechanical Turk participants because spending time one each behavior comes at the cost of completing another

Mechanical Turk task, for which they will earn money. Four hundred participants were recruited in the hopes of getting 100 participants per condition for a total of 300 participants. While 385 participants completed the pre-survey in the allotted time, 247 participants completed the follow-up study on Day 2. Ninety-two participants were randomly assigned to the Challenge Only condition. Seventy-three participants were randomly assigned to the Challenge Absent conditions, where they were not given the choice of level of challenge but were given the option to engage in the four remaining behaviors. Finally, 82 participants were randomly assigned to the All Five condition. Demographics were similar to previous studies.

Method

After consenting to participate, participants completed a pre-survey of demographic information, goal orientation, and Big-Five personality measures. They were then asked to read a passage and answer a question based on what they read. The passage served as an attention filter and misdirected the reader twice. Participants had to read the passage in its entirety to answer the question correctly. Those who passed the attention filter were invited to participate in a follow-up task one day later. Those who did not pass the attention filter were immediately rejected.

Taking on a Challenge

The next day, participants were given the LBM. Those in the Challenge Only and All Five conditions were asked to choose a level of challenge. They were told:

> *The following exercise is an image recognition task. There is no prior knowledge required to complete it but there are multiple levels of challenge. At the end of each challenge, you will be given a task to apply your knowledge.*

PLEASE USE THE SCALE BELOW TO CHOOSE YOUR LEVEL OF CHALLENGE

At the low end of the scale, you will be provided with minimal information and the task will be the least challenging. At the high end of the scale, you will be provided with maximum information and the task will be the most challenging.

Attend to Information

Those in the Challenge Absent and the All Five conditions were given the learning materials. They were shown pictures and given detailed instructions on how to read people's emotions by looking at the forehead, eyes, and mouth (Image 1.1).

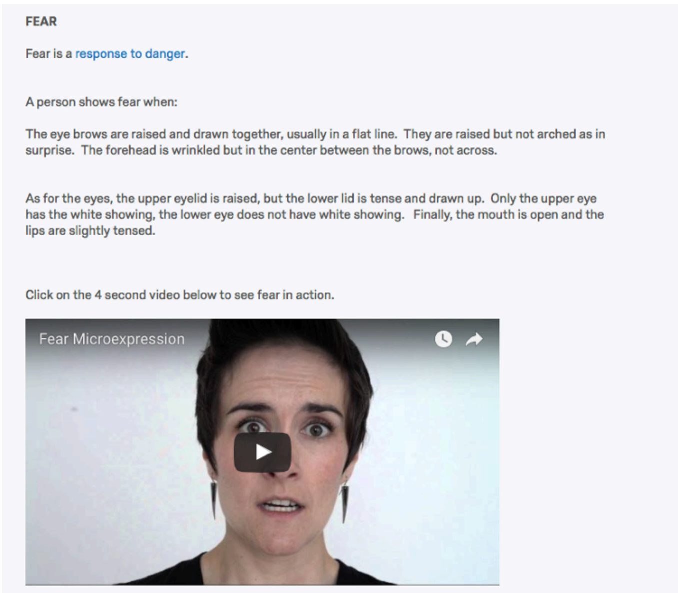

Image 1.1 Study 3 Attending to Information Learning Materials

(materials for video and text were adapted from http://www.scienceofpeople.com/2013/09/guide-reading-microexpressions/)

Form Meaningful Connections

Throughout the learning materials were hyperlinks to contextual information. Participants were told:

Throughout the following pages are hyperlinks that show how the expressions are and are not related to each other. You are not required to click on these links but may do so to deepen your understanding.

Putting information into meaningful context means associating the new information with existing knowledge, or developing an understanding of the relationships within the new domain (Ausubel 2012b; Piaget 1966). Because most people have some existing knowledge of facial expressions (e.g. smiling indicates happiness), this study leveraged both forms of contextual information. It associated new information with existing knowledge by providing reasons why certain expressions had certain features. For example, participants were told "*in fear we are tense, so the lower eyelid is tense and drawn up*." It also exposed the relationships within the new domain by showing which expressions had which features in common. For example, "*in both anger and disgust the eyes are narrow*." This text was highlighted to draw attention to it (Image 1.2).

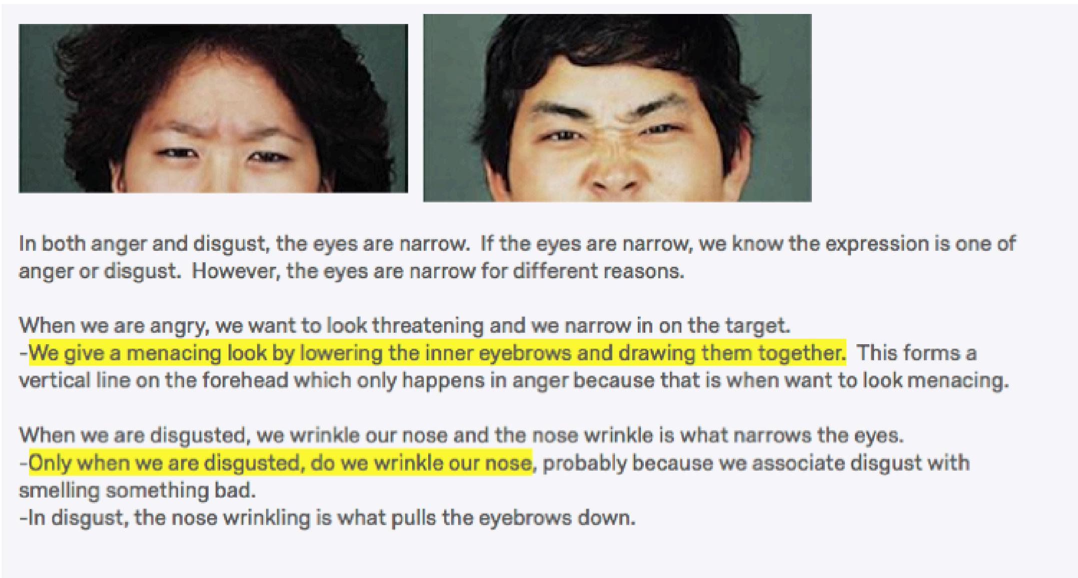

Image 1.2: Study 3 Contextual Information Available through Hyperlink

(contextual information was adapted from http://www.study-body-language.com/face-expressions.html and (Fabian Benitez-Quiroz, Srinivasan, & Martinez, 2016))

Repeated Practice

Once they completed the learning materials, all participants were asked to apply their knowledge by identifying compound expressions. While six basic emotions- happiness, surprise, sadness, anger, fear, and disgust- have been known for some time, research has shown that there are compound expressions, such as fearfully angry or happily disgusted, which are differentially expressed by the muscles in the human face (Du, Tao, & Martinez, 2014) - see Image 1.3.

Fig. 1. Sample images of the 22 categories in the database: (*A*) neutral, (*B*) happy, (*C*) sad, (*D*) fearful, (*E*) angry, (*F*) surprised, (*G*) disgusted, (*H*) happily surprised, (*I*) happily disgusted, (*J*) sadly fearful, (*K*) sadly angry, (*L*) sadly surprised, (*M*) sadly disgusted, (*N*) fearfully angry, (*O*) fearfully surprised, (*P*) fearfully disgusted, (*Q*) angrily surprised, (*R*) angrily disgusted, (*S*) disgustedly surprised, (*T*) appalled, (*U*) hatred, and (*V*) awed.

Image 1.3: Study 3 Compound Facial Expressions

Participants were shown six compound expressions (Du et al., 2014) on a given trial and asked to identify them by placing the correct expression under the corresponding picture using drag and drop (Image 1.4). To view any image in a larger, more proportioned format, participants could simply click on the image and it would appear in the large box on the right. After assigning all six compound expressions to a compound emotion, participants could hit a ‘Check Answer’ button, which highlighted their correct answers in green. After they received this feedback, ‘Try Again’ and ‘Quit Task’ buttons appeared. When this button was clicked, the faces were shuffled and the participants were asked to again identify six faces.

There were twelve unique expressions altogether, and across the first two rounds, participants were exposed to all twelve. Therefore, to experience the full task, participants were required to try at least two times. After two times, they could quit or try as many more times as they wished. Each time the faces were randomly shuffled and presented six at a time. Participants would receive feedback on which faces they got right, then hit ‘Try Again’ to shuffle the faces and attempt to identify a different set. This method enabled participants to receive immediate and relevant feedback on both their successes and failures, and it allowed them practice with all the faces multiple times if they wished.

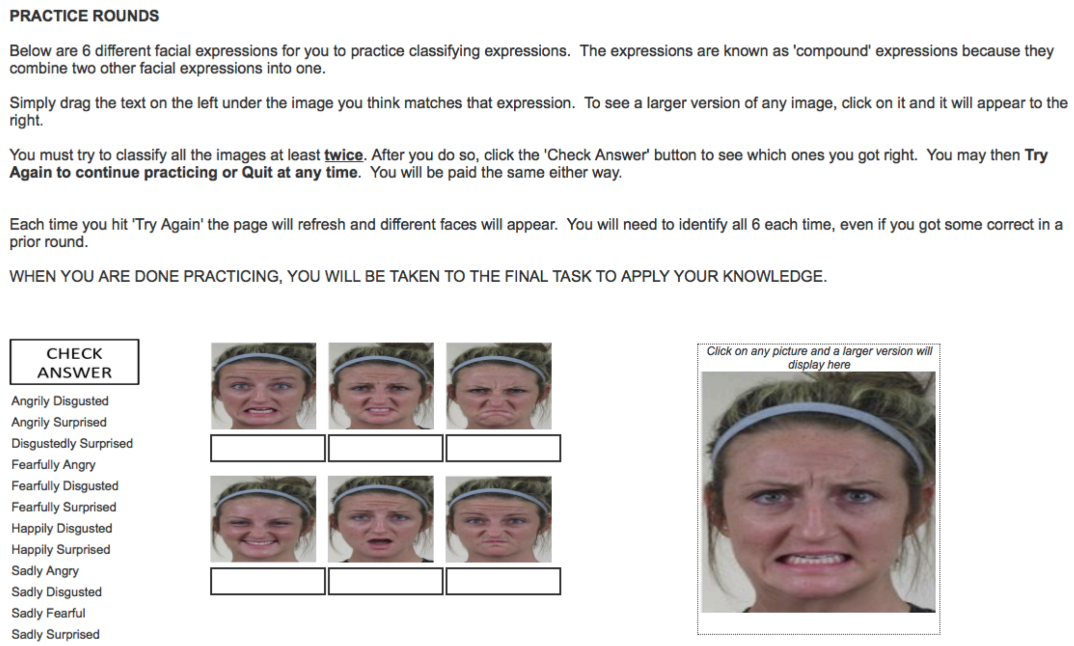

Image 1.4: Study 3 Repeated Practice with Feedback

Critical Reflection

Finally, participants were given the option to critically reflect on their learning. Because research has shown that reflecting on both successes and failures increases learning, participants were given specific instruction on how to reflect on their practice rounds as shown below:

> *Before you apply your knowledge, we would like to give you the option to reflect on your learning. You are not required to reflect, but may do so to deepen your understanding.*
>
> *To reflect on your learning, please think carefully about which faces were easier and which ones were harder for you to correctly identify. Try to figure out the underlying reasons for* ***why certain ones were harder than others****.*

*Were there any **patterns** you can detect? What understanding did you gain from this exercise?*

Performance

To determine the relationship between each behavior and participants' learning in this task, they were then asked to identify all twelve compound expressions of a different face (Image 1.5) again using a drag and drop method. They were given one chance to identify all the expressions.

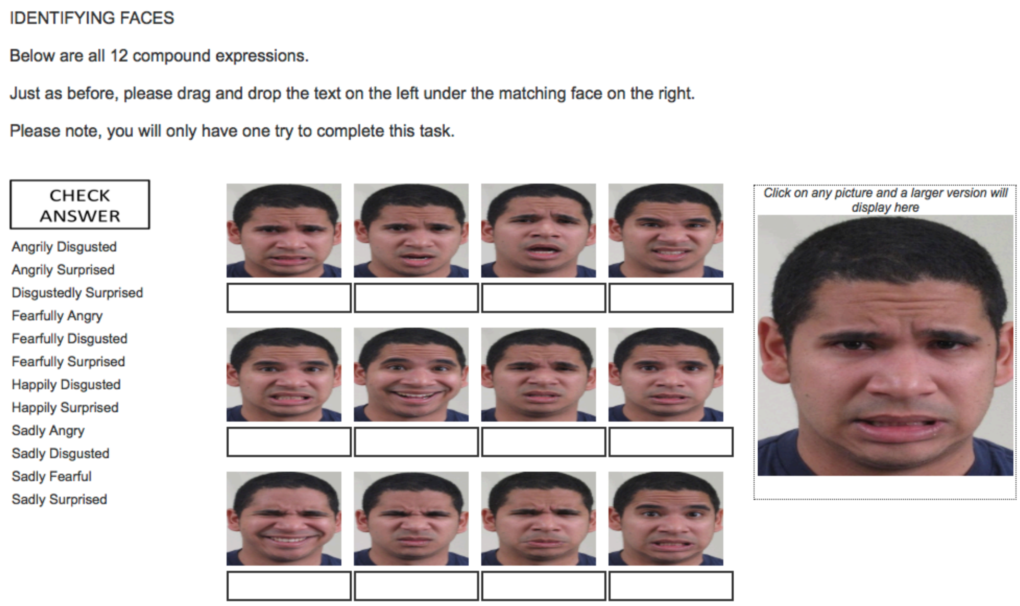

Image 1.5: Study 3 Performance Task

Finally, to check whether the Learning Behaviors Methodology was clearly understood and captured the behaviors as expected, participants were asked why they engaged in each of the behaviors.

Measures

Goal orientation was measured using Vandewalle's (1997) scale.

The *Big Five personality domains* were measured using Gosling, Rentfrow, and Swann's (2003) abbreviated scale.

Reading rate was measured by the time spent reading the attention filter. Since the filters required reading the entire passage to answer correctly, the time it took participants to read and comprehend the material was indicative of their general reading rate for this task.

Attending to information was measured by the total time spent reading the learning materials, controlling for reading rate and not including the time spent reading the hyperlinks.

Forming meaningful connections was measured by the number of hyperlinks (see Image 1.2) participants clicked while reading the learning materials, as well as how long participants spent on each hyperlink before returning to the materials. Each hyperlink contained 1-2 paragraphs of contextual information, so only hyperlinks that were open for at least 5 seconds were included in this measure.

Repeated practice with feedback was measured first by how many practice rounds the participants completed.

Since participants were given immediate and relevant feedback after each round, I also measured the *practice time spent on feedback* by the time between ending one practice round and beginning the next. After each participant clicked the 'Check Answer' button, they were shown which of the six faces they identified correctly and which ones they got wrong, along with their answers. Once they hit 'Try Again' the faces reshuffled so I was able to measure the time they took to look at the feedback in each round.

Finally, *critical reflection* was measured by whether the participant chose to write a reflection in the text box and the content of those reflections.

Results

Measure Checks

Results for the measure checks are available in Appendix 1. Participants were directly asked why they engaged in each behavior in a free text form. Answers were then coded into the categories presented in Appendix 1. For taking on a challenge, participants chose a lower level because primarily because they wanted an easier task (26%) or felt they would not be very good at facial recognition (26%). Participants chose a higher level of challenge because they wanted a challenge (57%) or thought the higher challenge would be more interesting (18%). Participants clicked on hyperlinks to learn more (44%), because they were curious (19%) or because they wanted to see how the faces related to each other (14%). Participants who did not click on hyperlinks reported that they did not need to (66%), or did not want to take the extra time (8%). For repeated practice, participants who tried only the minimum required number of times said they did so because that was what was required (16%), that twice was enough for them (21%), or because they had done so poorly (13%). However, some did report that they tried twice (the minimal) because they wanted to improve (16%). Those who tried more than the minimum did so because they wanted to improve (29%) or to get the application task right (27%). Finally, participants who critically reflected reported doing so in order to process feedback (23%), to improve or understand better (21%), or to share their thoughts (16%). Those who did not reflect did not feel they needed to (25%), didn't want to or had nothing to say (27%) or thought it would take too much time (11%).

Summary statistics for the quantitative measures are available in Table 1.6. Results demonstrate that there was good variance in all the learning behaviors using the newly developed Learning Behaviors Methodology. Participants spent an average of 4.3 minutes with the learning materials (SD=5.6), clicked on an average of 1.6 hyperlinks (SD=2.0), and practiced an average of 2.9 times (SD=2.0). They spent an average of 48 seconds (SD=67) reviewing feedback across all of their practice rounds and 58% percent of participants (n = 35) chose to reflect. However, nine reflections (25%) were flagged because participants did not follow the reflection instructions. Instead, they wrote about the difficulty of the task (see Appendix 2). Analyses were conducted both with and without the inclusion of these flagged reflections. In the following tables all those who wrote reflections, regardless of content, are included in the “Reflection write” variable while those who reflected on their learning per instructions are in the “Critical reflection” variable.

Table 1.6 Summary Statistics for Study 3 (n=247)

	Variable	N	Mean	Std. Dev.	Min	Max
1	Learning Orientation	247	4.7	0.9	1	6
2	Performance Prove Orientation	247	4.1	0.9	1	6
3	Performance Avoid Orientation	247	3.3	1.1	1	6
4	Taking on a challenge (level of challenge chosen)	174~	2.4	1.4	0	5
5	Attending to information (minutes reading/reading rate)	155^	4.3	5.6	0.2	52.2
6	Forming connections (number hyperlinks clicked)	155^	1.6	2.0	0	6
7	Repeated practice (number practice rounds)	155^	2.9	2.0	2	17
8	Practice time spent on feedback (seconds between practice rounds)	155^	48.2	67.3	5	532
9	Reflection write (wrote reflection)	155^	0.57	0.5	-	-
10	Critical reflection (wrote reflection on learning)	155^	0.52	0.5	-	-
11	Performance	247	7.5	1.5	3	11.5

~ Challenge Only and All Five conditions
^ Challenge Absent and All Five conditions

The data in the summary table also helps mitigate concerns about fatigue effects. This task could take up to 30 minutes and participants may have been more likely to engage in earlier behaviors and less likely to engage in behaviors at the end of the task simply due to fatigue. However, over half (57%) of participants chose to engage in critical reflection at the end of the task, and 51% of participants chose a higher level of challenge (3 or more) at the beginning of the task.

Hypothesis Testing

To test Hypotheses 1 and 2, I combined the results of the Challenge Only and All Five conditions since those conditions were identical up to the point where participants had chosen their level of challenge. Results show support for Hypothesis 1. Learning orientation once again predicted taking on a challenging task ($r(174)=.19$, $p<.05$). However, I did not find support for Hypothesis 2 that performance-avoid orientation would negatively predict taking on a challenge. Though the relationship was in the expected direction, it did not near significance ($r(174)=-.07$, $p=.35$).

Before testing Hypothesis 3 that learning orientation would only predict whether individuals engaged in the learning taking on a challenge, I first ran a series of t-tests to determine whether the self-perception of taking on a challenge impacted the extent to which participants engaged in those subsequent learning behaviors. Results in Table 1.7 show no significant differences between the two groups (n=155) on any of the learning behaviors or overall performance. .

Table 1.7: T-test results for condition comparison

Dependent variable	N (Challenge Absent)	N (All Five)	t	df	p
Attending to Information (minutes reading/reading rate)	73	82	-0.3	153	0.77
Forming Connections (number hyperlinks clicked)	73	82	1.1	153	0.29
Repeated practice (number practice rounds)	73	82	0.2	153	0.82
Practice time spent on feedback (seconds between practice rounds)	73	82	-0.7	153	0.47
Reflection Write (choice to write reflection)	73	82	-1.6	153	0.11
Critical reflection (choice to reflect on learning)	73	82	-1.5	153	0.14
Performance	73	82	-0.1	153	0.91

p<.05, **p<.01 ***p<.001

Therefore, to test Hypothesis 3, I combined the results of the Challenge Absent and the All Five conditions since both those conditions included the four behaviors of interest (see Table 1.5). As shown in Table 1.8, learning orientation was not related to attending to information, forming meaningful connections, repeated practice with feedback, or reflection providing support for Hypothesis 3.

Table 1.8 Study 3 Correlations of Goal Orientations and Learning Behaviors for the Challenge Absent and All Five conditions (n=155)

	Variable	1	2	3	4	5	6	7	8
1	Learning Orientation								
2	Performance Prove Orientation								
3	Performance Avoid Orientation								
4	Attending to information (minutes spent reading/reading rate)	0.01	0.03	-0.06					
5	Forming connections (number hyperlinks clicked)	0.03	-0.06	-0.05	0.02				
6	Repeated practice (number practice rounds)	0.07	0.19*	0.06	-0.02	0.17*			
7	Practice time spent on feedback (seconds between practice rounds)	0.02	0.1	-0.05	-0.02	0.21*	0.62		
8	Reflection write (choice to write reflection)	-0.03	-0.03	-0.02	-0.02	0.15	0.03	0.06***	
9	Critical reflection (choice to reflect on learning)	-0.03	-0.08	-0.03	0.01	0.12	-0.01	-0.01	0.89***

*p<.05, **p<.01 ***p<.001
note: taking on a challenge was not included because that behavior was not available in the Challenge Absent condition.

Relationship among the learning behaviors

The LBM also enabled examination of the relationships among the learning behaviors, something that, to my knowledge, has never before been tested through direct observation of behavior. As reported in Table 1.9, Study 3 showed that forming meaningful connections was significantly correlated with the two behavioral indicators of repeated practice with feedback, repeated practice rounds ($r(155) = .17$, $p<.05$) and practice time spent on feedback ($r(155) = .21$, $p<.05$). Those who clicked on hyperlinks practiced more and, subsequently, spent more time studying the feedback. Additionally, an analysis of the All Five condition shows that taking on a challenge predicts forming meaningful connections ($r(82)=.23$, $p<.05$), but none of the other behaviors.

These results shown that those who chose a higher level of challenge were more likely to form connections and those who formed connections were more likely to repeatedly practice and spend more time on feedback. However, taking on a challenge did not predict attending to information, repeated practice with feedback or reflection. Attending to information did not predict any of the other learning behaviors and forming connections and repeated practice with feedback did not predict reflection. In general, the learning behaviors were largely independent (see Table 1.9).

Table 1.9: Combined Challenge Absent and All Five Condition Correlations (n=82)

	Variable	1	2	3	4	5
1	Attending to Information (minutes spent reading/reading rate)					
2	Forming connections (number hyperlinks clicked)	0.07				
3	Repeated practice (number practice rounds)	0.23*	0.02			
4	Practice time spent on feedback (seconds between practice rounds)	0.15	-0.02	0.17*		
5	Reflection write (choice to write reflection)	-0.04	0.01	0.12	-0.01	
6	Critical reflection (choice to reflect on learning)	0.02	-0.02	0.15	0.03	0.89***

*p<.05, **p<.01 ***p<.001

Performance Results

Study 3 also showed that engaging in the learning behaviors of attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection led to greater performance than not engaging in those behaviors. This is first evident by comparing the Challenge Only condition with the performance of the Challenge Absent condition. In the Challenge Only condition, participants were not given the option to engage in the four behaviors of attending to information, forming meaningful connections, repeated practice with feedback, or critical reflection. In the Challenge Absent condition, participants were given the option to engage in those behaviors. T-test results show that those in the Challenge Absent condition performed significantly better in the Challenge Only condition (p=.02). I also compared the Challenge Only condition performance with the combined results of the Challenge Absent and All Five conditions' performance and results hold (p=.01).

In addition, Study 3 results shed light on the role specific learning behaviors play in short-term performance. Initial correlation analysis indicates that the learning behaviors of forming meaningful connections (r(155) =.14, p=.07), continued practice (r(155) =.17, p<.05) and the related time spent on feedback (r(155) =.18, p<.05) all predicted higher performance in the application task. However, all three of these behaviors were themselves correlated. Therefore, I conducted regression analyses to tease apart how each behavior contributed to performance. Results are included in Table 1.10. Model 1 shows that when both meaningful context and the repeated practice are included, repeated practice remains a significant predictor of performance. The same pattern emerges when forming meaningful connections and time spent on feedback are included in the model (Model 2). Therefore, I conducted a mediation analysis to determine the role of forming meaningful connections (Table 1.11). Using structural equation modeling, results show that forming meaningful connections significantly predicted repeated practice with feedback, which, in turn, significantly predicted performance (Model 3). Once again this pattern is even stronger when time spent on feedback is used to predict performance (Model 4). On average, individuals who clicked on hyperlinks to form meaningful connections practiced more times and spend more time on feedback between practice rounds. In turn, those who practiced more and spent more time on feedback between practice rounds performed better.

Table 1.10 Regression Analyses for Impact of Learning Behaviors on Performance

Variable	Model 1	Model 2
Forming connections (number hyperlinks clicked)	0.09	0.08
Repeated practice (number practice rounds)	0.11^{*}	
Practice time on feedback (seconds between rounds)		0.01^{*}

* p<=.05, **p<.01 ***p<.001

Table 1.11 Mediation Analyses for Impact of Learning Behaviors on Performance

Mediator Variable	Model 3	Model 4
Repeated practice (number practice rounds)	0.11^{*}	0.01^{*}
Time on Feedback (seconds between rounds)		
Independent Variable (effect on mediator)		
Forming connections (number hyperlinks clicked)	0.06^{*}	$.13^{***}$

* p<=.05, **p<.01 ***p<.001

Observable effects on short-term performance were not found individually for learning orientation, or the learning behaviors of taking on a challenge, attending to information, and critical reflection. Given the nature of the task, these results are not surprising. First, although learning orientation predicted taking on a challenge, it did not predict performance. This is likely because, in this task, the choice of challenge did not determine the actual level of difficulty of the task – all participants were given the same performance task. In addition, participants were randomly assigned to whether they were given the opportunity to engage in the subsequent learning behaviors, and it was this assignment that had a direct impact on performance.

Second, there was no control over the extent to which participants engaged in the learning behaviors. This study was not designed to show if minimal levels of engagement for performance were met. Although some participants spent more time reading materials (attending to information) than others, those differences were not large enough to impact performance. In addition, reading more without putting that information into context is unlikely to affect performance because newly acquired information is typically forgotten within 15-30 seconds unless it is repeated or contextualized (Ebbinghaus, 1913; Mayer, 2002). Finally, it would be surprising if critical reflection had effects with so few practice rounds. Only 15 (10%) of participants practiced more than 4 times and therefore, most participants did not have sufficient experience to meaningfully reflect on both successes and failures.

The LBM was designed to determine the extent to which working adults engage in learning behaviors when doing so competes with other work tasks. Though Study 3 provided general evidence that being given the option to engage in the learning behaviors of attending to information, forming meaningful connections, repeated practice with feedback, and reflection increased performance, it cannot definitively demonstrate the specific impacts of each behavior on performance because there was no experimental control over who engaged in which behavior. Rather, with regard to performance, Study 3 indicated only that multiple learning behaviors are needed for short-term performance gains.

Discussion

Study 3 showed that learning orientation predicts whether individuals will choose to take on a challenging task but not whether they will follow through by engaging in subsequent learning behaviors, providing full support for Hypothesis 1 and 3. Surprisingly, though, Study 3 did not replicate the finding from Study 1 and Study 2 that performance-avoid orientation negatively predicts taking on a challenge.

Study 3 also introduced the Learning Behaviors Methodology and showed that it enables direct observation of the way adults act in a learning task when there is competition for their time. At each juncture, participants had to make the choice of whether to exert effort towards learning or do the minimal amount possible to end the task quickly. The wide variance in the engagement in each of the learning behaviors indicates that this choice was real for the participants. The lack of correlation among the majority of the behaviors shows that this choice was also different across the specific learning behaviors. However, some patterns did emerge. Individuals who chose to take on a challenge were significantly more likely to form meaningful connections and individuals who formed those connections were significantly more likely to engage in repeated practice with feedback, including spending more time on feedback. However, taking on a challenge was not significantly related to repeated practice with feedback. This suggests that there are separate drivers for individuals who take on a challenge and form connections than for individuals who form connections and engage in repeated practice with feedback.

By comparing the Challenge Only and All Five conditions, Study 3 also showed that actually engaging in the learning behaviors does impact performance, beyond the simple act of taking on a learning challenge. However, there are important nuances in these results. First, simply attending to information does not itself impact performance; learners must put that information into meaningful context in order to successfully apply it. Second, effective practice requires repetition. There is general agreement that practice increases performance in known tasks (Jolles et al., 2010; Theisen, Rapport, Axelrod, & Brines, 1998; Yeo & Neal, 2004) especially with immediate and relevant feedback (Ericsson et al., 1993). These effects were demonstrated by the LBM, which showed that it was not repeated practice alone, but repeated practice and paying attention to feedback that increased performance. Finally, reflecting on success and failure to discover underlying patterns, does not impact short-term performance. This is not surprising since critical reflection typically requires a high level of competence so individuals can spot patterns over time. In the short-term critical reflection is unlikely to make a strong difference.

Overall, Study 3 strongly indicates the utility of the LBM as way to behaviorally measure self-directed learning. As a methodology, the LBM can be applied to a variety of tasks to measure the choices learners make when they engage in learning complex material. The methodology also allows for deep dives into individual behaviors. For example, if a given population is already familiar with a topic, researchers could give them the option to form meaningful connections to isolate both antecedents and consequences of that particular learning behavior. For instance, most employees have a general understanding of their job responsibilities but many may not understand the full context of how their work impacts others. Researchers could examine what individual differences and situational conditions impact whether new employees expend the effort to talk their colleagues and question their manager about how their work feeds into organizational systems and goals.

The most important innovation of the LBM is, however, the ability to look at all five behaviors both individually and together in a learning task. The LBM sets the stage for deep and critical exploration of what drives self-directed learning and what learners and managers can reasonably expect from given learning behaviors. I will address these issues in greater detail in Chapter 2.

Chapter 1 Discussion

Chapter 1 opened the black box of learning to shed light on the way working adults engage in learning when there is competition for their time and attention. It also revealed the extent to which learning orientation predicts that engagement. Consistent with prior research, it showed that, at the intra-individual level, learning orientation is a key predictor of whether working adults take on learning challenges. I drew from the existing literature on self-directed learning to identify five key learning behaviors and introduced a new behavioral measure of learning, which enabled me to also show that learning orientation does not predict whether individuals engage in the subsequent behaviors of attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection. By developing a new Learning Behaviors Methodology, I was able to show that the five learning behaviors are largely independent. This chapter contributes to work in self-directed learning in three ways. First, it shows the predictive value and limitations of learning orientation, as well as its relationship to related constructs. Second, it advances the study and measurement of self-directed learning by both specifying the five distinct learning behaviors and answering calls to move beyond surveys (Baumeister & Vohs, 2007) to directly measure relevant behaviors. Finally, it suggests that self-directed learning is a construct that consists of multiple, largely independent behaviors.

Predictive Value of Learning Orientation

Learning orientation is one of the most widely-studied antecedents of individual learning, particularly in work settings. Studies suggest it plays an important role in leadership (Janssen & Van Yperen, 2004), recruitment (Rynes & Gerhart, 1990), training (Colquitt & Simmering, 1998) and performance appraisal (VandeWalle & Cummings, 1997). At first glance, this chapter may seem directed at showing a limitation of learning orientation. On the contrary, it shows that learning orientation consistently predicts which working adults will overcome barriers and choose to take on challenging tasks. From a management perspective, this may be the most important learning behavior because, without it, self-directed learning is unlikely to occur.

Though learning orientation measures have their roots in the Implicit theory of intelligence (Dweck, 1986), the manifestation of this theory is likely more complex for working adults than for students. The Implicit theory of intelligence posits that when learners associate effort with learning outcomes, they are more likely to take on challenges and persist after failure. This proposition has been extensively tested with students in classroom settings, with positive results (see VandeWalle, 1997 for review). Although adults also have beliefs about innate talent or ability to learn, by the time they are working, they are likely more aware of their own abilities and limitations. Therefore, the extent to which they take on challenges may have less to do with their innate beliefs about intelligence and more to do with how they feel they will be able to meet those challenges within their particular work setting. In other words, for working adults, beliefs about the affordances and constraints of their current situation may override implicit beliefs about general ability.

Vandewalle's (1997) scale of learning orientation for work domains takes differences between children and adults into account by focusing on how employees approach work tasks. As shown in all three studies in this Chapter, this learning orientation measure does capture whether adults seek out challenges in their work or shy away from them. However, previously, this claim has never been explicitly tested by measuring whether, when given the option, learning-oriented adults are actually more likely to choose a higher level of challenge. The positive results of the studies in this chapter hold even though there was competition for their time, as so often happens in organizational settings. This means that learning orientation is a valuable predictor for how working adults actually behave when faced with both learning and performance challenges.

However, the studies in this chapter do point to a clear gap in research on adult learning. Based on initial work using goal orientation scales in academic and work settings, there has been an implicit assumption that learning-oriented individuals would not only be more likely to take on a challenge, but would also be more likely to engage in other learning behaviors, particularly ones that require attention to feedback. Vandewalle (1997) explicitly noted that learning orientation differentiated between individuals' "reaction to feedback provided on how to improve their behaviors and performance," with some perceiving such feedback as a blow to their self-esteem, while others find it useful for performance. However, Study 3 showed that learning orientation is not predictive of these subsequent behaviors. This finding is potentially useful to organizational scholars and managers alike, because it implies that there are other drivers of these behaviors that have been underexplored. In the next chapter, I delve into the possibility of such drivers, to suggest that each learning behavior may come with its own set of antecedents and outcomes. Learning Measurement

The measurement of learning outside of formal classroom settings has been notoriously difficult, and even in classroom settings, measurement of learning behaviors often relies on self-reports and survey measures (Bednall & Sanders, 2014; Cajiao & Burke, 2016; Carragher & Golding, 2015). While some advancements have been made using simulations (e.g. Lovelace, Eggers, & Dyck, 2016), a structured way to measure engagement in key learning behaviors had been missing. This chapter introduced the Learning Behaviors Methodology. I first integrated literature in education, cognitive science, and management to identify five key learning behaviors and then developed a way to directly observe the degree to which individuals engage in each of those behaviors while learning complex material. This methodology could be applied to a wide variety of learning topics. For example, Study 1 used the topic of learning about management, and Studies 2 and 3 used the topic of learning about facial expressions, The LBM can be adapted not only to new learning topics but also to the assessment of additional learning behaviors. While the five identified in this chapter are key to learning, they are by no means exhaustive. For example, the LBM could incorporate a way to measure the degree to which individuals seek help while learning, by giving them the option to seek advice from experts at various points in the learning process. It could also be adapted to consider other ways that each self-directed learning behavior is enacted in real-world settings. In this case, forming connections took the form of clicking on hyperlinks to prepared materials. Research has shown another powerful way to form these meaningful connections is to create conceptual maps of the relationships within the domain (Hay & Kinchin, 2008). Research on concept mapping would allow for a deeper understanding of whether and how active construction of meaningful context leads to better performance outcomes than, for example, relying on listening to experts.

Perhaps the most promising avenue for new research using the LBM is to systematically explore the full process of learning. In particular, the LBM could be used to understand the degree to which each learning behavior contributes to short and long-term learning. In addition, it could shed light on the optimal ordering of behaviors and how that ordering might vary based on factors such as the individual's initial level of expertise. For example, compared to novices, individuals with advanced knowledge of a domain likely iterate more quickly through the initial behaviors when learning something new within their domain. They can put new material into meaningful context with less effort and may have the requisite knowledge to rely on their own feedback of how well new strategies worked. The final way the LBM could advance the measurement and study of learning is by determining the number of iterations needed to make a difference to long-term learning, and under what conditions. While Study 3 showed that even one iteration increases short-term performance, research suggests that the learning process is long, often taking years of dedicated effort

(Ericsson et al., 1993). The LBM could be adapted to actually help individuals develop new levels of expertise in a given area, thereby capturing the way learning unfolds over time.

Independent Learning Behaviors

A somewhat counter-intuitive finding from Chapter 1 is that the learning behaviors themselves were largely uncorrelated. Taking on a challenge predicted forming meaningful connections. In turn, forming meaningful connections predicted the number of times participants practiced. No other significant relationships were found. This suggests that learning consists of multiple behaviors that are largely independent. Although, across all participants, there was a good degree of engagement in each of the learning behaviors in Study 3, results suggest that learners have individual preferences for some behaviors and resist others.

These preferences shed light on self-directed learning in both classroom and informal settings. When learning complex material, individuals may sometimes seem enthusiastic and motivated but unable to sustain their effort. At other times, individuals may seem resistant to the learning but then become more active and engaged as they move through the topic. If adults have individualized preferences for engaging in certain learning behaviors, their enthusiasm may follow such seemingly unpredictable trajectories. For instance, some may be drawn to learning detailed information and have the ability and motivation to pay deep attention to the learning materials, but find less value in understanding those materials in the larger context. Alternatively, some adults may prefer 'hands-on' learning and seem distracted and unmotivated when verbal learning materials are presented. They may be more deeply engaged once they can apply that learning in practice. When learners, instructors, and managers understand these differential preferences, they may be able to systematically design more effective learning situations.

These differential preferences also help explain why learning orientation is not as predictive of subsequent learning behaviors or performance as may have been expected. Learning-oriented individuals seem motivated to take on new things and not shy away from a task simply because it is challenging. However, because their preferences for subsequent behaviors differ, learning orientation is not directly predictive of those behaviors. In other words, while learning-oriented individuals have in common the desire to seek challenges, their preference for subsequent behaviors may vary. Some may prefer the detailed acquisition of knowledge, others the practical application, and still others the critical reflection. Therefore, although learning-oriented individuals are more likely to start the learning processes, they differ in how much they are drawn to each of the subsequent behaviors required for longer-term learning.

Limitations and Future Research

Although this chapter presented a new behavioral approach to learning and replicated its finding across two tasks, there are some key limitations to these studies. First, the studies did not use a topic specific to career advancement. The motivation to learn may be quite different when adults see learning the topic as required for their career. The participants from these studies were recruited from Amazon Mechanical Turk because that enabled me to test how learning unfolds when it is in competition with wage-earning performance. Spending additional time on each learning behavior came at the cost of performing another task for which participants could get paid. However, the learning itself did not advance their understanding of a topic critical to their careers. Future research could examine how working adults engage in the learning behaviors when they see the topic as valuable to their work. For example, the facial recognition task used in Study 3 could be administered to managers in a course on emotional intelligence and researchers could vary the perceived value of reading facial expressions for improving emotional intelligence. This would test the degree to which overall engagement, or engagement in specific behaviors, is impacted by valuing the learning outcome.

Second, this chapter did not measure long-term learning. The performance task for Study 3 was administered directly after the learning occurred. Therefore, this chapter only showed short-term performance effects. Further research could test how each behavior contributes to longer-term performance by testing, for example, how participants perform days or weeks later. Also, simply telling participants that the purpose of the task is for long-term learning may alter the degree to which they engage in particular learning behaviors. This could test whether viewing learning through a longer-term lens impacts how and when working adults are motivated to learn.

Third, this chapter did not find consistent support for Hypothesis 2 that performance-avoid orientation negatively predicted taking on a challenge. However, since that relationship was found consistently in Studies 1 and 2, this chapter provides tentative support for Hypothesis 2. This may be due to the fact that performance-avoid orientation captures the desire to avoid performing badly. If participants were overly confident in their existing ability, they would not be deterred by higher levels of challenge.

Finally, the findings in Study 3 regarding the relationship between learning orientation and the four learning behaviors of attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection were tested in a single study. Future research could replicate the findings using a similar task, as well as test if the results hold if the type of task is different, thereby examining these relationships across multiple settings. In addition, these data were observational. Confident causal statements cannot be made; there could be some third variable (an individual difference) that drove both engagement in these learning behaviors and subsequent performance. Since learning orientation is limited in its predictive ability, these future studies could employ the LBM to systematically examine what other individual differences or situational conditions might drive individuals to engage in the learning behaviors.

Conclusion

Individual self-directed learning is becoming more critical to both organizational survival and individual careers. Each contribution of this chapter helps to advance our understanding of the way self-directed learning occurs when working adults are tasked with learning something new in the midst of performing work tasks. Identifying five key learning behaviors sheds light on *what* is needed to engage in the full process of self-directed learning. Revealing that learning-orientation predicts taking on a challenge provides insight into *who* is most likely to start the self-directed learning process. Finally, introducing a way to directly observe self-directed learning behaviors suggests *how* that process unfolds as learners fluctuate in their motivation to learn.

CHAPTER 2: MAPPING LEARNING BEHAVIORS IN THE LEARNING AS BEHAVIORS (LABS) MODEL OF EXPERTISE DEVELOPMENT

Abstract

In this chapter, I build off the findings in Chapter 1 to theorize how the self-directed learning behaviors of taking on a challenge, attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection relate to the long-term learning need to develop expertise. I introduce the Learning as Behaviors (LABS) model of expertise development, which is based on the cognitive science definition of learning as a change in long-term memory. The LABS model, therefore, maps each self-directed behavior to a process step in long-term memory formation. Research has shown that experts become experts by building a vast reservoir of knowledge and skills in long-term memory. In contrast to short-term or working memory, there does not seem to be a storage limit to long-term memory. Once knowledge and skills are embedded in long-term memory, they remain available for immediate use on an as-needed basis. Therefore, long-term learning can be understood as the process of building that reservoir. The LABS model deconstructs that process by identifying five key stages, behaviors, and learning outcomes of long-term learning. I then use the new Learning Behaviors Methodology to empirically test the relationship between key learning behaviors and the predicted outcomes. I find that the learning behaviors do contribute to long-term memory formation, but in different ways. Together, the LABS model and the findings give rise to three novel propositions: 1. each of the five learning behaviors is required for long-term learning, 2. each stage of expertise is dependent on automating the learning outcomes of the previous stage, 3. any one individual is unlikely to freely choose to engage in all five behaviors.

Introduction

Developing workplace expertise has become more important and more difficult as the business environment becomes more dynamic. Experts are distinguished from novices by their ability to perform consistently in novel situations (Ericsson et al., 1993), a distinction that is critical to the increasing number of organizations that regularly face novel problems. Yet as organizations rely on experts more than ever, the lifespan of expertise in many fields is shortening, requiring employees to more quickly and efficiently develop expertise in new and often unpredictable domains.

However, developing expertise is not easy nor does it happen quickly. As Feltovich et al. (2006, p. 45) noted "one of the great puzzles to be solved" in expertise development is "how to scaffold sustained consistent purposeful effort over very long periods of time." Despite the demand placed on employees to develop expertise in new areas, sustained effort towards learning over a long period of time is hardly an option most of them have. Therefore, it is useful to deconstruct expertise into its component parts to understand what behaviors drive the achievement of expertise, the optimal orders of those behaviors, and the antecedents of each behavior. Chapter 1 of this dissertation pulled together research from education, cognitive psychology and management studies to categorize individual self-directed long-term learning into five key behaviors of taking on a challenge, attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection. This chapter will extend that work.

Beginning with the definition of learning as a change in long-term memory (Ericsson & Kintsch, 1995), this chapter will draw from work in cognitive neuroscience to show how each of the five learning behaviors contributes to the long-term memory process. Research has shown that experts are able perform consistently in novel situations because they draw from a vast reservoir of knowledge in long-term memory (H. A. Simon & Chase, 1973).

Essentially, once knowledge and skills are consolidated in long-term memory, they have been learned. So, although the literature has, cumulatively, identified key learning behaviors for long-term learning, and although there are well-established models of long-term memory formation (R. C. Atkinson & Shiffrin, 1968), we lack a process model that integrates what is known about memory with the sequence of behaviors that constitute expertise development.

This chapter presents the Learning as Behaviors (LABS) model of expertise development, which details how learners achieve the ability to adapt in novel situations (expertise) in a given domain. First, this chapter maps the individual self-directed learning behaviors of taking on a challenge, attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection to long-term memory formation processes. Taking on a challenge is the stimulus or trigger for learning something new (Dweck, 1986; Piaget, 1966). Attending to information enables storage of the information in short-term memory. Forming meaningful connections builds the neural connections needed to translate the information from short to long-term memory. Repeated practice with feedback reinforces those connections through retrieval. Finally, although little is known about the relationship between reflection and long-term memory, reflection likely further reinforces neural connections through retrieval and enables building new connections (R. C. Atkinson & Shiffrin, 1968). Building from this mapping, the first proposition of the LABS model is that each learning behavior is required to develop expertise.

The second proposition of the LABS model is that there is an optimal ordering to the learning behaviors based on the way information becomes embedded in long-term memory. Information flows from short to long-term memory so it must be attended to before it can be given meaning (Ebbinghaus, 1913; Nissen & Bullemer, 1987). Attending to information should therefore occur before making meaningful connections to that information. In addition, research has shown that novices who practice their new knowledge and skills by attempting to solve problems often struggle because they don't understand which information is important to the situation at hand (Hmelo-Silver, 2004). Therefore, practice should follow, not precede, forming meaningful connections. Finally, critical reflection is a review of successes and failures that occur during repeated practice with feedback (Ellis & Davidi, 2005a; Mezirow, 1990) and, thus, cannot occur until the learner experiences these successes and failures.

This is not to suggest that individual self-directed learning always occurs in a tidy linear sequence. Developing expertise more than likely requires multiple cycles through the five key behaviors and learners often regress throughout the learning process (Fischer & Bidell, 2006). Dual Process Theory (Wason & Evans, 1974) suggests that learning, with the exception of critical reflection, is an exercise in moving from deliberate, conscious effort to quick, automated performance. Considering this alongside Dynamic Skill Theory (Fischer & Bidell, 2006), which suggests that there are peaks and valleys to skill development but overall progress is forward-moving, the LABS model posits that each subsequent behavior is dependent on the previous one becoming automated but, during the actual learning process, learners may experience peaks and valleys of achievement as they progress.

The third proposition of the LABS model hypothesizes a previously undiscovered barrier to developing expertise: learners likely have to engage in some behaviors they resist. Drawing on expectancy value theory (Vroom, 1964), I argue that individuals have different expectations that a given behavior will result in learning based on the their self-efficacy in the learning process at that stage. Because learners may believe that some behaviors are more effective for learning, they will be motivated to engage in some behaviors over others. In addition, the preference to engage in each behavior likely relies on individual differences. For example, the individual with a high need for achievement may naturally prefer to repeatedly practice to master a skill rather than spend time ensuring they understand the full context of learning materials.

Indeed, these preferences may, at times, even be oppositional. For example, the ability to focus and avoid distraction while attending to new learning materials may interfere with the open exploration that facilitates forming meaningful connections. The LABS model, therefore, predicts that any one individual is unlikely to freely choose to engage in all the requisite behaviors. Beyond concerted time and effort, expertise development faces the counter-intuitive barrier that trying harder in a single preferred behavior may actually hinder the process because it crowds out the other learning behaviors. This means that the learning behaviors are likely differentially motivated in that the individual differences that impact one learning behavior may not affect, or may even undermine, other behaviors.

In the existing research on expertise, there is an implicit assumption that trying longer and harder can overcome the barriers to becoming an expert (Duckworth, Peterson, Matthews, & Kelly, 2007; e.g. Ericsson et al., 1993). This paper challenges that assumption and embraces the possibility that developing expertise involves exerting effort towards fundamentally different kinds of learning behaviors, some of which any given individual may resist. Consider the young teacher who has learned the theory and concepts of k-12 education but has never actually taught a class. Reading more theory will not progress her learning; she needs to actually put her knowledge to practice to become a good teacher.

The LABS model is a conceptual framework describing the stages, behaviors, antecedents, and outcomes of individual self-directed learning. As learners progress through the stages - from being a novice to becoming informed, then knowledgeable, then competent, to finally achieving expertise - they engage in behaviors that may sometimes be related but are not the same. Each of these behaviors contributes to long-term memory formation, but in a different way. Therefore, the motivation to engage in these behaviors will differ based on learners' personal preferences and their self-efficacy in the learning process at that stage. With an explicit understanding of what it takes to develop new expertise, employees and managers can more purposefully exert time and effort towards learning from and in workplace settings.

The LABS Model: Learning and Long-term Memory Formation

The LABS (Learning as Behaviors) model outlines five stages of expertise development: novice, informed, knowledgeable, competent, and expert. As shown in Figure 2.1, each of these stages is marked by a certain level of ability or learning outcome. A novice is at the starting point and is not yet familiar with information in the domain. The informed learner is familiar with content in the domain and is able to recall information in the short-term. The knowledgeable learner is able to recall this information in the longer-term. The competent learner is able to reliably apply that information in practice. Finally, the expert is able to adapt in novel situations. To achieve each of these stages, learners engage in the five key learning behaviors of taking on a challenge, attending to information, forming meaningful connections, repeated practice with feedback, and critical reflection, in sequence.

The LABS model also suggests that expertise is a continuum, rather than a dichotomy. Learners are not either novices or experts but increase levels of expertise at each stage and through each iteration of the behaviors. A single iteration may result in expertise in a very small part of a given domain, such as learning a single new concept but, to develop expertise in a domain, multiple iterations with new and broader concepts are most certainly needed. For example, the manager who wants to develop new expertise in handling large budgets may be able to do so by attending to information on how to manage budgets, putting that information into broader context of the organizational budgeting process, repeatedly practicing and receiving feedback on how to actually create and manage a budget, and critically reflecting on which strategies do and don't work. However, becoming an expert manager entails far more than dealing with budgets. Achieving expertise will take multiple iterations through each stage to learn different concepts and skills. In turn, as each new concept or skill is acquired, the manager will be better able to relate them to each other and understand the full scope of the domain. However many iterations are needed, the LABS model asserts that the five key behaviors are critical to the process.

Taking on a challenge is the first learning behavior and it provides the trigger that sets off the learning process. The second learning behavior is attending to information. When new information is available, learners must know what to pay attention to and direct attentional resources towards the learning materials or towards models who can demonstrate the requisite knowledge and skills (A. Bandura, 1977). The third learning behavior is forming meaningful connections because research has shown that putting information into meaningful context overcomes the tendency to quickly forget newly acquired information (Glaze, 1928; Noble, 1952). Forming meaningful connections enables learners to apply the information in the form of repeated practice with feedback (Jolles et al. 2010), the fourth learning behavior. These successes and failures provide the content for the final learning behavior of critical reflection. During critical reflection, individuals examine their (and others') performance in an attempt to understand the underlying principles of the domain (Ellis & Davidi, 2005a; Mezirow, 1990).

This chapter will show how each behavior leads to each level of ability based on how that behavior contributes to long-term memory. It will then describe three experiments, which demonstrate that the behaviors of attending to information, forming meaningful connections, and repeated practice with feedback do lead to the expected levels of ability.

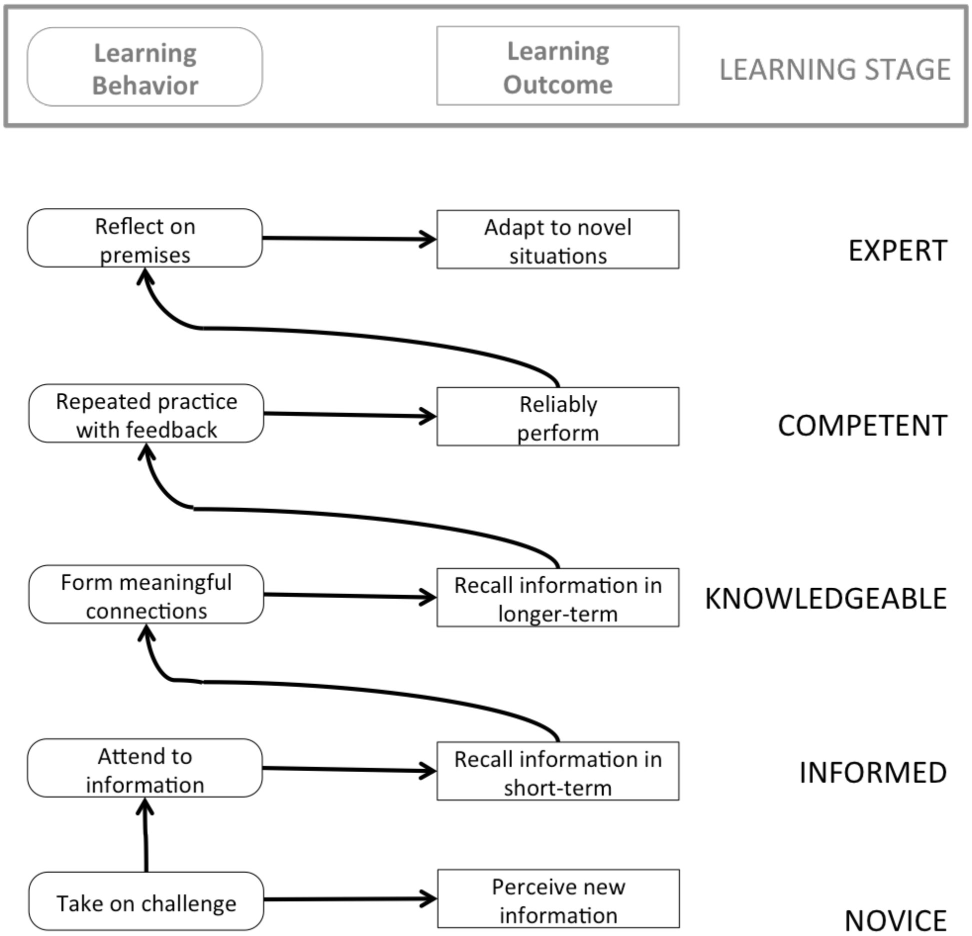

Figure 2.1 Partial Learning As Behaviors (LABS) Model: Stages, Behaviors, and Outcomes

Mapping the five key learning behaviors to specific memory activities is based on Atkinson & Schiffrin's (1968) model of long-term memory formation, depicted in Figure 2.2.

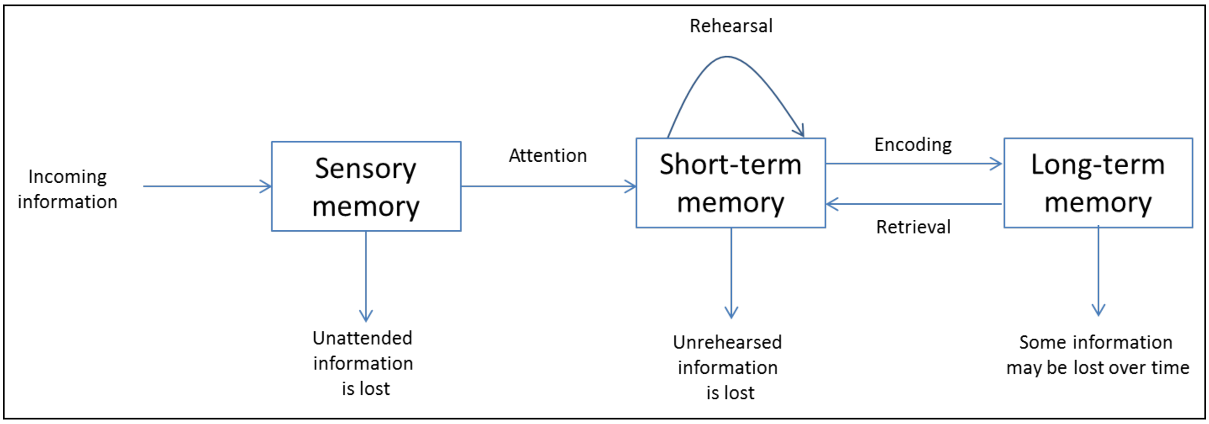

Figure 2.2 Atkinson & Shiffrin's (1968) Model of Long-term Memory Formation

In this model, memory formation occurs through a process of perceiving, attending to, encoding, storage, and retrieval. While the model has been updated to include the role of working memory (Baddeley, 1992), the basic processes hold (Unsworth & Engle, 2007). First, information is perceived through one of the senses. When attended to, it is encoded into a format that enables storage in short-term memory but this information decays rapidly (typically 15-30 seconds) unless it is transferred to long-term memory (R. C. Atkinson & Shiffrin, 1968). Two control mechanisms enable this transfer: rehearsal and association. When the information is repeated, attached to pre-existing associations, or new associations are made, the information trace is elaborated and stored in long-term memory (Alba, Alexander, Hasher, & Caniglia, 1981). Initially, this elaborated information trace is quite vulnerable to interference upon retrieval because recalling information from long-term memory relies on a search process. As associations gain strength, the search process becomes more robust, so the more associations there are (elaboration) and the more times they are reinforced (practice), the easier it is to retrieve information (Karpicke & Blunt, 2011). Over time and use, information becomes consolidated in long-term memory and is less subject to interference (R. C. Atkinson & Shiffrin, 1968).

The classic case of "H.M." from cognitive psychology demonstrates what happens when the memory formation process is interrupted and one is unable to change long-term memory (Corkin, 1984). H.M. had severe hippocampal damage and was unable to convert short-term memories into long-term ones. This means that, after his injury, H.M. could not remember any newly encountered person or event for more than a few minutes. He greeted cognitive psychologists he worked with for decades as new acquaintances upon each meeting. However, H.M. had a normal functioning working memory. He scored normally on tests where he was asked to remember a series of random digits (Milner, Corkin, & Teuber, 1968). After his injury, H.M. was unable to take on learning challenges because he was only able to retain knowledge consolidated before his injury. Because H.M. was unable to change long-term memory, he was unable to learn.

Therefore, each learning behavior should increase the likelihood of changing long-term memory. Figure 2.2 outlines the pathway from each behavior to a particular memory formation step – a learning outcome.

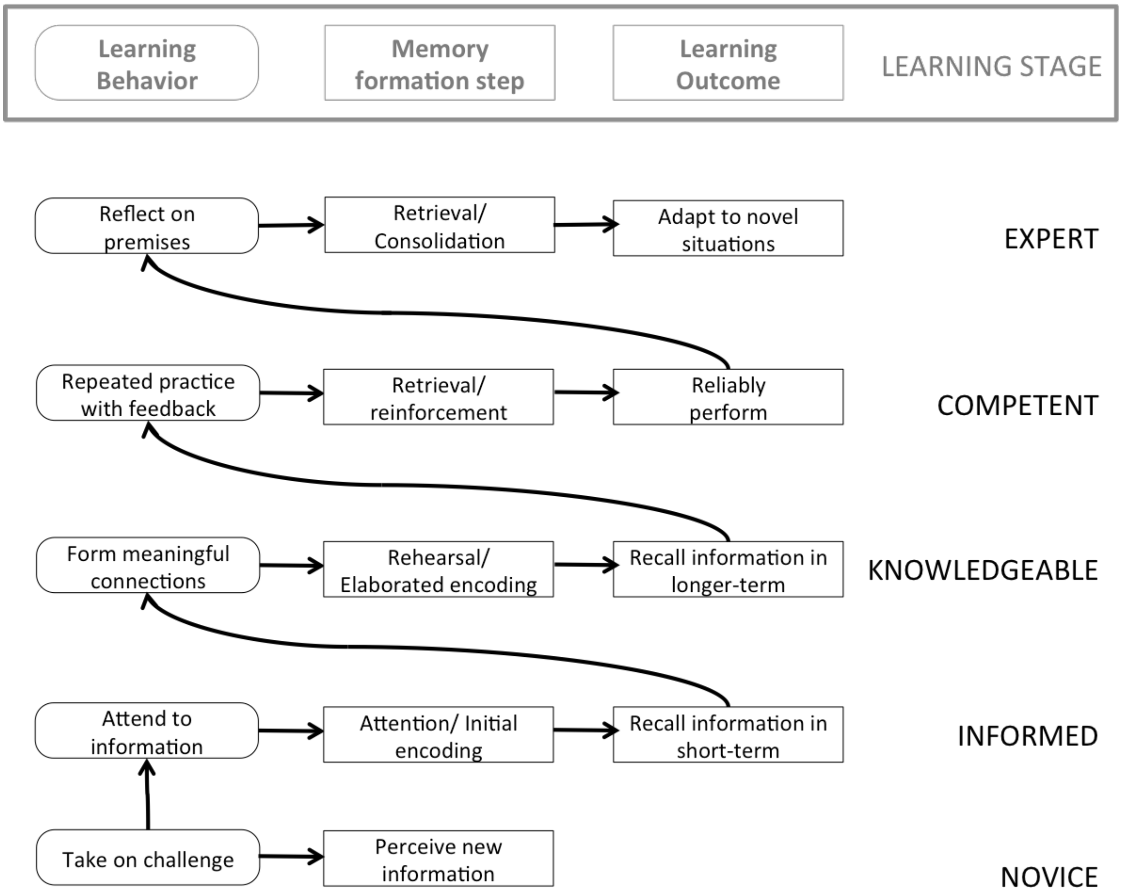

Figure 2.3: Partial LABS model: Stages, Outcomes, Memory Formation Steps, and Behaviors

The hypotheses that follow from the model are drawn from the cognitive science findings detailed below. They are presented to set the stage for Study 1, which tests these learning outcomes with the new Learning Behaviors Methodology.

Taking on a challenge provides the stimulus or trigger indicating that something is new (Piaget 1966) and brings it into the perceptual field, directing attention towards a learning goal. While learning can occur incidentally (Marsick & Watkins, 2001) and without conscious awareness (Tulving & Schacter, 1990), the self-directed process of changing long-term memory requires active participation on the part of the learner (Garrison, 1997) and access to learning opportunities (Dragoni et al., 2009). Taking on a challenge is a conscious choice to learn to do something you do not already know how to do.

However, taking on the challenge does not, in itself, change long-term memory, because the perception of the new information can be subsequently ignored, in which case it will be quickly forgotten (Ebbinghaus, 1913; Murre & Dros, 2015). Research has shown that ignoring errors (Tucker & Edmondson, 2003), engaging in short-term easy fixes (Argyris, 1976), and demonstrating what you already know how to do (Dweck, 1986) inhibit the learning process precisely because new learning does not get triggered. Altering long-term memory means a change must occur. As indicated in Figure 2.1, the challenge provides the opportunity, but memory is unaffected unless the individual's mind attends to the new information. This indicates that taking on a challenge is necessary to begin the learning process, but not sufficient, in and of itself, to result in a learning outcome.

To achieve the first learning outcome of short-term recall, individuals must attend to the new information, which means avoiding distractions and paying attention. It maps to the memory processes of initial encoding, which is surface-level processing of information so it can be stored in short-term memory (Craik & Lockhart, 1972). Particularly in performance settings, employees must selectively attend to information (Pashler et al., 2001) and these limited attentional resources drive what gets learned (Shipstead et al., 2015). Early research on attention shows that when individuals are distracted from attending to information, they are unable to recall it, even in the short term. Craik & Tulving (1975) showed that when reading a list of words, individuals who were told to count a given letter, thereby distracting them from attending to the information, scored lower on recall tests than individuals who were simply asked to read the list. Attending to information is critical for encoding information into short-term memory for further processing (Shipstead et al., 2015). Thus, if this behavior does lead to the performance outcome of short-term recall as specified in the LABS model, interference with that task should result in poorer short-term memory performance.

H1A: Individuals who are distracted from attending to new information in the Learning Behaviors Measure will have worse immediate recall of that information than individuals who are not distracted from attending to it.

Attention drives what information is encoded in short-term memory, but research has also shown that newly acquired information is quickly forgotten unless it is either repeated or contextualized (Ebbinghaus, 1913; Mayer, 2002). Although repetition is a powerful memory tool, it is limited because it does not associate the new information to existing knowledge. Therefore, repetition alone stalls the learning process – individuals can remember the new information but are unable to meaningfully apply it (Mayer, 2002).

Alternatively, forming meaningful connections creates associations with the new information and furthers the encoding process (Craik & Lockhart, 1972). It maps to the memory formation process of elaborated encoding, which enables storage in long-term memory (Craik & Tulving, 1975). Memory is associative and encoding information in long-term memory involves building the neural circuitry between multiple areas of the brain (Fanselow & Poulos, 2004). Elaborated coding is characterized by the effort to make new associations: "A congruous [associative] encoding yields superior memory performance because a more elaborate trace is laid down and …can be utilized more effectively to facilitate retrieval" (Craik & Tulving, 1975, p. 268). Particularly in semantic recall, when learners are making sense of new information, the degree to which learners are able to associate the new information with existing knowledge drives their ability to remember it (Alba et al., 1981; Craik & Lockhart, 1972).

Forming meaningful connections, therefore, means either associating existing knowledge with new information or, as learners progress, beginning to create new mental models of the domain (Shuell, 1990). In essence, forming meaningful connections gives progressively deeper meaning to the information so, although learners do rehearse the information in the process of forming connections, they no longer rely on rote memorization for recall (Cavallo, 1996; Mayer, 2002). When learners understand information in context, it is more likely to become embedded in long-term memory and be available beyond the 15-30 second limit of short-term memory (Roberts, 1972). Therefore, if forming meaningful connections aids in embedding information in long-term memory, it should lead to longer-term recall.

H1B: Individuals who are presented with meaningful connections for new information will be better able to recall that information after a delay than individuals who are not presented with meaningful connections.

Repeated practice is the application of newly acquired knowledge. It maps to the memory formation process of retrieval. Applying the information requires retrieving it (Karpicke & Blunt, 2011), and with repeated practice, retrieval becomes less subject to interference and performance becomes more automated (Garavan et al., 2000) signaling an increase in neural efficiency (J. R. Kelly & McGrath, 1985). When combined with feedback, repeated practice appears to help learners generate new associations (Ericsson et al., 1993). Karpicke & Blunt (2011) showed that learners who repeatedly tested their understanding by reviewing both right and wrong answers scored higher on inference tests (tests that required them to connect multiple new concepts) than learners who engaged in elaborated encoding practices, such as concept mapping. The application setting allows for a richer associative context in which to deepen meaning and store the information about the new domain. Therefore, repeated practice with feedback increases performance because it involves both repetition and meaning-making (Jolles et al., 2010).

H1C: Individual performance will improve over multiple practice attempts that include access to immediate and relevant feedback.

Reflection is the fifth individual-level learning behavior and it is the most difficult to map to the memory formation process. Like practice, it seems to be a combination of retrieval (Packer & Cunningham, 2009) and meaning-making (Mezirow, 1990) that supports long-term memory consolidation. Memory consolidation refers to the "transformation over time of experience-dependent internal representations" (Dudai, Karni, & Born, 2015, p. 20). It transforms raw information into reliable mental models and can take years. It is possible that, since memories are effectively rebuilt each time they are recalled (Kandel, 2001), reflection creates space for individuals to insert new meaning into the memory. From a dual-process model perspective (Moskowitz, Skurnik, & Galinsky, 1999), reflection has the potential to bring the automated System 1 processes that resulted from repeated practice with feedback back to conscious awareness for critical examination with System 2 processes (Anseel et al., 2009), thereby enabling a comprehensive, systems-view of the domain and facilitating memory consolidation. However, the mechanisms underlying reflection and learning are not well understood and are beyond the scope of this chapter. Nonetheless, existing evidence suggests the importance of including critical reflection as the fifth learning behavior in the LABS model.

The LABS model suggests that reflection can aid in memory consolidation and there is a long line of research suggesting that reflection is critical to deeper levels of learning (Anseel et al., 2009; Argyris, 1976; Mezirow, 1990; Senge, 1990). As such, it fits both criteria for inclusion as a key individual learning behavior. However, memory consolidation occurs over the very long term, often taking years. Therefore, it is unlikely that differences in learning outcomes will emerge after engaging in reflection in a single learning task (as participants do in the LBM). Further, examining the mechanisms underlying reflection and long-term memory is beyond the scope of this study.

Empirical Tests of the Relationship between Learning Behaviors and Learning Outcomes

The purpose of these tests was to determine whether the individual learning behaviors lead to the learning outcomes hypothesized in Figure 2.1 and articulated in the previous section, using the facial-recognition LBM introduced in Chapter 1. Study 1A tested whether attending to information leads to immediate recall (Hypothesis 1A). Study 1B tested whether forming meaningful connections leads to recall after 24 hours (Hypothesis 1B). Study 1C tested whether repeated practice with feedback leads to performance improvements (Hypothesis 1C). The first behavior of taking on a challenge was not tested because taking on a challenge is not, by itself, hypothesized to lead to learning without engaging in subsequent behaviors. The fifth behavior, reflection, was also not tested for learning outcomes because those outcomes are not well understood in relation to long-term memory and likely occur over the long term.

Study 1A: Attending to Information

Study 1A tested Hypothesis 1A, that attending to information leads to immediate recall.

Participants

Participants were 120 working adults recruited on Amazon Mechanical Turk. Fifty-eight participants (48%) were female. Participants had an average age of 36 and worked an average of 37 hours per week. Because these studies are targeted to working adults, only participants who worked at least 20 hours per week were allowed to participate in the study; however, participants were not aware of this criterion. The variance on race was low and was not shown to drive results, so it is not reported here.

Procedure

Study 1A first asked participants to give their consent and to fill out a short demographic survey. They were then asked to read a passage, which served as an attention filter. The passage misdirected the reader twice, and participants had to read the passage in its entirety to answer a question correctly. Only participants who answered the attention filter correctly were permitted to participate in the experiment. Participants were then randomly assigned to either a Learn or a Count condition. Participants in the Count condition were asked to count the number of capital letters in the learning materials, thereby distracting them from attending to the learning materials (Craik & Tulving, 1975). In addition, since the materials also included pictures, they were asked to count the pictures of people with blond hair. The participants in the Learn condition were asked to use the materials to acquire information.

All participants were then given the same learning materials. The materials included pictures and detailed written instructions on how to read people's emotions by looking at the forehead, eyes, and mouth (see Image 1.1 in Chapter 1). Therefore, the independent variable was the behavior of attending to information, and it was implemented by the manipulation of asking participants to acquire knowledge or count the capital letters and pictures with blond hair in the learning materials.

Participants in the Count condition were then asked to enter counts for the number of capital letters and pictures with blond hair. Pilot testing showed that this took an average of 15 seconds; thus, participants in the Learn condition were given a 15-second delay screen. Next, all participants were taken to a multiple-choice knowledge test of the learning materials. The knowledge test required them to match facial features to each expression (see Image 2.1). Participants received a point for each correctly identified match and lost a point for every incorrectly identified match. Participants were given 90 seconds to complete the test.

Please indicate which expressions include which facial features. You may choose more than one expression for each facial feature.

	Surprise	Anger	Fear	Sad	Happy	Disgust
Forehead wrinkled	☐	☐	☐	☐	☐	☐
Eyebrows arched	☐	☐	☐	☐	☐	☐
Eyebrows drawn together	☐	☐	☐	☐	☐	☐
Eyebrows raised	☐	☐	☐	☐	☐	☐
Eyebrows pulled down	☐	☐	☐	☐	☐	☐
Inner corner of eyebrows drawn	☐	☐	☐	☐	☐	☐
Upper white of eyes showing	☐	☐	☐	☐	☐	☐
	Surprise	Anger	Fear	Sad	Happy	Disgust
Lower white of eyes showing	☐	☐	☐	☐	☐	☐
Crows feet around eyes	☐	☐	☐	☐	☐	☐
Cheeks raised	☐	☐	☐	☐	☐	☐
Nose wrinkled	☐	☐	☐	☐	☐	☐
Mouth open	☐	☐	☐	☐	☐	☐
Mouth tense	☐	☐	☐	☐	☐	☐
Corner of lips drawn down	☐	☐	☐	☐	☐	☐
	Surprise	Anger	Fear	Sad	Happy	Disgust
Corner of lip drawn back and up	☐	☐	☐	☐	☐	☐
Lower lip pout	☐	☐	☐	☐	☐	☐
Lower lip raised	☐	☐	☐	☐	☐	☐
Jaw juts out	☐	☐	☐	☐	☐	☐
Jaw raised up	☐	☐	☐	☐	☐	☐

Image 2.1: Study 1 Facial Expression Knowledge Test

Measures

Reading rate served as a control variable and was measured by the time it took to read the attention filter passage.

Time spent reading was also tracked to pilot test it as an operationalization of attending to information. If time spent reading, controlling for reading rate, predicted knowledge test scores for those in the Learn condition, then it is reasonable to assume that more time spent reading meant greater attention to information.

The dependent variable, *immediate recall*, was measured using the score on the knowledge test.

Results

I conducted t-tests by condition and found that participants in the Learn condition (M = 2.3; SD = 8.8) had significantly higher scores than participants in the Count condition (M = -3.7; SD = 11.7), $t(118) = -3.2$, $p = .002$. Results held when controlled for reading rate (p = .002) in a multiple linear regression analysis. In addition, there were no significant differences in reading rate (p = .28) or time spent on the learning materials (p=.86) by condition.

Finally, I wanted to test whether time spent reading served as a proper operationalization of attending to information. I used multiple linear regression, which showed that time spent reading predicted knowledge test scores for participants in the Learn condition, controlling for reading rate ($b = .05$, $p < .01$).

Study 1B: Forming meaningful connections

Study 1B tested Hypothesis 1B that forming meaningful connections leads to greater recall after a delay. Previous research in memory and cognition shows that unless information is given meaningful context, it is unlikely to be remembered beyond the limits of short-term memory, which is typically 15-30 seconds (Cavallo, 1996; Mayer, 2002). Study 1B served as a conservative test because it tested recall after 24 hours.

Participants

Eighty working adults were recruited from Amazon Mechanical Turk. Participants were told that the task involved two parts that would be administered 24 hours apart. Of the initial 80, 62 participated in both parts of the experiment. There were no significant differences in demographics or Day 1 scores between those who participated on Day1 plus Day 2, and those who participated only on Day 1. Of the 62 full participants, 34 (55%) were female. Participants had an average age of 35 and working an average of 37 hours per week.

Procedure

Participants in this study were first told that the task involved two parts that would be administered 24 hours apart. Once again, after participants gave their consent and filled out a short demographic survey, they were asked to read a passage and answer a question based on what they read. The passage served as an attention filter and those answered correctly were given the same learning materials as those used in Study 1A (with no request to count letters or blond photographs). After reading through the materials, participants were randomly assigned to either a Meaningful Connections condition or a Repeat Only condition. In the Meaningful Connections condition, participants were given ways to connect the new information to existing knowledge, or understand how the new information was related (see Image 1.2 in Chapter 1).

Since the Meaningful Connections condition included a repeat of some information from the initial learning materials (e.g. the lower eyelid is drawn up when we express fear), it was compared to a Repeat Only condition, wherein participants saw the initial learning materials twice. Therefore, the independent variable was the behavior of forming meaningful connections, and it was implemented by the manipulation of whether participants were given additional contextual material or attended to the same information twice.

All participants were then immediately given a knowledge test identical to that used in Study 1A. They did not receive feedback on their performance in this initial test. Twenty-four hours later, participants were given the knowledge test again.

Measures

Reading rate served as a control variable and was measured by the time spent reading the attention filter passage.

The dependent variable was *recall after 24 hours*, and it was measured by the score on the knowledge test on Day 2 of the study.

Results

Participants who were given meaningful connections (M = 3.22, SD = 7.36) scored significantly better on the Day 2 knowledge test than participants who read the information twice (M = -1.03, SD = 9.13), $t(60) = 2.02$, $p < .05$. Results held when controlled for reading rate in a multiple linear regression. Time spent reading was again a significant predictor of performance for both Day 1 ($b = .14$, $p = .03$) and Day 2 ($b = .15$, $p = .03$) in both conditions. In addition, the difference between conditions on the Day 2 knowledge test was greater when controlled for Day 1 scores, $t(60) = 2.35$, $p = .02$,. However, there was not a significant difference in Day 1 scores between the two conditions, indicating that repetition and forming meaningful connections have similar effects in the short-term.

Study 1C: Repeated Practice with Feedback

Study 1C tested Hypothesis 1C that repeated practice with feedback leads to increased ability to practically apply knowledge in a performance task.

Participants

Participants were 34 working adults recruited on Amazon Mechanical Turk. Forty participants met the criterion of working at least 20 hours per week, but six were dropped because of a technical glitch that did not capture their first round score. Of the 34 participants 19 (56%) were female. Participants had an average age of 34 and worked an average of 35 hours per week.

Procedure

Study 1C was an observational study that tested whether repeated practice with feedback led to performance increases over time. As in Study 1A and 1B, participants were asked for their consent and filled out a short demographic survey. Once again, they were asked to read a passage, which served as an attention filter. Those who passed the attention filter were told that they would be given information on reading facial expressions and would be asked to perform a task based on what they read. All participants were given the learning materials used in Study 1A, plus the contextual information used in the Meaningful Connections condition of Study 1B. Once they completed the learning materials, all participants were asked to apply their knowledge by identifying compound expressions (see Chapter 1, Image 1.4)

Because Study 1C was conducted to test whether continued practice leads to improved performance, it employed a within-person, repeated measures design. It tracked average performance differences after each round of practice. After reading the materials, all participants were asked to attempt to identify the 21 separate facial expressions and were required to participate in 10 rounds to do so. After each round, participants clicked on a "Check Answer" button that told them how many (but not which ones) they got right. Since participants were not told which faces they identified correctly, their scores could go up or down each round unless they learned which faces were correctly identified through repeated practice with feedback. This low level of feedback served as a conservative test of this hypothesis. In addition, this measure was intended to capture repeated practice with feedback after failure. With the minimal feedback, the task was rendered difficult enough that, even with 10 practice rounds, no one was able to successfully complete it, though they were able to improve their performance.

Measures

The dependent variable was *increased performance*, and it was measured by whether performance improved by each practice round.

Results

Study 1C showed that individual performance improved after practice, as shown in Figure 2.4.

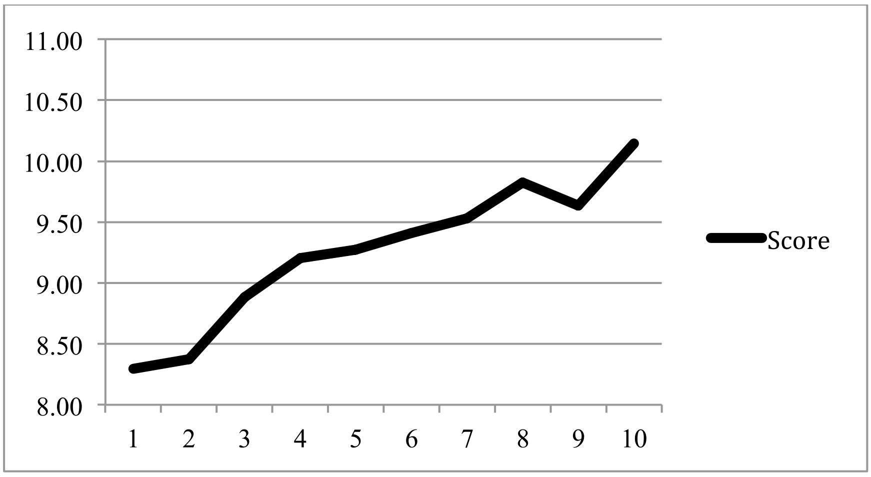

Figure 2.4 Effect of Practice Round on Score (Number of expressions correctly identified out of 21 photos)

Average scores went up after each performance though individual scores fluctuated, mimicking the real-life experience of learning something new. Regression analysis shows that scores significantly increased with each round ($b=.19$, $p<.001$), providing support for Hypothesis 1C. Regressions results also show that time spent reading the contextual materials had a significant effect on average scores ($b=.29$, $p<.001$), controlling for the effects of practice round. This demonstrates that the learning behaviors of forming meaningful connections and repeated practice with feedback independently contribute to increased performance. The learning behavior of attending to information did not significantly increase scores revealing that, though attending to information increases short-term knowledge retention as shown in Study 1A, it is not enough to impact performance.

Finally, deeper analysis also reveals that significant differences in performance from the first round only emerged after the fourth round ($t(34) = -3.3$, $p < .01$) and increased through the tenth round. Further, differences between any two consecutive rounds tended to be small, demonstrating that with this measure, learning occurs incrementally with repeated practice with feedback.

Study 1 Discussion

Studies 1A, 1B, and 1C were conducted to test whether engaging in the key learning behaviors of acquiring information, forming meaningful connections, and repeated practice with feedback led to the outcomes predicted in the LABS model. Together, they showed that, when an individual is learning complex material, attending to learning materials increases short-term retention, forming meaningful connections increases knowledge retention beyond the short-term, and repeated practice with feedback increases performance. In fact, these studies demonstrate that forming meaningful connections both increases longer-term knowledge retention on a factual test and independently contributes to increased performance. This aligns with the LABS model, which suggests that forming meaningful connections enables increased performance because it frees up attentional resources to concentrate on the task at hand.

Because each learning behavior contributes to learning outcomes, the LABS model suggests that the self-directed long-term learning needed to develop expertise is dependent on engaging in all five behaviors. Without taking on a challenge, self-directed learning will not begin. Attending to information enables retention in short-term memory, a pre-requisite for transfer to long-term memory. Forming meaningful connections facilitates transfer to long-term memory and frees up memory resources during practice. Practice requires retrieval from long-term memory, which, along with even minimal feedback, helps to strengthen the memory and increases performance. Although not shown empirically, research suggests that performance trials provide the content for critical reflection (Anseel et al., 2009; Mezirow, 1990), which may help build new meaning and consolidate information into long-term memory.

Of course, these studies did not demonstrate expertise development or learning beyond 24 hours. However, they did show that each behavior contributes meaningfully to the different learning outcomes that cumulatively result in expertise over time. These observations lead to the first proposition of the LABS model:

Proposition 1: All five learning behaviors are required to achieve expertise.

Optimal Order of the Learning Behaviors

Thus far, this chapter has named five stages of expertise, the learning behaviors needed to achieve each stage, and the learning outcomes of those behaviors. In addition, long-term learning likely requires multiple iterations through the behaviors and stages, and the development of true expertise certainly requires a large number of iterations. In fact, it can be detrimental to dwell too long on one behavior, rather than iterating repeatedly through the process. For example, in a meta-analysis of deliberate practice, Macnamara et al. (2014) (2014) showed that repeated practice with feedback alone predicted increased performance only in highly stable domains in which knowledge changes little over time. In rapidly-changing professional settings, new levels of expertise are reached by continually taking on new challenges, gathering more information, forming more connections, practicing more difficult tasks, and reflecting more deeply on underlying principles. While true novices start with no information -at iteration zero- some expertise is gained with each iteration.

Although expertise development is iterative, in this section, I will argue that it is also both sequential and dynamic. I will integrate Dual Process Theory (Wason & Evans, 1974) with Dynamic Skills Theory (Fischer, 1980) to posit that each behavior is reliant on the previous one and enables the next, and that learners will move back and forth through the behaviors depending on the extent to which they have accomplished each stage. Specifically, I will argue three points. First, that the most efficient way to learn is to go through each stage sequentially and not move to the next stage until the relevant learning outcome has become automated. Second, that each stage must be completed for expertise development. Third, that, due to the dynamic nature of learning particularly in organizations, learners will regress within stages and regress to earlier stages such that, in reality, learning appears to be a back and forth, rather than sequential, process. Figure 2.5 depicts the iterative, sequential and dynamic nature of the LABS model.

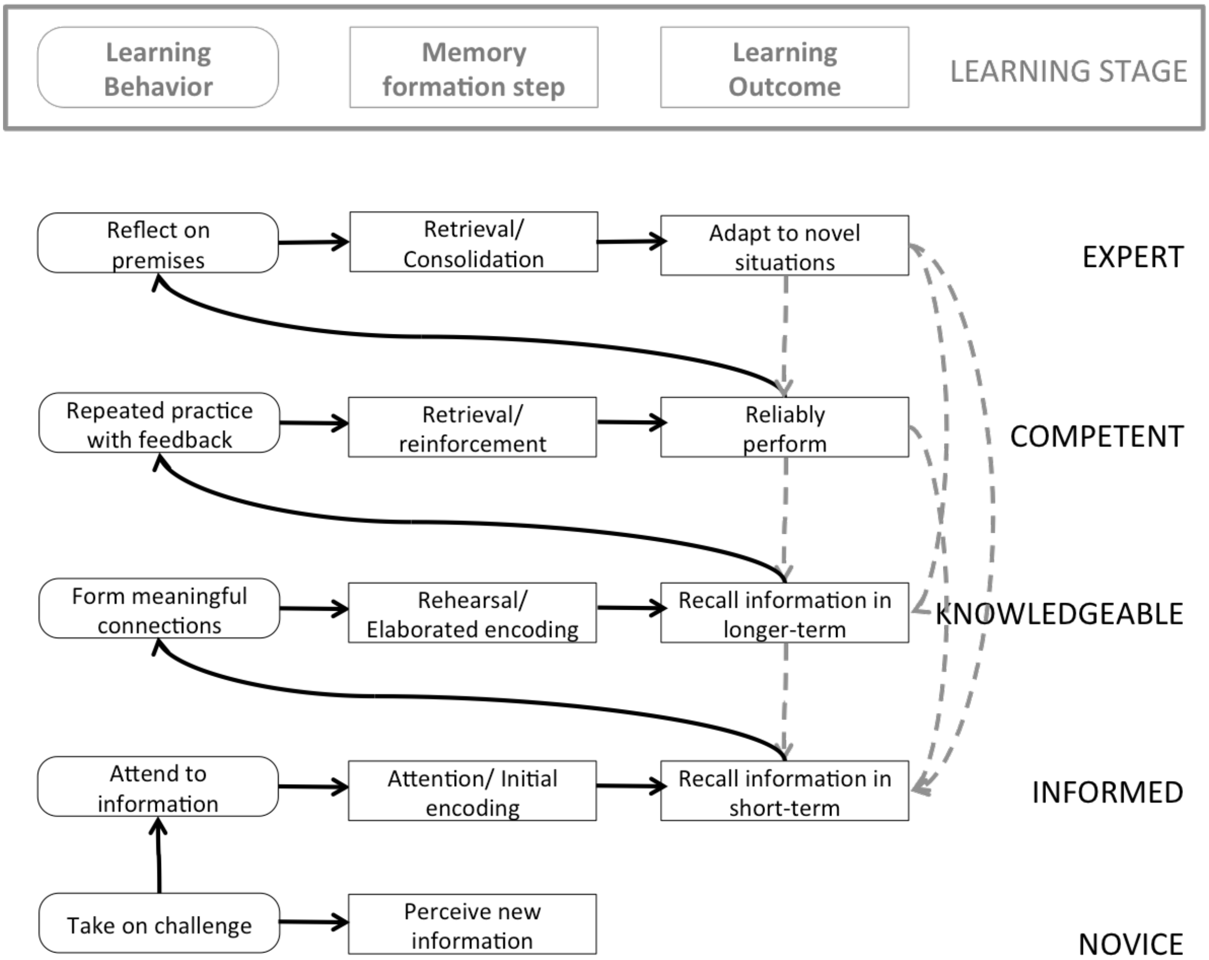

Figure 2.5 Partial Learning As Behaviors (LABS) - Dynamic Stages

Dual Process Theory (Wason & Evans, 1974) suggests that thinking and reasoning involves two distinct types of processes. System 1 processes are intuitive, fast and autonomous (occurring without conscious effort), while System 2 processes are reflective, slow and cognitively demanding (Evans, 2003). These processes relate to learning in different ways. System 1 is characteristic of implicit knowledge, which is not easily articulated but is readily accessible for practical application (Reber, 1993). System 2 is characteristic of explicit knowledge, which is more readily articulated, but is cognitively demanding to apply (Rolison, Evans, Dennis, & Walsh, 2012). Distinguishing between these automated (System 1) and controlled (System 2) cognitive processes has engendered a large body of research which argues that the automation stems from cognitive processes that were once controlled and conscious (Chaiken, 1980; Evans, 2003; Kahneman, 2011; Shiffrin & Schneider, 1977). While further research has shown that implicit knowledge can be acquired without conscious awareness, self-directed learning is, by its nature, a conscious choice (Reber, 1993; Sun et al., 2014). The cognitive processes underlying the LABS model move from conscious deliberate action (System 2 processing) to automated performance (System 1 processing) – and, sometimes, back again.

The main proposition of Dual Process Theory that applies to the LABS model is that deliberate thinking requires access to working memory, while automated thinking does not (Evans, 2003). Viewed through this light, the learning behaviors can be seen as ways to move knowledge and skills from requiring the limited resources of working memory to relying on the seemingly unlimited capacity of long-term memory (Ericsson & Kintsch, 1995). At each stage, the learner gains a new capacity. The informed learner is familiar with the new domain but can only recall information in the short term. Recalling information in the short-term is a necessarily conscious process but it is a pre-requisite to the more automated recall that occurs through deeper understanding. The knowledgeable learner understands to some extent how the new information connects with what they already know and has formed new associations. As these associations become solidified, the knowledgeable learner can recall the information with little conscious effort. This sets the stage for applying that knowledge through repeated practice with feedback. The competent learner is able to apply the information automatically and consistently. In the process, the competent learner has acquired a good amount of practical experience, including both successes and failures. Therefore, only the competent learner is able to engage in critical reflection on those experiences. Finally, through critical reflection, the expert is able to apply the information in novel situations. Critical reflection helps learners detect underlying patterns within the domain and discover fundamental principles. Therefore, experts can tackle situations they have never before experienced because they understand the principles involved (H. A. Simon & Chase, 1973). Each new stage is reached when the learner moves from the high cognitive demands of deliberate effort to reliance on the automated tacit knowledge.

However, Dynamic Skills Theory asserts that learning is dynamic and learners regress throughout the learning process due to “the pervasive variability of human activity” (Fischer & Bidell, 2006, p. 315). By integrating Systems Theory with studies of cognitive development, research using the tools of Dynamic Skills Theory shows that because learning is a supported process, learners often regress in their learning (Fischer & Paré Blagoev, 2000). Specifically, learners, even self-directed learners, rely on others’ knowledge and expertise throughout the learning process. Whether it is paying attention to the learning materials developed by experts, reaching out to experts to help form meaningful connections, or relying on experts for relevant feedback, individual learning is built on the knowledge of others. Therefore, learners’ progress can be impacted by the extent to which knowledgeable others (or their materials) are available throughout the learning process. For example, consider how easy it is to understand a difficult concept when talking with an expert about it but how you might struggle later when you are on your own. Learners regress throughout the learning process but move forward as they gain independence over their learning.

The work in Dynamic Skills Theory is built on the observation that what students can do in the classroom with a teacher is not necessarily representative of what they can do at home by themselves, at least while in the learning process (Vygotsky & Cole, 1978). Overall, learners generally do make progress, but not in a linear fashion. Fisher (1980) notes that humans seldom function at peak performance for sustained periods of time so regression is a natural part of the learning process. In addition, so much time may have passed that previous learning needs to be refreshed. Therefore, although learners may have previously achieved a given stage of expertise when supported, they often have to re-engage in that stage to move forward in their learning. Knowledge and skills that were once automated need to be refreshed through conscious effort.

Moreover, I will argue that this regression occurs in a predictable manner in that learners will need to re-establish automated processing of either the current or earlier stage before they can move forward, as illustrated in Figure 2.4. If regression occurs within a given stage, learners need to exert conscious deliberate effort toward automating the learning outcome of that stage. For example, practicing more purposefully to regain a previously accomplished skill and once again achieving the "competent" stage (see Figure 2.4). If regression to an earlier stage occurs, learners need to exert conscious deliberate effort toward automating the learning outcome of that earlier stage. For instance, although learners may once have previously had a good conceptual understanding of a domain, they may regress to the point that they have to work to recall even basic facts.

This regressive pattern is likely amplified in organizational settings where the course of learning is consistently interrupted by work demands, and priorities change. Long-term memory, though vast, is subject to interference prior to consolidation (Shiffrin & Atkinson 1969). Therefore, throughout the learning process, interruptions, changes in priority, or lack of use at a given stage will result in a regression of learning and the learner must re-establish previous neural connections. Below I will suggest how these dynamics play out for each learning behavior and stage of expertise.

Taking on a challenge

Taking on a challenge is a bit different from the other behaviors because it is simply a choice rather than the actual exertion of effort required by the other learning behaviors. Nonetheless, self-directed learning cannot occur without making this choice. Taking on a challenge is critical because choosing to engage in learning is the characteristic of self-directed learning that differentiates it from incidental learning (Marsick & Watkins, 2001) or learning from experience alone. Learning can occur without conscious effort, but developing expertise depends on, and is accelerated by, ongoing conscious effort (Duckworth et al., 2007; Ericsson et al., 1993).

In self-directed learning, the learner must actively choose, for example, whether to pay attention to online training or check her email, whether to listen deeply to a client or assume she knows the answer, and whether to figure out how to correct an error or ignore it. Each time she is choosing to either engage in slow, deliberate learning, or rely on the knowledge she already has in her long-term memory. This is not to suggest that once the choice is made, the learner will never deviate from it. More than likely, learners have to actively choose to learn multiple times during the learning process; each time, the choice is needed before self-directed learning can occur.

Attending to information

When learners attend to information, they first rely on conscious deliberate processing to acquire the data, but they quickly and automatically make associations with what they already know. In essence, they rapidly move from System 2 to System 1 processing at this early stage of learning. For example, when individuals encounter a new word while reading, they first put that word in the context of the sentence and may think of other similar words or roots to decipher it. Individuals initially connect new information to fit into an existing schema or mental model of the world (Piaget, 1966). This rapid adaptation enables individuals to make sense of novel stimuli so that individuals can simply categorize things by key features and quickly process variations of known stimuli (Rosch, Bloom Lloyd, & Science Research Council US, 1978). This means, for example, that individuals do not need to learn an entirely new category each time they encounter a different species of dog, but it also means individuals are prone to stereotyping (C. T. Miller, 1986).

Overall, however, this automatic categorization is a powerful tool for remembering new information. In a series of experiments, Ausubel (1960) showed that when readers were given a title to a passage that described an everyday activity (clothes washing) they were able to remember more words and details than readers who read the same passage but were not given the title. These 'advanced organizers' enabled individuals to automatically categorize the new information with what they already knew, thereby increasing retention. This process is automatic and serves to free cognitive resources to deal with truly novel information.

However, this retention is short-lived and the new information is quickly forgotten unless those connections are reinforced (Ebbinghaus, 1913). When attention is diverted, the learner may regress to the novice state, as if they had never attended to the information at all. Because attentional resources are limited (Nissen & Bullemer, 1987; Pashler et al., 2001), short-term memory is quite fragile, as demonstrated in Study 1A. In addition, the rapid categorization is less helpful in retaining truly novel information. For this, the learner must create new categories by exerting deliberate effort to form meaningful connections.

Forming meaningful connections

When new information doesn't fit into an existing schema or does not immediately connect to existing knowledge, more deliberate System 2 effort is required. This can take one of two forms, rote memorization or building new meaning. Rote memorization is a powerful tool for remembering things in the long-term and individuals will, eventually, be able to recall the information automatically, without taxing working memory. Each of us can still likely recite songs, prayers, or other anthems learned from childhood. However, rote memorization is limited in its use (Mayer, 2002). Memorizing a passage is distinct from understanding it and applying the lessons from it – in other words, for developing true expertise. Therefore, forming meaningful connections is a more effective way of automating knowledge for further use (Rick & Weber, 2010; Shuell, 1990). It takes deliberate and conscious effort to build or learn the connections between ideas and understand the meaning of information in a new domain but once accomplished, that information is not only automated, it is available for practical application (Perkins & Blythe, 1994).

However, Dynamic Skills Theory would suggest that maintaining these connections can be difficult because meaning is often derived from the learner's environment and that environment is dynamic (Fischer & Bidell, 2006). The classic example of how the environment impacts meaning during learning is Bandura & Ross's (1961) famous Bobo doll experiment. In this experiment, children watched an adult behave either aggressively or non-aggressively toward a Bobo doll and were then put into a room with the Bobo doll and other aggressive (mallet, dart gun) and non-aggressive (tea set, crayons) toys. They showed that children discerned how to act towards the doll through their observation of the adult's behavior. Applying this to a more relevant organizational example, consider the newly onboarded employee. When she first begins work, she makes meaning of her responsibilities by how they contribute to a departmental or organizational goal. Therefore, she attends to information specific to that goal and makes connections between her work and that goal as she learns how to perform her work. However, if either that goal is not reinforced (her manager doesn't support it) or the goal changes due to organizational shifts, the meaning itself is unstable. Forming meaningful connections takes time and is subject to both interference in the learning process and changes in the environment that convey the meaning. This suggests that learners are not just susceptible to regression, but are actually likely to regress in this stage and will need to recreate meaning as they seek to develop expertise in a new domain.

Repeated practice with feedback

The meaning developed through forming connections is critical to the learner's ability to move to the next stage of repeated practice with feedback. Research in problem-based learning has shown that learners struggle when trying to solve problems without requisite knowledge in long-term memory (Hmelo-Silver, 2004). Specifically, they cannot discern between surface and diagnostic aspects of the problem, so their working memory is consumed by tasks that are not useful in finding the solution. However, once learners have an understanding of the domain, they are more able to concentrate on the task at hand and repeatedly practice applying the knowledge.

Repeated practice with feedback provides perhaps the most straightforward example of transfer from System 2 to System 1 thinking, as well as learner regression. Cognitive and procedural skill acquisition occurs over time, with practice (Ackerman, 1988; J. R. Anderson, 1982). In a study using an air traffic control simulation, Kanfer & Ackerman (1989) found that before performance routines become automated, learners' cognitive resources are directed towards mastering the process rather than attaining a specific level of performance. Early on, practice takes conscious deliberate effort and this effort is specifically directed at automating skills and knowledge (Seijts et al., 2004).

However, reaching consistent automated performance is also dependent on not only receiving feedback (Ericsson et al., 1993) but receiving the right kind of feedback (Hammond, Summers, & Deane, 1973; Kluger & DeNisi, 1998). In learning situations where there are straightforward right and wrong answers, immediate and relevant feedback helps learners reinforce the correct neural connections and forget incorrect ones(Karpicke & Blunt, 2011). However, in more complex learning situations where relationships are not always fully predictable, such as learning how to diagnose medical issues based on symptoms, feedback needs to take a different form. Research on multiple-cue probability learning shows that feedback about the relationships between the cause (disease) and effect (symptom) is superior to feedback about whether a given answer is right or wrong(Steinmann, 1976). In both cases, however, practice increases neural efficiency (J. R. Kelly & McGrath, 1985). The effectiveness of the feedback relies on which connections are targeted. Repeated practice with feedback is an exercise in moving from conscious deliberate effort to automatic, quick, and accurate performance.

Practice occurs through repeated retrieval from long-term memory but this retrieval is vulnerable to interference (Wickelgren, 1974) until the information is consolidated, which can take years (R. C. Atkinson & Shiffrin, 1968). Practice helps build and solidify neural connections through retrieval of stored information. However, Ericsson & Kintsch (1995) show that experts don't just store information, but use it skillfully. They assert that expert individuals rely on retrieval cues to quickly access accurate information during task performance and that, in addition to the increasing skill levels, practice helps build and reinforce these cues. For example, when tackling a physics problems, experts know *which* information to recall to solve the problem, making the process much more efficient. Not knowing these cues is akin to having the full internet at your disposal but not knowing which search words will get you the information you need. Retrieval cues are related by close association to the stored information and are available through the situation at hand. Thus, there are two parts of retrieval that are subject to interference during learning. The first is the stored information being recalled. The second is the cue to call up the most relevant information. Learners can regress in either one of these areas. Particularly in work contexts, where there is rarely structured time set aside to practice skills and receive feedback, learners can backslide in skills they have previously accomplished, causing them to re-engage in deliberate conscious processing before the skills are once again automatically available.

Reflection

Critical reflection represents a reversal of the System 2-to-System 1 processing that characterizes the earlier stages of learning. Critical reflection involves making the effort to bring automated thoughts, processes, and beliefs to conscious awareness (Ellis & Davidi, 2005a; Mezirow, 1990). While the previous three learning behaviors are directed toward more efficient learning, critical reflection is a deliberate break in that efficiency. It involves slowing down and examining the tacit knowledge developed in the previous stages. Therefore, while reflection can occur at any point in the learning process, critical reflection is only useful after all previous stages have been accomplished. However, just as in previous stages, critical reflection is likely highly dependent on environmental factors and supports. Specifically, critical reflection is most useful in novel situations where automated practices are ineffective. To perform well in novel situations, individuals must understand the underlying principles of the domain (Chi et al., 1981). It is this causal understanding that allows experts to analyze, evaluate and generate new knowledge, which are the highest levels of learning (L. W. Anderson, Krathwohl, & Airasian, 2001). Critical reflection is needed to 'solve problems so they remain solved' when new situations arise (Argyris, 1976; Schön, 1983; Zollo & Winter, 2002).

However, critical reflection is difficult, time-consuming, and often requires intervention (Argyris, 1983), so organizations are unlikely to provide the time and support for reflection to employees unless and until existing systems are explicitly disrupted. This prevents competent learners from developing into experts. In addition, because critical reflection is most useful in novel situations, which don’t occur as often as standard performance issues, even experts are likely to regress in their knowledge and skills. Experts can adapt readily because they define new problems through key principles (Chi, Glaser, & Rees, 1982) and have the requisite knowledge in long-term memory to free up cognitive resources (Ericsson & Kintsch, 1995) to deal with the problem at hand. However, there may be long periods of time between events that call on this depth of knowledge. This lack of use may then require experts to revisit causal connections and key understandings before they can apply them accurately again.

In this section, I integrated Dual Process Theory (Wason & Evans, 1974) with Dynamic Skills Theory (Fischer & Bidell, 2006), to argue that each stage of expertise is reliant on accomplishing the previous stage but that, due to the dynamic nature of learning, particularly in organizational work environments, learners will often regress and need to re-engage earlier stages before they can move forward in the learning process. Therefore, the LABS model suggests that, although the five learning behaviors are best enacted in the order depicted in Figures 2.1 and 2.3, learner regression means that the actual order occurs more dynamically in practice.

Proposition 2: *Successful achievement of each stage of self-directed learning is reliant on the previous stage, but learners will often regress in each stage in dynamic in predictable ways.*

Relative Independence of the Learning Behaviors

The final prediction of the LABS model is that, because the five learning behaviors are likely differentially motivated, any one person is unlikely to enact all five behaviors without intervention. In the first chapter I found that only some of the learning behaviors are correlated. Those who chose a higher level of challenge were more likely to form connections and those who formed connections were more likely to continually practice. However, none of the other behaviors were related. In other words, taking on a challenge did not predict attending to information, repeated practice with feedback or reflection. Attending to information did not predict any of the other learning behaviors and forming connections and repeated practice with feedback did not predict reflection. In general, the learning behaviors were largely independent.

In this section, I draw on expectancy value theory to argue that the five learning behaviors are differentially motivated and that the degree of effort exerted by the learner on each learning behavior changes as a function of the learner's motivation for that behavior.

Expectancy value theory posits that behavior is a function of the expectancy of a successful outcome and the value to the individual of achieving that outcome (Vroom, 1964). In the LABS model, I identify the expected outcomes of the behaviors as short-term recall, longer-term recall, reliable performance, and the ability to adapt to novel situations. In organizational settings, these outcomes will be valued differentially by the learner according to the nature of the assignment, which may not always call for a fully developed expert. Short-term recall, long-term recall or consistent performance may be perfectly sufficient for the task at hand. In some cases, for example, an employee may need to learn only enough biographical information to introduce someone in a presentation. Likewise, there will be different expectancies of success for the behaviors based on individual differences. A review of the learning behaviors reveals that they have, at times, nearly opposite antecedents. Thus, it is unlikely that one individual will freely choose to enact all five. Figure 2.5 outlines potential drivers for each learning behavior, making particular note of those that seem to drive one behavior and interfere with another.

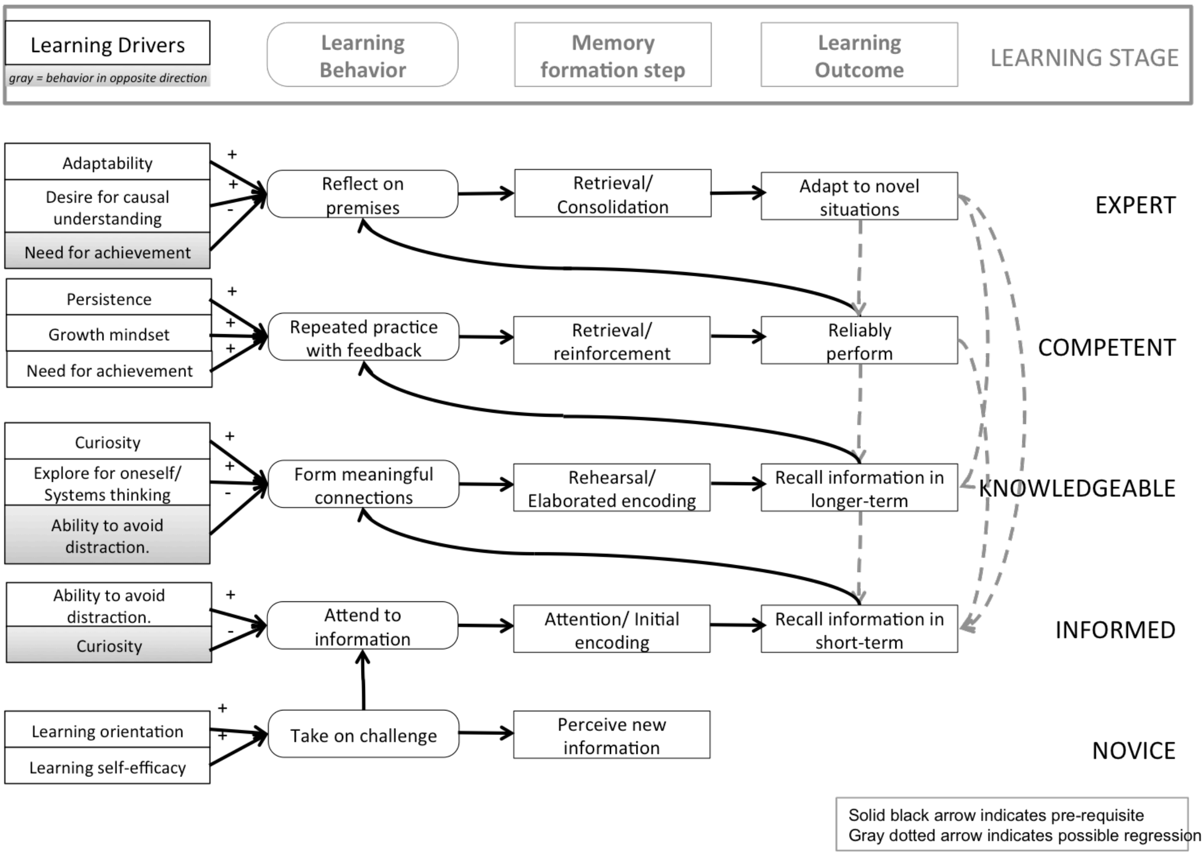

Figure 2.5 Full Learning As Behaviors (LABS) Model

Taking on a challenge

Because taking on a challenge typically occurs prior to having knowledge of the new domain, the expected outcome is nothing more than a general sense of setting out to learn the new domain or meet the challenge. In other words, though there is no actual learning outcome from taking on a challenge alone (as shown in the LABS model), learners typically perceive the outcome of taking on a new challenge in general terms. Particularly in organizational settings, the intense cognitive demands of being a novice in a new domain (Ericsson & Kintsch, 1995) may interfere with the ability to perform well in one's established domain of expertise. Taking on a new challenge rarely means the rest of the work stops. Therefore, individuals must be sufficiently self-efficacious in their ability to learn that they believe they will be able to handle the new challenge (A. Bandura, 1977) without sacrificing existing performance.

Those who value learning will be more likely to take the risk of a dip in performance (Dweck, 1975; Wigfield & Eccles, 2000). As discussed in Chapter 1, the value individuals place on learning at work is captured in scales of learning orientation, which is a dimension of goal orientation (Dweck, 1986). Goal orientation scales, originally designed to capture differences in how children respond to failure when facing a challenge (Dweck, 1986), have been adapted to workplace settings. Because most work environments prioritize performance over learning, the adapted learning orientation items instead capture the value that a worker places on learning in that environment (Button et al., 1996; VandeWalle, 1997). Chapter 1 directly tested this and empirically showed that learning orientation predicts taking on a challenge but not the subsequent learning behaviors.

Therefore, the learning behavior of taking on a challenge calls for a confident (high self-efficacy) employee who values learning challenges. However, taking on a challenge is not the same as following through on it (Hollenbeck & Klein, 1987; J. T. Klein, 2008) and the thrill of a new challenge can quickly translate to frustration when confident employees face the cognitive demands of being a novice again.

Attending to information

Meeting these demands begins with attending to information in the new domain. The outcome of this learning behavior is short-term retrieval. Achieving this outcome calls for the ability to pay attention and ignore distractions. In some ways, this learning behavior is the easiest because, in today's information-rich environment, learning materials tend to be readily available. Research has shown that employees typically engage in local search (immediately available information) and leverage existing resources (Baum & Dahlin, 2007; March, 1991) when they need new information as problems arise. This increases the efficiency of learning because it relies on the established knowledge reservoirs of experts.

However, engaging with the content can be tedious. Research on self-regulated learning shows that those who can protect their intention to learn by ignoring distracting stimuli are more likely to complete difficult and tedious learning tasks (Corno, 1986; Kuhl & Kazén, 1999). The learning behavior of attending to information calls for the ability to focus and diligently pay attention. The person who is eager to take on the challenge may struggle when she needs to follow through on it by ignoring other potentially exciting stimuli or pressing work tasks, and focusing on attending to new information. However, the employee who is focused enough to ignore distractions and attend to information may struggle with forming meaningful connections because doing so means having the curiosity to explore beyond readily available information.

Forming meaningful connections

Whereas information acquisition occurs through local search and existing resources, forming meaningful connections calls for curiosity (Camp, Rodrigue, & Olson, 2006; S. H. Harrison, Sluss, & Ashforth, 2011) and variance-seeking behaviors (R. McGrath, 2001). Curiosity is defined as the motivation to engage in exploratory behaviors, such as exploring the context of a new domain to give information meaning (Voss & Keller, 2013). To retain information and build a knowledge reservoir, individuals must abandon the disciplined effort of studying readily available information in favor of the possibly distracting work of exploring the breadth of the new domain. The outcome of forming meaningful connections is longer-term recall, which requires having a higher-level (Burgoon, Henderson, & Markman, 2013) systems view (Senge, 1990) of the learning content.

The learning behavior of forming meaningful connections calls for a curious individual who seeks to understand the domain in their own right. This activity tends to be cognitive, rather than hands-on. Forming meaningful connections means explicitly making mental connections between new and existing information and deliberately working to construct a new mental model (Shuell, 1990). Engaging in the learning behavior of forming meaningful connections may have less appeal to someone who highly values hands-on practical experience.

Repeated practice with feedback

However, practical application relies on meaningful understanding of the domain (Hmelo-Silver, 2004). Before skills are automated, practice takes deliberate effort. The less learners have to rely on calling up memorized facts or looking up information, both of which tax working memory, the more they can concentrate on the task at hand (Shipstead et al., 2015). The learning outcome of practical application is consistent performance. The behavior calls for persistence, particularly in the face of failure. Trying again after failure requires overcoming the tendency to attribute failure to factors that cannot be changed, such as innate inability (A. Bandura & Wood, 1989; Dweck, 1986; A. Thomas, 1979). Research has shown that people with a growth mindset, who believe they can improve with effort, are more likely to persist when they experience failure, particularly during learning (Dweck, 1986). Adopting an experimental mindset (Campbell, 1969; Sitkin, 1992) by viewing learning failures as feedback can maintain the positive self-image needed to persist in the face of failure (Diwas, Staats, & Gino, 2013).

Continuing to try, even in the face of failure, is also likely driven by the need for achievement (J. W. Atkinson & Feather, 1966). The need for achievement is the desire to become excellent and reach high levels of performance. It has been linked to both learning and performance outcomes in a variety of settings (see Spangler, 1992 for a review). As individuals develop new skills, those high in need for achievement are more likely to continue practicing to keep improving and may be more motivated by the longer-term goal of excellent performance, and less vulnerable to the short-term setbacks and regressions of the learning experience. Also, if they practice more consistently because of their desire for excellence, they will experience fewer regressions and more progress, which itself can be motivating (Amabile & Kramer, 2011).

In summary, then, the learning behavior of repeated practice with feedback calls for a persistent individual with an adaptive relationship to failure and high need for achievement. Once again, this behavior seems quite distinct from the previous learning behaviors. For one thing, failure is more salient and visible during practical application, and openness to feedback is more critical. In addition, individuals who find earlier behaviors more cognitively tedious may enjoy actively trying to apply and build skills, even if it means failure is more likely.

Critical Reflection

Critical reflection is the least studied and therefore least understood learning behavior. Its outcome is the ability to apply knowledge in novel situations through understanding fundamental principles. In organizations, being highly competent - the outcome of repeated practice with feedback - is often seen as the end-point of expertise development. Understanding fundamental principles only becomes important when a novel situation occurs. Research in dynamic capabilities (Zollo & Winter, 2002) shows that codification of knowledge enhances the ability to adapt to novel situations. Although the dynamic capabilities literature focuses on the organizational level, the critical analysis of processes and events that allows organizations to adapt to change is performed by individuals (Helfat & Peteraf, 2015). Dynamic capabilities rely on understanding the causal factors driving events in organizations – that is, why certain efforts succeeded or failed. Such understanding can then be applied to related but novel situations.

Similarly, at the level of individual learning, critical reflection stems from a desire for causal understanding by questioning underlying assumptions. However, the answers to these questions may be threatening to highly competent performers. Work by Dane (2010) argues that highly competent individuals can become cognitively entrenched, rendering them less flexible when faced with novel situations. Therefore, the competence developed through repeated practice with feedback stands at odds with the detached analysis of success and failure that characterizes critical reflection (Ellis, Carette, Anseel, & Lievens, 2014; Mezirow, 1990). In addition, someone who prefers immediate feedback and has become highly competent may have difficulty stepping back to reflect, which is less immediate process.

Consideration of the differentiated nature of the learning behaviors involved in expertise development suggests a new piece to the puzzle of why expertise development is so hard. The learner must be highly self-confident while valuing others' expertise, diligently focused yet curious and exploratory, doggedly persistent yet critically analytic. The LABS model therefore predicts that, without intervention, it is highly unlikely that any one individual will engage in all five learning behaviors.

Proposition 3: Any one individual is unlikely to freely choose to engage in all five learning behaviors.

Discussion

This chapter drew from the findings in Chapter 1 to develop a new model of individual expertise based on self-directed learning behaviors, the Learning As Behaviors (LABS) model. First, I drew from Atkinson and Shiffrin's (1968) well-established model of long-term memory to describe how each learning behavior leads to a different learning outcome. Then, using the Learning Behaviors Methodology introduced in Chapter 1, I presented three studies that empirically demonstrated that three of the behaviors lead to the predicted outcomes. Second, I integrated Dual Process Theory (Wason & Evans, 1974) with Dynamic Skills Theory (Fischer & Bidell, 2006) to derive the optimal sequence of the behaviors, taking into account natural learner regression in the actual process. Finally, I drew from expectancy value theory to reveal a previously unexplored barrier to expertise development: any one individual is unlikely to engage in all five learning behaviors.

The LABS model and its attending propositions make three novel contributions to individual learning research. First, demonstrating different outcomes for each behavior presents a way to conceptualize learning as a systematic process rather than a unitary construct. Learning requires different behaviors and different outcomes based on the stage of the learner, but these stages, behaviors, and outcomes are systematically driven by the way information flows from short to long-term memory. This conceptualization enables researchers to more precisely target optimal learning environments for each learning behavior, with the understanding that these environments may, and likely do, differ as learners progress.

Second, though learners overall tend to progress forward in their learning, learner regression is often overlooked as a natural and predictable process in organizational learning. The LABS model asserts that self-directed learning operates in a given order but that learners tend to regress both within and across stages of expertise. This insight may help integrate work on informal learning (Marsick & Watkins, 2001) and workplace training in active learning interventions (Bell & Kozlowski, 1984). Active learning is characterized by integrating training related practices with self-monitoring and feedback to enable greater training transfer (S. Kozlowski & Bell, 2009). The active learning framework is particularly relevant for self-directed learning interventions because it puts the learner at the center of the design. By applying the LABS model to the active learning framework, training designers can consider the optimal order of the learning behaviors along with the regressive nature of learning, thereby more directly addressing learner needs throughout the full dynamic process of learning.

Third, the revelation that learners have preferences for engaging in some behaviors and resist others contributes to research on growth mindset (Dweck, 2006). Work on growth mindset proposes that people have different implicit theories of learning based on domain (Dweck, 2006). For instance, individuals may believe they are naturally good at math but don't have any talent for drawing. The LABS model further refines this perspective by suggesting that individuals also likely have different implicit theories about each learning behavior, even within the same domain. Therefore, although someone may believe they are talented in math, they may also feel they only 'really' learn it through practice with feedback. In this case, their learning would be inefficient because the LABS model implies they would need some conceptual understanding prior to being able to meaningfully practice a new math skill.

Finally, I argued that, at times, the preferences that drive the learning behaviors are oppositional. I posited that these preferences were based on individual differences and learning self-efficacy. However, it is highly likely that situational conditions also likely differentially impact whether learners engage in each of the learning behaviors. Although there are many streams of research that examine what conditions motivate learning (Cole, Feild, & Harris, 2004; Colquitt & Simmering, 1998; e.g. Dweck, 1986; Kuhl, 1981), one that has had a strong impact in the field of management is that of external goal-setting, which has found that different types of goals motivate learning based on the level of competence of the individual (Locke & Latham, 1990). The LABS model provides further explanation for the differential effects of goals on learning outcomes by delineating different levels of competence for each stage of learning.

Conceptualizing Self-Directed Learning

While there is a vast body of research on individual learning in education and cognitive psychology, work in management is limited (Noe et al., 2014). In addition, it is difficult to bring together what work has been done because of the tendency to treat all learning activities under a single umbrella of learning, thereby muddling what we mean when we study learning. For example, research in active learning conceptualizes experimenting, seeking feedback, and reflecting on results under a single umbrella of "exploratory learning" (S. Kozlowski & Bell, 2009). Therefore, work using the active learning framework theorizes about the psychological conditions and environmental factors that impact an overarching construct (Noe & Tews, 2010). However, this work has led to inconsistent findings (Naveh, Katz Navon, & Stern, 2015). The LABS model suggests a reason for this inconsistency. If engagement differs based on the learning behavior, the optimal learning climate for each behavior also likely differs. Where individuals may need access to information and a quiet space to focus and attend to information, they may need to actively reach out to multiple sources to put that information into meaningful context. By identifying each stage, behavior, and outcome of learning, the LABS model provides a path forward for identifying the learning climates that will be most effective throughout the long-term process.

The previous lack of a clear measure of individual learning in the management literature is likely due to a lack of conceptual clarity about how to capture learning in a methodologically rigorous way. While studies at the team level (Edmondson, 1999; Savelsbergh, van der Heijden, & Poell, 2009) and organizational level (Baum, Li, & Usher, 2000; Epple, Argote, & Devadas, 1991; Madsen & Desai, 2010) examine learning as a series of behaviors, researchers working at the individual level rely heavily on self-reported learning orientation (for a review, see Payne et al. 2007) or self-reported learning (Beenen, 2014; Lankau & Scandura, 2002). The few studies that capture specific learning behaviors, such as knowledge acquisition (Seijts et al., 2004) and exploratory learning (Reyt & Wiesenfeld, 2015), strongly contribute to the understanding of how situational conditions can impact a given learning behavior, but remain a-theoretical about the place of that specific behavior in the learning process. The LABS model does not indicate a single unitary measure of learning because a single definitive measure is impossible. Instead, the model clarifies specific learning behaviors and their expected outcomes for each stage of the learning process.

The implication for organizational studies is that researchers now have the means to determine which measure or set of measures is appropriate for a given study. The stage of expertise development of the participants guides the expected outcome. The Learning Behaviors Methodology presented in Chapter 1 provides a practical template for how to capture the underlying behaviors. For example, when employees first take on a new role or assignment, it would be too soon to measure their responses to failure, because they do not yet have the requisite knowledge to determine what responses to make. Alternatively, finding that highly competent employees are more likely to acquire information may actually indicate a resistance to learning a new level of expertise, which requires critical analysis of that information. Simply gathering more information about what you already know may refresh your memory but is unlikely to lead to long-term increases in expertise.

The Dynamic and Progressive Nature of Learning

In much of the learning literature, scholars focus on either formal or informal learning environments but neither seems fully adequate to meet learner needs. This may be because formal learning provides the support needed for learners to feel progress and develop new understanding (Fischer & Bidell, 2006; Vygotsky & Cole, 1978) but, the formal learning environment lacks the context needed to apply that understanding through repeated practice (Blume, Ford, Baldwin, & Huang, 2010). However, while informal learning provides opportunities to form connections and apply knowledge (Marsick & Watkins, 2001), it often lacks the formal support to check one's understanding and receive immediate and relevant feedback. As noted by learning scholars (S. Kozlowski & Bell, 2009; Noe et al., 2014) and suggested by the LABS model, an integrated approach may best serve learners' needs.

Kozlowski & Bell's (2009) framework for active learning describes how formal and informal learning activities can be integrated to serve the longer-term needs of the learner. They consider the self-regulatory processes needed to structure training interventions to optimize learner effort towards practice behaviors, feedback processing, and self-efficacy. They then divide outcomes into proximal learning and distal transfer delineating between what the learner can do at the completion of the training and how to apply that knowledge and skill set on the job.

Applying the LABS model to the active learning framework can help active learning researchers consider which learning outcome is most appropriate for the task at hand. They can also seek ways to support provide more meaningful connections in formal settings and more formal support during informal learning. For example, in most cases, the desired outcome of a learning intervention won't be deep expertise. A new manager doesn't need to discover underlying principles through critical reflection. However, she does need to attend to information, form meaningful connections, and repeatedly practice with feedback. In other words, she needs to understand key principles about how to structure her group, set goals, and handle standard people management, and practical ways to put those principles into action.

Therefore, the training strategy can consider the best way to provide information in a way that helps the new manager form meaningful connections in a formal training setting. Once the manager has a deeper-level understanding, the training intervention can provide practical techniques for how to apply learning. In particular, the intervention could provide access to experts so the new manager can know when to apply new techniques and receive accurate and timely feedback. This structure provides direction for formal and informal training activities and it helps the learner develop the self-regulatory skills to eventually monitor her progress (Karoly, 1993) and evaluate her performance (Kanfer & Ackerman, 1989).

Growth mindset

The LABS model also provides a new way to consider growth mindset (Dweck, 2006) because the model implies that the self-directed learning of adults is influenced by their beliefs of whether certain learning behaviors will lead to desired learning outcomes. This is especially true if individuals conceptualize learning as a single construct and don't realize that reaching some outcomes relies on engaging in multiple behaviors. Therefore, they would be more willing to exert effort towards some behaviors than others.

Research on growth mindset shows that when individuals feel a sense of control over their ability to learn, they are more willing to exert effort towards learning. Specifically, those with a growth mindset believe they can become more intelligent through effort, while those with a fixed mindset believe that intelligence is set and they cannot get smarter (Dweck, 1986). Further, Dweck (2015) argues that we are all a mix of growth mindsets in some domains and fixed mindsets in others. As previously mentioned, a person may believe that she can get better in math but not drawing.

The LABS model suggests that people not only have different implicit theories based on domains, but that they also likely have different implicit theories about each learning behavior, even within the same domain. The LABS model deconstructs learning to show that different behaviors lead to different, but required, outcomes. Therefore, learners may be eager to achieve that specific outcome and only engage in the behavior that directly leads to it. That is, they implicitly believe that their effort will lead to learning through some behaviors but not others. For example, some individuals may believe that they will learn if they acquire new information, but that exploring meaningful connections is a distracting waste of time. Others may feel that they don't really learn until they are able to practice new skills in a hands-on task. People may, therefore, work very hard at learning, but only in select behaviors. However, if successfully engaging in learning behaviors is dependent on achieving previous outcomes, working harder is not enough to gain expertise. Rather, individuals need to work hard at multiple behaviors, some of which they might wish to avoid.

Oppositional Learning Behaviors

Indeed a strong preference for one behavior may actually discourage engaging in other learning behaviors. The LABS model implies the counter-intuitive notion that the learning behaviors may actually stand in opposition to each other. The model provides likely antecedents to each behavior and highlights that what drives one behavior might negatively impact the likelihood of engaging in the others. For example, the focus needed for attending to information is contrary to the open curiosity needed to form connections. Dedication to practical competence likely inhibits the critical analysis of failure that is needed for critical reflection. Given these tensions, expertise development may face the decidedly insidious barrier that engaging in one behavior could undermine engagement in the others.

The idea that antecedents to learning could be harmful to the learning process contributes to understanding both the individual differences, as noted above, and the situational conditions that impact the learning process. For example, work in goal-setting theory shows that urging people to do their best led to better performance than giving people specific challenging goals, when the task required knowledge acquisition (Winters & Latham, 1996). The LABS model would suggest that this is because knowledge acquisition is an effort in moving from conscious deliberate recall to automated recall – the learner is in the stage of forming meaningful connections. This means they don't yet have the requisite understanding to know what contributes to high performance. At this early stage of the learning process, specific challenging goals are too cognitively taxing and take away the attentional resources needed to attend to information and form connections.

However, as learners gain competence, specific challenging goals were more effective because learners had the requisite knowledge and skill to meet the goal (Seijts et al., 2004). From the LABS model perspective, once conceptual understanding is automated and learners can recall relevant information with little effort, learners need guidance on what to try and what feedback to seek during repeated practice. Therefore, specific challenging goals actually free up attentional resources by narrowing attention to the goal. Therefore, the learner can focus on improving performance. Work in goal-setting provides empirical evidence that the conditions that drive knowledge acquisition do not serve the learner who is gaining competence through repeated practice.

Further work delineates goal acceptance from goal planning (Sun et al., 2014). Goal acceptance is equivalent to taking on a challenge; it is the choice of whether or not to strive for a given goal. Goal planning is measured through the amount of resources an individual reports she is willing to allocate towards meeting the goal. Sun et al., (2014) found that self-efficacy is positively related to goal acceptance but negatively related to goal-planning. Thus, they provide further early evidence of the LABS model prediction the antecedents of one learning behavior may interfere with engagement in the others. Integrating the LABS model behaviors with the Learning Behaviors Methodology provides the means to directly observe what resources individuals are willing to allocate towards learning goals (Sun et al., 2014) and the interactive impact of different conditions on the motivation to engage in each learning behavior.

Limitations and Further Research

While the LABS model outlines the stages of expertise, along with required behaviors and expected learning outcomes, it by no means covers all possible individual self-directed learning behaviors. For example, seeking help from others is critical in multiple stages of expertise but is not included as its own behavior in the LABS model. For instance, learners likely need to reach out to gather multiple perspectives when seeking to form meaningful connections. Experts are particularly poised to provide relevant feedback and the learner who relies and listens to expert feedback likely has an advantage. Another behavior that is not explicitly explored is experimentation. Although experimentation is inherent in repeated practice, it likely takes different form as individuals who are already competent seek to learn more. Especially in fields that require innovation, highly skilled employees who experiment with new ways to accomplish their work likely learn more than those who rely on routine behavior.

Beyond this there are multiple ways to engage in each behavior. However, the LABS model does not provide different ways in which individuals might engage in each behavior. For example, an employee could form connections by reaching out to known experts and having conversations, by gathering perspectives from multiple expert and non-expert sources, or by gathering relevant information and systematically putting it together, as in the formation of concept maps (Hay & Kinchin, 2008). In addition, there are many ways to seek and respond to feedback (Kluger & DeNisi, 1998). In some cases, employees gather subjective feedback about their performance from their peers, managers or clients. However, learners could also set up ways to track the impact of their and others' performance over time to determine what leads to success or failure. For example, Diwas et al. (2013) found that surgeons improved most when they reviewed their own successes and other's failures. Organizations and managers could provide data on learners' repeated practice to provide more relevant feedback and find out what really is, and is not, working. The LABS model does not consider how these different ways of engaging in each behavior may impact learning outcomes.

The LABS model would also benefit from studies to empirically test each of the propositions presented. Experiments that systematically remove the ability to engage in each of the behaviors could reveal the extent to which each is needed for short and long-term learning. For example, it could be that learning simply takes longer if behaviors/stages are skipped, or, alternatively, it could be that missing a given behavior may actually prohibit moving forward in the learning process, as predicted by the LABS model. Also studies that test for individual differences can examine the extent to which those differences predict behavior. For example, whether people who are curious resist attending to information but embrace forming meaningful connections.

Beyond these empirical studies, the LABS model opens new streams of research to contribute to work on individual self-directed learning. The first is to examine more in-depth the social nature of learning (Bandura, 1977). Even self-directed learning does not occur in isolation. Bandura's (1977) social learning theory was built off work from Vygostky (1978), which noted that learning does not happen in isolation but is strongly dependent on the support of others and the ability to model desired behaviors and skills. Social learning occurs both at the team and individual level. In organizations, social learning is likely highly influenced by hierarchy and power. Research has shown that manager learning orientation impacts employee learning and performance (Kohli et al., 1998) and that manager style impacts employee learning orientation (Sujan, Weitz, & Kumar, 1994). However, it remains unclear how others' actions might influence each learning behavior identified in the LABS model. For instance, a manager may highly value skilled competence but give little time or value to reflection. A leader may expect a team member to gather information but fail to enable the dialogue required to form meaningful connections about the learning topic within the team. Systematic examination of the learning behaviors could reveal which ones are more socially dependent and which are more immune to the influence of others.

Finally, the vast majority of individual learning research has been done in academic (A. Bandura, 2001; Diener & Dweck, 1980; Dweck & Leggett, 1988; Seijts & Latham, 2001) or formal training (Blume et al., 2010; Salas & Cannon-Bowers, 2001) settings. In these settings, learning is not in direct competition with everyday task performance, and learning is prioritized. Despite the need for employees to readily adapt to develop new areas of expertise, little research directly addresses just how and when employees choose to engage in learning behaviors in the course of daily work. For example, future research should examine how employees form meaningful connections about the learning topic – perhaps by relying on social networks, trusted written resources, group conversation, or managerial insight. Field studies could also help researchers understand in what ways employees practice new skills. Skilled learners may create safe spaces to try new things and get feedback. Insightful managers may put a premium on risk-taking, rewarding process over outcomes as employees are learning. Finally, there is a dearth of research on the ways in which employees reflect. Although studies have found that reflection on both successes and failures boosts learning more than reflection on failures alone (Ellis & Davidi, 2005a), little is understood about what motivates employees to take the time to step back and reflect. Chapter 3 of this dissertation is an attempt to address this question.

Conclusion

We typically assume that expertise development is so hard primarily because of the intense intellectual effort and the fabled "10,000 hours" required; people become experts primarily by putting in more time and working harder. This chapter challenges that assumption. It suggests that expertise development is iterative and that reaching the next level of performance may mean spending less time engaging in behaviors we prefer and more in behaviors we resist. The complete expertise development process is therefore something we are unlikely to carry out without some sort of intervention. The LABS model and the findings from Chapter 1 also suggest that learning is not a single entity. Each of the behaviors is a different type of learning effort or, more accurately, a part of the learning process. Developing the ability to perform consistently in novel situations is, therefore, more than a matter of intelligence and effort. It requires engaging in behaviors that are not inherently aligned, and that may even sabotage each other.

Expertise has a short half-life these days. Studies conducted by Google have shown that college GPA only matters in the first three years of post-college hiring (*New York Times*, June 2013), which implies that much of what is learned through the first 16 years of schooling loses value in less than one-fifth of that time. The pace of technological and scientific advancement, along with the complexity of working and living in a global society, demand a level of thinking and learning unprecedented in human history. Delineating a clear conceptual model of expertise development and revealing some of its heretofore hidden barriers is a step towards providing employees a sane way of meeting that demand.

CHAPTER 3: RAISING AWARENESS WITH EMPLOYEE REFLECTION

Abstract

While research has shown reflection to be a valuable part of individual learning, little has been done to understand how reflection raises conscious awareness of workplace learning. Drawing from Dual Systems Theory, this chapter explores how regular written reflection may increase employee awareness of everyday learning opportunities. It argues that, by getting employees into the habit of reflecting on their learning at work, they will become more aware of the learning opportunities inherent in the everyday challenges they face. I conducted a large-scale field experiment, including 195 employees from an international bank in Europe, where some participants were asked to reflect on their learning twice a week for eight weeks. However, getting busy employees to habitually reflect is no small feat and attrition rates for voluntary reflection are notoriously high. To address this, I included a simple intervention in which one group was given access to their previous reflections, while the other group was not able to see what they had previously written. I found that individuals who were able to review their previous reflections wrote significantly more reflections that those who were not able to see them. In addition, those who could review their previous reflections used more words related to learning and cognition. Finding a simple intervention to motivate ongoing reflection on learning proved important because attrition rates were even higher than expected. Due to the small final sample sizes, even though descriptive statistics indicated that employees who reflected did become more aware of everyday learning opportunities than those who did not, these differences did not near significance.

Introduction

Learning opportunities abound in today's dynamic business environments. Research on job design (Oldham & Fried, 2016), developmental assignments (Dragoni et al., 2009), work characteristics (Skule, 2004), and informal learning (Marsick & Yates, 2012) demonstrate that, particularly in knowledge work, there is opportunity to learn from everyday work tasks. However, in order to do so, employees must be aware of these opportunities and frame work as learning (Raelin, 1997). Unfortunately, there are strong barriers to viewing work as learning because, in many organizations, short-term performance is often prioritized over long-term learning (Benner & Tushman, 2003). As a result, learning is often viewed as occurring at the expense of working (Levinthal & March, 1993). Training takes place 'outside of work', time is 'set aside' for performance reviews, and employees often don't feel psychologically safe to admit they need to learn at work (Edmondson, 1999). Therefore, increasing awareness of learning opportunities at work likely requires a reframing or, more specifically, a re-categorization of what both work and learning mean to employees (Rosch et al., 1978).

Categorization is an automatic cognitive process that occurs from a very early age (Rosch et al., 1978). Though categories are developed with increasing sophistication as individuals get older, people still automatically view situations through that situation's similarity to their existing categories (Johnson-Laird, 1983; Piaget, 1966). These similarities are typically based on diagnostic characteristics that provide cues to the individual about how to make sense of the situation (Huang-Pollock, Maddox, & Karalunas, 2011). Therefore, if work and learning are separate categories that are based on characteristics that are at odds with each other, employees are unlikely to view even challenging work tasks as learning opportunities. For example, work might be categorized as fulfilling the need to meet organizational goals, while learning is something done to improve oneself. Essentially, even if they are learning through work, employees may not be aware of it. This awareness matters because employees who report having opportunities to learn at work are more satisfied (Skule, 2004) and perform better over time (Dragoni et al., 2009).

One promising approach for re-categorizing work as learning is reflection. As in previous chapters, this chapter is specific to individual self-directed learning behavior. Individual self-directed reflection can be defined a cognitive process aimed at increasing awareness of one’s experience in ways that increase the likelihood of learning from them (Hullfish & Smith, 1961). Reflection can surface assumptions and engage individuals in more systematic ways of thinking and problem-solving (Argyris, 1983) because it involves making tacit knowledge, such as categories, explicit. Reflecting on both failed and successful experiences produces richer cognitive structures (Ellis & Davidi, 2005a). Further work has shown that reflection in the form of counter-factual thinking can increase the ability to learn from experience (Morris & Moore, 2000). Therefore, asking employees to reflect on their learning at work may help them reframe work as learning, and learning as part of everyday work.

Adult learning researchers have long noted that reflection is a critical component of deep learning, specifically referring to learning as a cycle of action and reflection (O'Neil & Marsick, 1994; Schön, 1983). Argyris (1976) argues that the need to step back and reflect is critical because action without reflection can lead to problem-solving that is temporary, ineffective, and even damaging, rather than finding ways to "solve the problem so that it remains solved" (p. 368). In a review of the impact of systematic reflection, Ellis et al. (2014) argue that reflection can increase both self-efficacy and a learner's motivation to revise knowledge structures. However, little is known about whether reflection increases one’s ability to learn from new situations.

Unlike most learning, which seeks to increase efficiency in performance, reflection is an exercise in slowing down and bringing tacit knowledge to light. As discussed in Chapter 2, from a Dual Process Theory perspective (Evans, 2007), reflection is the attempt to move information from the more automated subconscious knowledge structures in System 1 thinking to the slow, conscious, and deliberate thinking characteristic of System 2. The idea is to reframe one's situation such that information and cues are brought into conscious awareness for critical evaluation. But reflection tends to be focused on past events. The first aim of this study is to examine whether reflection on learning can increase future awareness of learning opportunities.

Reframing an existing situation in a new way does not happen overnight. Ellis et al. (2014) argue that, in order for reflection to be effective, it needs to be systematic. In other words, employees need to get into the habit of reflecting. However, getting busy employees to reflect is notoriously difficult. Most reflection studies include either strong coaching or facilitation (Argyris, 1983; Seibert, 1999), structured group reflection such as after-event reviews (DeRue, Nahrgang, Hollenbeck, & Workman, 2012; Ellis & Davidi, 2005a), or single mandatory reflections (Anseel et al., 2009). Little, if any, work has been done on the factors that motivate individual employees to get into the habit of voluntary systematic reflection.

Research on rediscovery and narrative-building suggests that, when individuals are able to make connections to previous events in their lives, those events become more salient. Research has found that individuals derive more pleasure than they expected when they rediscover past events. For example, Zhang et al. (2014) found that individuals underestimate the pleasure they will feel when they re-visit even mundane past experiences. The authors argue that, by documenting the present, people give themselves the opportunity to experience the pleasure of connecting to the past. Further, if documented events can be used to construct a written narrative, re-visiting them may also serve the cognitive function of organizing those experiences in ways that promote sense-making (Pennebaker & Seagal, 1999). Together, these lines of work suggest that writing can be a powerful way to make sense of the world and that connecting past and present events is a pleasurable and motivating experience. Therefore, the second aim of this study is to investigate whether giving employees access to their past reflections on learning motivates them to reflect in the present.

I conducted a large-scale field experiment to test the extent to which regular written reflection on learning might raise awareness of learning opportunities, and whether viewing previous reflections might help busy employees to stay motivated to continually reflect. One hundred and ninety-five employees participated in an experiment where they were first asked to list the learning opportunities they noticed at work in the last 2 days. Employees were then divided into a Control group, a Previous Reflection group, and a One-at-a-Time reflection group. The Previous reflection and One-at-a-Time reflection groups were then asked to reflect on their learning at work twice a week for eight weeks. Each participant in these groups received an email prompt every Tuesday and Thursday for eight weeks. The prompt asked them to write a written reflection on their learning, but writing the reflection was not mandated by management or by the experimenter. The only difference between the reflection groups was that participants in the Previous reflection group were able to see all of their previous reflections each time they wrote a new reflection, but the One-at-a-Time reflection group was not. At the end of the eight weeks, all groups were asked to again list the learning opportunities they noticed at work in the last two days.

I found that those who were able to see their previous reflections wrote significantly more reflections than those who did not; in other words, they continued to reflect for longer. In addition, the Previous reflection participants used more words about learning and cognition in their reflections than did the One-at-a-Time participants. However, even though employees who reflected reported more learning opportunities than the Control group by the end of the study , this difference did not near significance.

Dual Process Theory and Reflection

The dual nature of human thinking has been studied in many forms and under many different names in psychology, stemming from research on rational versus heuristic thought in decision-making (Tversky & Kahneman, 1974). Evans (2007) provides an overview of the various labels researchers use to differentiate System 1 automated, tacit knowledge from System 2 rational, conscious thinking. Examples include Schneider and Shiffrin's (1977) automatic versus controlled thinking, Chaiken's (1980) heuristic versus systematic thinking, and cognitive neuroscience's distinction between reflexive and reflective thought (Lieberman, Jarcho, & Satpute, 2004). Evans (2007) notes that, while these different names do not represent exact replicative definitions, there is widespread agreement that System 1 thinking is rapid, automatic and high-capacity while System 2 thinking is conscious, slow and deliberate (Kahneman, 2011). The key dimension on which I will focus is that of automated versus conscious thought, particularly in the form of attention.

Attention is a limited resource and humans are incapable of directing attention to multiple events, even when those events are out of the ordinary. The phenomenon of inattentional blindness describes how people often miss even highly salient cues when their attention is focused on a task. Famously, Simon & Chabris (1999) showed that individuals who are counting the number of passes in a basketball game fail to notice a man in a gorilla suit weaving in and out between the players. Even this simple task of counting passes was enough to fixate observers on the ball, at the expense of noticing a truly bizarre event. Considering the cognitive, social, and psychological demands vying for an employee's attention in daily work, inattentional blindness likely abounds in organizational settings. In short, attention is selective and employees have immense competition for their attention.

Employees also have only limited control over what stimulus wins the competition for their attention because, beyond being limited, attention is also selective. Selective attention can be either involuntary and stimulus-driven, or voluntary and goal-driven (Egeth & Yantis, 2003). Since work is often characterized by routine-driven processes, employee attention is often habitually directed toward fulfilling the expectations of the routine (Cyert & March, 1963; Feldman, 2000). In addition, the signals given by those higher in status or hierarchy (A. Bandura, 1977) direct employee attention towards some efforts and away from others, often without full conscious knowledge by the signal giver or receiver. In particular, reward systems based on high-level performance can encourage employees to pay attention to doing their current job well now, at the expense of improving on it for the future. However, as Egeth & Yantis (2003) discuss, attention can also be voluntary and goal-driven. If a manager gives employees the explicit instruction to improve their skill, they can certainly choose to direct their attention towards improvement. This suggests that employees have the power to redirect their attention, at least temporarily. The question, however, is whether they can sustain this goal-driven attention in the longer-term.

Bias and categorization.

There are certain selective attention biases that may help employees purposefully re-direct their attention. I will argue that recency bias and confirmation bias (Kahneman & Tversky, 1979) can be leveraged to help employees spot more learning events in everyday work. I will then draw on the literature on category learning to argue that continually drawing attention to these patterns can re-direct attention in the long-term. Specifically, employees may be able to re-categorize everyday working events as learning opportunities through consistently and purposefully directing their focus towards those opportunities.

It is not uncommon that once we notice something, we begin to notice it everywhere. Humans are particularly good at detecting patterns, whether those patterns actually exist or not. This tendency to perceive patterns, known as apophenia (Goldfarb & King, 2016) occurs through a combination of the selective attention biases of recency and confirmation (Tversky & Kahneman, 1974). Recency bias is the tendency to give more attention to things that have occurred more recently than those from the past, and this effect is particularly strong in how we recall events (Murdock, 1962). Thus, if employees begin to take notice of work events as learning opportunities and are repeatedly prompted to do so, those events should remain part of their recent past. This may then prompt them to notice more learning opportunities each day in a virtuous cycle of attention.

Once work events are seen as a learning opportunities, confirmation bias (Tversky & Kahneman, 1974) predicts that other work events are more likely to be seen as learning opportunities in the future. Conformation bias is the tendency to select information that conforms to one's current thinking or existing worldview. Research has shown that when individuals form hypotheses, they are more likely to seek information that confirms that hypothesis (Mynatt, Doherty, & Tweney, 2007). Essentially, they begin to notice more things that are consistent with what they believe to be true. Therefore, if employees begin to see that work events can serve as learning opportunities, they are more likely to hold to that view by noticing more opportunities as they arise. Together these biases indicate that individuals notice recent events more and, once noticed, systematically reinforce their viewpoint of those events by seeking information aligned with that viewpoint. While these biases can interfere with fully rational thought, they can be leveraged to purposefully alter employees' views about daily work. Specifically, if individuals are prompted to give attention towards work events as learning opportunities and then are able to repeatedly re-visit similar events through reflection, they may selectively attend to more learning opportunities through the course of their daily work.

If this prompt is repeated over time, the reflection may result in re-categorizing work events as learning opportunities. Category learning is one of the earliest forms of learning, initially appearing in infancy (Greenough & Black, 1987), and it is critical to how we interpret the world. By categorizing along concrete dimensions, humans are able to make sense of information across situations. By creating the category "chair," we can quickly understand the use of a new chair even if we have never seen that particular chair before. As humans develop, they become able to categorize based on multiple dimensions and form abstract concepts (Sloutsky, 2010). As with most learning, the more the categories are reinforced, the more automated they become. This forms the basis for both rapid sense making and stereotypes (C. T. Miller, 1986). Categories allow for rapid movement of new information from System 2 conscious thought to System 1 automatic processing, shortcutting the need for slow learning whenever new information is encountered. Imagine if we had to relearn the purpose and structure of a chair each time we saw a variation of the form. The downside is that, once categorizations are made, they can be difficult to overcome. So, for example, when women are associated with weakness, it is difficult to view them as independently strong.

However, evidence suggests that adults do have the ability to form new categories based on dimensional cues. Dimensional cues are aspects of the object that help place it in a certain category. Adults selectively attend to cues that are diagnostic in nature (Hoffman & Rehder, 2010). Diagnostic cues are aspects of an object that may not be typically noticed but are closely aligned with the desired categorization of that object. For example, in contrast to children, adults are able to more easily categorize between a tame and feral cat because they can focus on the behavior of the cat even though the two animals are remarkably similar in appearance. The behavior of the cat, rather than, for example, the color of its fur or shape of its eyes, is diagnostic of whether it is tame or feral. However, children will be more attentive to obvious features such as the cat's physical appearance.

Through the use of eye-tracking, Rehder & Hoffman (2005) found that adults are also able to shift between diagnostic and non-diagnostic dimensions when a given dimension no longer bears relevance to the category. This means that adults can focus on different features of an object depending on which category they are trying to define, even if the object itself is the same. So, while the cat's behavior helps to classify between tame and feral animals, adults would be able to shift away from focusing on behavior when categorizing cats based on their likelihood of causing an allergic reaction. Adults would attend to the length of the cats' fur and how much they shed because these features are more diagnostic of allergy induction than the cat's behavior. Dang and Sloutsky (2016) argue that it is this selective attention towards diagnostic cues that drives the development of new categories in adult learning. Adults have sophisticated mechanisms for category creation and are able to reframe features or dimensions based on how they create the new category.

Additionally, adults are highly attentive to top-down, goal-driven categorization (Deng & Sloutsky, 2016). That is, adults can be directed towards a goal and focus on the dimensions of the information that are most diagnostic for meeting the goal. Combining this with the importance of social cues in learning (A. Bandura, 1977) and the power and status hierarchies in organizations, adults can make sense of workplace events based on features or dimensions that are abstract, and selectively ignore more obvious aspects of the situation. For example, even if a given managerial training touted by organizational leaders has been shown to be ineffective, employees may view access to that training as a signal of status, even if, based on certain diagnostic dimensions, it is a waste of time. Deng & Sloutsky's (2016) work shows that top-down attentional cues drive categorization, and categorization drives what is learned, particularly for adults.

Therefore, in order to become more aware of learning opportunities at work, adults don't just have to start to notice them, they have to categorize work events as learning opportunities through diagnostic information about the event. This means they have to start associating certain events with learning, even if some dimensions of the event bear a strong resemblance to their existing category of 'work task'. Furthermore, they have to do so multiple times with multiple events featuring the diagnostic dimension of "learning," to confirm that association.

Individuals tend to give attention to recent events and notice things more once they are in their attentional field. When this is combined with the ability of adults to create new categories based on multiple abstract dimensions, it may be possible to purposefully reframe how employees view work events. Thus, I theorize that employees whose attention is repeatedly drawn to categorizing work events as learning opportunities, through a reflective exercise, should notice more opportunities for learning at work after the reflective exercise, whether or not they are actually able to take advantage of those opportunities right away.

H1: Employees who repeatedly reflect on their learning at work will notice more learning opportunities in their daily work life than employees who are not asked to consider their learning at work.

H1A: Employees who repeatedly reflect on their learning at work will notice more missed learning opportunities in daily work life than employees who are not asked to consider their learning at work.

Motivating Systematic Reflection

Repeatedly prompting employees to reflect may not be enough to get them into the habit of reflection, especially if this reflection takes time from the workday, and is not mandated. Indeed, most work on reflection shows that it often requires strong intervention (Argyris, 1983; O'Neil & Marsick, 1994; Seibert, 1999) or systemized processes (DeRue et al., 2012; Ellis & Davidi, 2005a). Shedding light on what motivates individuals to reflect on their own may help both scholars and managers find ways to encourage employees to get into the habit of reflection.

In this section, I will argue that systematic reflection may help individuals make connections between experiences, which may, in turn motivate them to continue to reflect. First, Zhang's et al's (2014) work on rediscovery shows the power of revisiting previous writing in making past experiences more salient. Individuals can re-experience the satisfaction they gained from the previous writing and connect directly to that experience. Second, individuals who can see previous writings may build an internal narrative of their experience and this narrative may be motivating for future action (Pennebaker & Seagal, 1999).

Revisiting previous effects can be powerful. Research by Zhang et al., (2014) shows that documentation of everyday mundane events can have profound effects when those events are re-visited. These researchers found that people regularly underestimated the pleasure they would feel in revisiting even ordinary and routine experiences, and that this was linked to their erroneous faith in their memory of daily events. Individuals tend to believe they will remember more than they will. This is likely especially true for learning. Because learning is typically triggered by a dis-equilibrating event (Argyris, 1976; Piaget, 1966), the learning event may cause individuals to think they will be more likely to remember it. A dis-equilibrating event challenges one's view of the world, which can be a meaningful or traumatic experience. Therefore, individuals may be overconfident that they will remember it. However, in work situations, the demands for attention are high and learning is not always prioritized (Levinthal & March, 1993). The memory of these events is highly vulnerable to interference, and documenting them may capture those moments of insight.

Having direct access to previous learnings may also enable employees to construct new narratives of their learning. Zhang et al's (2014) work shows that individuals underestimate how meaningful previous events are when re-visited. This suggests that individuals create narratives about re-visited events that they would not have created if they had never had the chance to re-visit those events. In addition, the ability to build an internal narrative by connecting past events to current situations may motivate continued reflecting.

Pennebaker & Seagal (1999) suggest that the formation of a narrative is critical for understanding complex experiences. These narratives form when participants can make connections across events. This suggests that writing, in general, may help employees to process multiple work experiences, and develop more complex understanding. In addition, since research on expressive writing tends to focus on writing that is emotionally driven, i.e. participants write about traumatic experiences (Pennebaker & Kiecolt-Glaser, 1988) or difficulty in dealing with health issues (Gortner, Rude, & Pennebaker, 2006), these findings also imply that writing on learning, in particular, may help when employees face the often uncomfortable events that lead to learning.

However, it may take time to process these dis-equilibrating events, and employees may not be ready to make full sense of learning immediately after it occurs. Revisiting previous events may help employees build a progressive narrative of the impact of the event over time. In other words, learning occurs over long periods of time and building a narrative may help individuals notice progress in their learning, when it would otherwise be invisible. Amabile & Kramer (2011) found that experiencing even small increments is motivating. This work suggests, if employees can re-visit what they wrote in the past, they may be more motivated to write again in the future.

H2: Individuals who can review previous reflections will be more likely to continue reflecting than individuals who are not able to review their previous reflections.

Research and Setting

A large multi-national bank based in Europe served as an ideal setting for my study because high-level leaders of the bank were specifically interested in directing the attention of employee alumni of a costly managerial training program towards everyday learning opportunities. In addition, alumni of this program included employees at all levels and across multiple countries, allowing me to generalize my results beyond a single group, level of hierarchy, and even country. The employees tended to work in different areas or departments, which protected both the anonymity of the participants and the confidentiality of the experimental conditions. Finally, the company had partnered with academic researchers in the past and was familiar with randomization requirements and the anonymity needed for experimental studies. For example, while company managers were included on the initial email to the participants, all correspondence with participants took place directly and only with the researchers. The company was never made aware of who did or did not choose to participate among the pool of candidates.

Participants

Participants were 195 employees of an international bank based in Europe. Participants were recruited from a pool of alumni of a career-advancement training program, as requested by the company. Participants were from 18 countries, primarily Austria, Germany, Italy, and Romania, and not specific to any division or role within the company. Ninety-two participants (47%) were female and 103 were male, and 26% were between the ages of 31 and 39, while the majority (70%) were between the ages of 40 and 49. Ninety percent of participants had obtained a university degree. The organizational tenure of the participants varied a bit more, with 9% (17) of participants only having been at the company for 1-3 years, 55% (107) for 4-7 years, and 64 (33%) for 8-12 years. Only 3 participants had worked at the bank for more than 12 years.

Procedure

Initially, all participants were asked to fill out a series of surveys. The first was a standard demographics survey. The second asked participants to list the learning opportunities they noticed at work, and were able to act upon, in the last 2 days. The third asked participants to list the learning opportunities they noticed at work, and were NOT able to act upon, in the last 2 days. The fourth was a job satisfaction survey, which was included as a control.

After the initial surveys, participants were randomly assigned to one of three conditions. The company had engaged in reflection programs in the past and anticipated a 15% dropout rate. Therefore, I randomly divided a randomly-selected subset of 138 participants into two experimental conditions (69 each) and assigned the remaining 57 participants to a Control condition. The two experimental conditions were identical except that, in one - the Previous Reflection condition, participants were able to read each of their previous reflections on the same page they wrote a new reflection. In the other, the One-at-a-Time condition, participants were not shown their previous reflections. Participants in the Control condition did not reflect.

In the experimental conditions, participants were emailed a survey early in the day every Tuesday and Thursday for eight weeks; they were asked to complete the survey by the end of that workday. The survey asked them to 'write 2-3 sentences reflecting on your takeaways in the past few days at work'. The word 'takeaways' was used because previous research within the organization had revealed that, for many employees, the word 'learning' was negatively associated with having a competency gap. In each reflection instruction, 'takeaways' was defined as "new information, knowledge or insight you have gained within the context of your work." At the end of the two months, all participants were asked to again complete the learning opportunities and job satisfaction surveys.

Measures

Awareness of Learning Opportunities was measured by the number of learning opportunities listed as being able to act upon on the post survey, controlling for those listed in the pre-survey.

Awareness of Missed Opportunities was measured by the number of learning opportunities listed as being unable to act upon on the post survey, controlling for those same listings in the pre-survey.

Job satisfaction was measured using a subset of Brayfield & Rothe's (1951) index of job satisfaction scale, an adaptation and validation of the original 18-item scale by Curry et al. (1986).

Continued reflection was measured by the total number of reflections entered by each participant.

Engagement was measured by the average number of words per reflection.

Reflection on learning was measured by the use of cognitive processing words as analyzed by the LIWC software (Tausczik & Pennebaker, 2016). Cognitive words are further broken down to include words of insight (e.g. learn, think, know, consider), causality (e.g. because, effect, hence), discrepancy (e.g. should, would, could), tentative (e.g. maybe, perhaps, guess), certainty (e.g. always, never), and differentiation (e.g. with, and, but, except). Research has shown that causal and insight words, in particular, represent a reappraisal or reframing of a given situation (Tausczik & Pennebaker, 2016). Therefore, increased use of these words may indicate a reframing of how participants viewed their learning at work.

Results

The main finding is that those in the Previous Reflection condition wrote significantly more reflections than those in the One-at-a-Time condition, providing support for Hypothesis

2. In addition, participants in the Previous Reflection condition wrote significantly more insight words and marginally significantly more causal words than those in One-at-a-Time condition. Individuals in the Reflection conditions did become somewhat more aware of learning opportunities, both realized and missed, than those in the Control group, but this difference did not near significance. Thus, there was no support for Hypothesis 1 or Hypothesis 1A. Summary statistics are presented in Table 3.1.

Table 3.1 Reflection Study Summary Statistics

Variable	Control (N)	Mean	Std. Dev.	**One-a-a-Time (N)**	Mean	Std. Dev.	**Previous (N)**	Mean	Std. Dev.
Number Learning Opportunities listed in Pre-Survey	55	4.47	2.9	68	3.79	2.1	68	4.56	2.54
Number of Missed Learning Opportunities listed in Pre-Survey	55	1.78	1.07	68	1.76	0.99	68	1.76	1.09
Job Satisfaction in Pre-Survey	55	3.5	0.58	68	3.29	0.66	68	3.47	0.62
Number Learning Opportunities listed in Post Survey	46	3.71	2.3	44	3.98	3.08	50	4.48	4.14
Number of Missed Learning Opportunities listed in Post Survey	46	1.72	0.98	44	2.02	1.39	50	1.98	1.81
Job Satisfaction in Post Survey	46	3.58	0.57	44	3.33	0.65	50	3.53	0.72
[Participants who did not write any reflections are omitted from the data below]									
Number of reflections written	56	7.41	4.23				63	8.4	3.79
Number of words related to cognition	56	11.9	3.67				63	12.56	3.15
Number of insight words (e.g. learn, think, know, consider)	56	3.52	1.37				63	3.98	1.43
Number of causal words (e.g. because, effect, hence)	56	1.9	1.21				63	2.2	0.89
Number of discrepancy words (e.g. should, would, could)	56	1.2	1.06				63	1.22	0.82
Number of tentative words (e.g. maybe, perhaps, guess)	56	2.55	1.43				63	2.36	1.25
Number of certainty words (e.g. always, never)	56	1.41	1.04				63	1.24	0.87
Number of differentiation words (e.g. with, end, but, except)	56	2.66	1.6				63	2.62	1.39

Since I had both pre and post measures as well as a randomized experiment, I conducted a difference-in-differences analysis to examine Hypothesis 1. This analysis is appropriate when both time and conditions differ for the outcome variable. The difference-in-difference estimation computes the difference between time 0 (pre-reflections) and Time 1 (post-reflections) for each condition, and then compares those differences to test if there are significant differences between conditions. I eliminated any participant who did not complete both the pre and post surveys as well as 18 participants in the Reflection conditions that did not write any reflections. This resulted in comparing 45 in the Control group with 93 in the combined Reflection groups for a total of 138 participants. Results in Table 3.2 showed that those who did not reflect listed fewer opportunities after the reflection exercise (M: 4.60 to M: 3.78), and those who reflected listed slightly more after the reflection exercises (M: 4.23 to M: 4.26). However, the difference-in-difference analysis showed that these effects were not significant (p=.26). Results were also not significant for missed learning opportunities (p=.62). Therefore, I did not find support for Hypothesis 1 or 1A.

Table 3.2 Reflection Study Difference-in-differences model of Learning Opportunities Listed

Variable	Time	Control	Reflection	Difference
Learning Opportunities Listed				
	Pre	4.60 (3.13)	4.24 (2.15)	0.36
	Post	3.78 (2.30)	4.26 (3.67)	-0.48
Difference-in-differences				0.84(p=.26)
R-Squared	.01			
N		**45**	**93**	
Missed Opportunities Listed				
	Pre	1.80 (1.14)	1.91 (1.13)	-0.11
	Post	1.73 (0.99)	2.01 (1.63)	-0.27
Difference-in-differences				0.16(p=.62)
R-Squared	.01			
N		**45**	**93**	

To examine Hypothesis 2, that individuals are more likely to reflect if they can view their previous reflections, I again excluded 18 participants (6 in the Previous Reflection condition and 12 in the standard condition) who did not write any reflections and were, therefore, not exposed to the manipulation, for a total 119 participants. Because I am measuring changes over time, I conducted a repeated measures logistic regression to analyze the impact of condition on whether individuals reflected at each of the sixteen possible times to determine if the difference in the pattern of results in Figure 3.1 is significant.

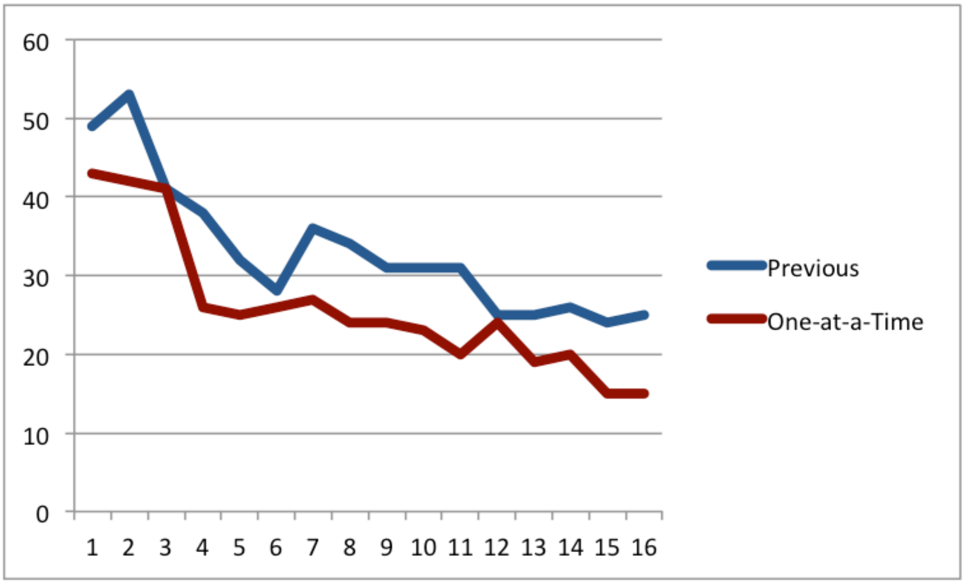

Figure 3.1 Reflection Count over Time by Condition

The repeated measure analysis treats each opportunity to reflect as a binary measure, coding 0 if the person did not reflect and 1 if the person did. It compares the population average over time. Results in Model 1 of Table 3.4 show a main effect that participants in the Previous Reflection group were significantly more likely to reflect over time than participants in the One-at-a-Time group (p=.05). Not surprisingly, for both groups, reflections decreased over time. Model 2 shows a significant difference between conditions when controlling day and demographic variables, though only age and education level were significant (Model 3). Therefore, I found support for Hypothesis 2.

Table 3.3 Repeated Measures Logistic Regression of Reflection Counts (n=119)

Variable	Model 1	Model 2	Model 3
Condition	-0.31*	-0.37*	-0.36*
Day		-0.14***	-0.14***
Education level		-0.68**	-0.75**
Age		-0.46	-0.43
Gender		0.01	
Years at Work		-0.01	
Job Satisfaction		-0.16	
Constant	0.81***	5.65***	5.20***
* p<=.05, **p<.01 ***p<.001			

For a deeper analysis, I examined the extent to which participants reflected on their learning. Recall that the instructions were to reflect on takeaways, defined as 'new information, knowledge or insight you have gained within the context of your work.' Therefore, I used the content of the reflections to determine if there were differences in the number of learning-related words within the text of the reflections. Using the LIWC software (Tausczik & Pennebaker, 2016), I examined the use of cognitive words. The cognitive words were categorized into words of insight, causality, discrepancy, tentativeness, certainty, and differentiation.

Summary statistics are available in Table 3.1. I conducted OLS regression analysis for each of the six categories, including demographic controls for gender, age, and years of education. In these analyses, I examined the impact of condition on the use of each word category, using participant as the unit of analysis and controlling for demographic variables. Results reveal that participants in the Previous Reflection condition wrote significantly more insight words ($p<.05$) controlling for gender (men wrote more insight words than women). In addition, participants in the Previous Reflection condition used somewhat more causal words ($p=.12$) in their reflections. Neither insight ($r=-0.03$, $p=.78$) nor causal ($r=-0.02$, $p=.76$) words were correlated with the number of reflections written, so those who wrote more reflections were not more likely to use those specific words. No other significant or near-significant relationships were found in the word analysis.

Discussion

This large-scale field experiment sheds light on a key question regarding reflection at work - what motivates individuals to reflect? While scholars across disciplines have noted the importance of reflection for sense making (Weick, Sutcliffe, & Obstfeld, 2005), learning (Ellis & Davidi, 2005a), professional development (Figler Osterman & Kottkamp, 2004), perspective-taking (Seih, Chung, & Pennebaker, 2010), critical thinking (Mezirow, 1990), and systems-thinking (Senge, 1990), little has been done to understand what motivates people to reflect. This study suggests a solution to this motivation problem: When individuals can review their previous reflections, they are more likely to continuing writing reflections in the future.

This study also demonstrated that viewing previous reflections increased the use of insight words in the reflections overall. This experiment asked participants to reflect on their learning so the use of insight words would be expected. However, those who were able to review what they previously wrote used more insight words on average, even though the use of insight words was not related to the total number of reflections written. This demonstrates that viewing past reflections on learning increases both future reflections in general, and future reflections on learning specifically.

This study offers some suggestion that reflection may raise awareness of learning opportunities. While those who reflected did not report significantly more learning opportunities at the end of the study period that those who did not reflect, results were in the expected direction, and the lack of significance may be due to the higher than expected attrition rates. Only 3% of people in the reflection conditions completed the full study and only 13 people (9%) wrote reflections in the last two weeks of the study, directly prior to the post-survey. It is likely that not enough people participated in the experiment for enough time to re-categorize work events as learning opportunities.

This study suggests that the ability to revisit or review previous writings on even mundane experiences increased the motivation to reflect. The content of the reflections themselves reveals that, at times, reflection can be a rather mundane activity, as shown below.

> *"No main takeaways over the past two days: only ordinary and recurrent activities."*

> *"I have to repeat the same how to treat, react, cowork, manage, that is my everyday experience."*

> *"I have to admit, that the last days were not particularly "special". I just came back from vacation and started to work through my unread emails and trying to catch up on recent developments. It seems that I didn't miss a lot as it was a calm period."*

However, the content of the reflections also showed that participants sometimes used reflection to process dis-equilibrating experiences from which they could learn.[3]

> *"Everyone has to pay attention to his own job because you can't always trust your colleagues. When one is leaving the company to join another one, you can really see his professionalism and respect. We can be transparent and true even if our environment is dark and unfair."*

> *"it is interesting that a lot of people have the same opinion or view, but nothing changes. Still endless discussion are ongoing. Some people just do not understand when you are saying some basic things, such as 'I cannot attend the meeting due to what ever reason'."*

> *"I have received a tough mail from a colleague of mine. She was blaming me and my team about how we have approached and followed an activity. I have learned that I'll never send an email like that. First of all because this kind of email can be sent only if you are in a managerial position. Second, because if I receive an email like that, in my mind, I think immediately that I do not want to cooperate with a person who thinks that I work in a ineffective way. Yesterday a colleague of mine told me that she needs to have a surgery immediately because she has a preliminary form of cancer in the liver. This news has devastated me. The only very obvious thing I have thought*

[3] Minor punctuation, spelling and grammatical edits were made to the provided quotes for clarity of reading.

about it is that all the job concerns and disappointments counts less than zero in comparison with this kind of news."

Participants reflected on issues with other departments/entities:

> *"My takeaways in the last few days were mainly about how it is important to know very well the workflow of every process and the goals of other departments units connected with mine in order to set up a very quick solution for daily problems."*
>
> *Also I learned how to deal with corporations (they are important in parts of our business) and I took away some helpful information about the organisation of events for our customer."*

Some participants used reflection to process their feelings about the challenge of their workday.

> *"Patience is sometime necessary. Keep calm and express your feeling having in mind an option to solve the issue and guide your proposal. The perfect world doesn't exist in a company. Compromise is the only solution. Keep the energy for the activities that give you more satisfaction. no takeaways it's a sign that I'm getting tired and bored ;)"*
>
> *"Today I found out that due to work I didn't put attention enough in the other parts of my life, above all in people that I love. But I also get used to go to the gym during the lunch breaks. My boss gave me a really tough plan of activities for the incoming two weeks. I feel a little bit scared about that."*

Finally, participants used the reflection exercise for overall sensemaking.

> *"1. An employee would perform better if her or his merits would be recognized, and sustained efforts would be appreciated and also remunerated accordingly. 2. The activity that we do, must be done with maximum interest. Also in times when are you fed up with the things that you do. 3. New, innovative ways of making us as a team to interact can help us in our business activity."*
>
> *"Professional growth never stops. As well as it seems I can't stop having job interviews within my Group. Takeaway: learn to always be ready knowing where I want to go, how and when, and about my personal professional strengths and weaknesses."*

Altogether, the content of the reflections suggests that, though mundane at times, reflection is a useful mechanism for learning because it allows people the opportunity to process events that they may not otherwise articulate. This processing can help them make connections between what they experience and what they take away or learn from that experience. Each of the issues in the above reflections occurred through the course of daily work. By reflecting, these individuals may have began to view those experiences as learning opportunities.

This study is unique among studies of reflection because it did not ask participants to reflect on a single event, such as a training (Anseel et al., 2009) or traumatic event (Pennebaker & Kiecolt-Glaser, 1988). Rather, it asked employees to reflect on events they interpreted as important for their learning. Furthermore, it did not require participants to reflect but gave them the option to do so twice a week for eight weeks. Therefore, it was particularly suited to examine whether, given a simple electronic prompt, employees would choose to engage in the act of reflection. This is critical because reflection is an ongoing process and a single reflection is unlikely to add much value to the learning process.

By studying the act of repeated reflection, the research presented in this chapter also builds on work on re-discovery, which has shown that when individuals can view their own writing from the distant past (several months), they give greater meaning to and find pleasure in even mundane past experiences (Zhang et al., 2014). They show that individuals systematically underestimate the pleasure they will receive and the meaning they will find in past events. The present study extends this work because participants were able to view their previous writing on a regular basis, and only days after it was written. This suggests that re-reading past reflections can be powerful, even when done repeatedly in a short span of time.

Research on repetitive events shows that, when individuals experience events on a regular basis, the sequence of the events that make up the experience matters in how likely, and how soon they are to repeat the event. Specifically, the experience at the end of the event is a stronger driver than the experience at the beginning of the event, because the memory of the end interferes with the memory of the earlier part of the experience (Oberauer & Kliegl, 2006). For example, Garbinsky et al. (2014) found that final moments of gustatory experiences have a stronger influence than initial moments, for people's decisions about the number of days until consumption of the same food is repeated. Those who had better final moments when eating a given food wanted to wait less time to eat the food again than those who had better initial moments of eating that food. In the act of writing, satisfaction with the experience is more likely felt at the end, when thoughts have been expressed (Gortner et al., 2006). Therefore, participants in the Previous Reflection condition may have been more motivated to reflect because, when viewing the past writing, they were cued to remember the satisfaction they felt after they expressed themselves.

Individuals are also likely to be better able to make connections between events and build an internal narrative when those events occur closer together. As suggested earlier, getting into the habit of reflection may result not just from repetition, but also from recency bias (Tversky & Kahneman, 1974). Repeatedly reflecting, and doing so often, makes it easier to remember the context and circumstances of previous learning opportunities. This may help individuals start to detect patterns in their work and learning life. Once employees begin to notice the patterns, continuing to reflect may help them solidify their learning, which may itself be motivating.

This suggests two possible mechanisms by which viewing previous and recent writing motivates future reflection. One is past-oriented, whereby individuals re-experience past pleasure, which motivates them to the action of reflection. The other is future-oriented, whereby individuals build connections from the past to events in their current reflection, enabling learning that will be useful in the future. In addition, it may be that individuals differ in which pathway they find more motivating. For those who already value reflection, the ability to make connections for future learning may keep them in the habit of reflecting when they are short on time. However, if others do not see reflection as a valuable learning tool, at least at first, they may be more motivated by the sheer pleasure of expressing themselves and explicitly processing their experience (Gortner et al., 2006; Spera & Buhrfeind, 1994).

Limitations and Future Research

The Reflection study opens new avenues for research into the role of reflection in learning and the motivation to reflect. However, it also has some limitations. First, although this study found a positive effect for viewing previous reflection on the motivation to reflect, it did not address mechanisms by which viewing previous reflections might be motivating. Future research could examine ways to get employees into the habit of reflecting through demonstrating the pleasure in engaging in the activity so employees will want to re-experience it. For example, researchers could manipulate the salience of reflection as a pleasurable activity by including a condition in which participants are asked to rate the pleasure they felt at the end of reflecting. They could then be reminded of those ratings prior to their next reflection. Alternatively, researchers could manipulate the value of reflection. They could include a condition that informs participants of the value of reflection for making connections to events that may, otherwise, be forgotten. Reflection would then allow them to capture missed learning opportunities. These studies examine if manipulating either the pleasure or value of reflection prompts individuals to reflect more. Finally, research could compare pleasure with value to see if one was more effective in motivating reflection or if individual differences moderate the effectiveness of either.

In addition, in the Reflection study, all Reflection condition participants were prompted to reflect; it is unknown whether participants would have continued to reflect on their own, without prompts. Future researchers could examine whether viewing previous reflections prompts the act of reflecting on one’s own. One promising source for such data could be the diary-like blogs that are now ubiquitous and readily accessible.

Second, it is unclear why viewing previous reflections prompted increased use of insight words within the reflections. It is possible that because participants were prompted to reflect on learning, those who could view previous learning reflections were able to make stronger connections between learning experiences, and therefore draw more insight. Future research could explicitly direct some participants to make connections between past and future events to determine if these connections result in participants building explicit narratives to process complex information and learn from it (Pennebaker & Seagal, 1999).

Finally, I did not find support for Hypothesis 1, that reflection raises awareness of learning opportunities, although results trended in the hypothesized direction. Previous studies have shown that reflection improves performance over time (Anseel et al., 2009) but scholars argue that the potential of reflection for learning lies not so much in performance improvement but in the sensemaking (Weick et al., 2005) and transformative thinking (Mezirow, 1990) that can occur through challenging assumptions and critically analyzing events. A key trigger of this type of transformative thinking is raising awareness of the learner as to when opportunities arise to change their perspective, challenge their viewpoint, or generate new knowledge. While this study did not find significant results in raising awareness of learning opportunities, the results did go in the expected direction even with the high attrition rates of the participants. Therefore, further research could mandate reflection on learning to determine if ongoing reflection impacts employee awareness of learning through everyday work events. The frequency of the reflection may also come into play. Future work could determine if more frequent (daily) reflections may help employees reach the consistent level of awareness needed to actually change categories.

Conclusion to Chapter 3

This study investigated a new question about individual self-directed reflection - what motivates individuals to reflect on a continual basis? It showed how a simple intervention of enabling individuals to view what they had previously written could motivate them to get into the habit of reflection. Reflection and awareness are intertwined and together they can have profound effects on how individuals learn and make sense of the world (Dittrich, Guérard, & Seidl, 2016; Reynolds, 1998; Schön, 1983). Studies in psychology have convincingly demonstrated that many of our daily thoughts, actions, and interactions are driven by subconscious process that we are not aware of in the moment (Evans, 2003; 2007; Rolison et al., 2012; Spencer, Steele, & Quinn, 1999). Reflection is the act of bringing those subconscious activities to the surface for critical examination. Indeed, many learning scholars argue that deeper learning cannot occur without reflection (Cope, 2003; Mezirow, 1990; O'Neil & Marsick, 1994). However, little previous work has been done to understand what motivates working adults to reflect. As employees and leaders become more single-mindedly focused on the action of working, scholars can meaningfully contribute to ongoing learning and development by shedding light on ways to step back, reflect, and direct that action more productively.

Conclusion

This dissertation presented individual self-directed learning as consisting of multiple behaviors, each of which has different learning outcomes and may have different individual and situational drivers. Chapter 1 integrated research in cognitive science, education, and management to identify five key individual self-directed learning behaviors. It then introduced a methodology to directly observe working adults as they engaged in those behaviors to show that learning orientation predicts taking on a challenge, but does not predict whether individuals follow through on that challenge. The findings from Chapter 1 also revealed that the learning behaviors themselves are largely independent in that, with a few key exceptions, engaging in one behavior does not predict engagement in the others. Chapter 2 builds on these findings to introduce the Learning As Behaviors (LABS) model, which maps each behavior to a process step in long-term memory formation (R. C. Atkinson & Shiffrin, 1968). The LABS model presents five stages of expertise. They are: novice, informed, knowledgeable, competent, and expert. The model names specific learning outcomes for each stage, and shows theoretically and empirically how the key learning behaviors lead to those outcomes. Chapter 2 concludes by revealing a previously undiscovered barrier to expertise development - beyond concerted time and effort, it requires learners to engage in behaviors they would otherwise avoid. One particularly difficult behavior to motivate, especially in busy organizational settings, is the learning behavior of reflection. Chapter 3 described a large-scale field experiment, which showed that a simple intervention of allowing individuals to see previous reflections motivated them to continue reflecting. Since so much of organizational research is focused on leadership and management learning, this dissertation is an attempt to pioneer a new way to think about, study, and understand the way that the vast majority of the organizational population - the ordinary employee - learns from challenging work.

Theoretical next steps

Theoretically, the next step for the research presented in this dissertation is to integrate work on working memory with Dual Systems Theory (Wason & Evans, 1974) to better understand the capacity and limits of processing information during learning. In Chapters 2 and 3, I drew on Dual Systems theory to argue that each learning behavior is an exercise in moving from System 2 slow, deliberate action to System 1 automated performance, with the exception of reflection which is a specialized learning behavior that moves in the opposite direction. Research has shown that working memory plays a key role in the ability to learn (Baddeley, 1992). Shipstead et al. (2015) define working memory as the "cognitive system in which memory and attention interact to produce complex cognition" (p.1863). Individual differences in working memory predict academic outcomes (Ashcraft & Krause, 2007), language comprehension (Daneman & Merikle, 1996), and reasoning (Carpenter, Just, & Shell, 1990), and these differences hold even in the face of training and experience (Hambrick & Meinz, 2011).

It may be that working memory is the intersection of System 1 and System 2 processing. Working memory draws from automated knowledge to provide the capacity for slow deliberate processing of information that requires attentional resources. In addition, it seems that working memory is the pathway to move from System 2 deliberate processing to System 1 automated performance. Information is stored briefly in short-term memory but forming any connections between the new information and existing knowledge seems to require retrieval from long-term memory and the ability to access that connection in working memory. For example, when confronted with a math problem, individuals need to pull from long-term memory to understand symbols, (e.g. + - =) and then apply those symbols correctly with the numbers presented to them. This processing means holding the numbers, the symbols, and the knowledge of what to do in working memory.

Therefore, it seems that working memory plays a critical role in each of the key learning behaviors. First, individuals with greater working memory capacity may be more likely to take on learning challenges because they may be more confident in their ability to learn (A. Bandura, 1977). Second, individuals may be able to give attention to more information at any given time due to greater capacity in working memory (Oberauer & Kliegl, 2006). Third, individuals may be able to more quickly and readily put that information into meaningful context, retrieving what is needed from long-term memory while still holding the new information for processing (Baddeley, 1992). Fourth, processing information is, in part, based on working memory capacity (Ashcraft & Krause, 2007; Daneman & Merikle, 1996) and individuals with greater capacity may need less practice and be more able to respond productively to feedback. Finally, critical reflection requires the ability to draw on vast amounts of knowledge and process it in new and meaningful ways to detect patterns, an ability that seems highly reliant on the capacity of working memory.

The LABS model would benefit greatly from integrating the exciting research on working memory with the proposition that each learning behavior (except for reflection) is an exercise in moving from slow deliberate thinking to automated performance. Considering each behavior in turn, as well as looking at the role of working memory throughout the full process of learning could shed light on why some individuals may struggle with certain learning behaviors and could, more importantly, give trainers, managers, and scholars clues to how to overcome barriers to generate more effective learning interventions.

The LABS Model would also greatly benefit from empirical testing of its three propositions. First, conceptually mapping all five learning behaviors to the long-term memory formation process suggests that each behavior is needed for long-term learning. Using variations of the LBM, wherein the ability to engage in certain behaviors is removed or amplified, future research could test what happens when individuals skip some learning behaviors.

Second, the LABS model posits that there is an optimal order to the behaviors. An additional variation of the LBM, wherein learners choose, or are given variety in the order of the behaviors, could shed light on whether this ‘optimal’ order is universal. In addition, it could reveal whether learners go back to previously skipped behaviors in predictable ways. For example, will learners who skip right to practice realize they don’t have enough knowledge and eventually engage in the behaviors in the order predicted by the LABS model?

Third, while the LABS model and existing research suggests that all five behaviors are needed, it is unlikely that working adults are aware of this for their own learning. Drawing on research on metacognition (Mayer, 1998) and self-regulation (Sitzmann & Ely, 2011), and again using the LBM, studies could examine whether simply telling people about the five behaviors and their role in learning increases engagement and performance. Further, reminding learners of the role of each behavior directly prior to engaging in it may have profound effects on the degree to which they value that behavior. If participants can directly name the learning outcome of a given behavior, they may be more likely to see engaging in that behavior as worthwhile.

Finally, the LABS model suggests that attention plays a critical role in workplace learning. Longer-term observational studies of working adults could lead to a greater understanding of how performance distractions impact the learning process. Specifically, if adults are working to meet a learning goal alongside performing their work, how often do they revisit previous learning behaviors to ‘catch up’ and advance their learning? Observing the behaviors adults do and don’t engage in when they undertake a long-term training or learning effort would examine the longer-term learning costs to constantly re-allocating attentional resources between learning and performance. It could also expand the usefulness of the LABS model to apply to more informal, everyday learning that is necessarily interrupted and driven by performance demands (Marsick & Watkins, 2001).

Expanding the LABS model with the Learning Behaviors Methodology

In Chapter 1, I introduced the Learning Behaviors Methodology (LBM), which is a way to study how working adults learn. It moves beyond self-report and even others' evaluations of learning to directly observe how working adults act when they are faced with learning complex material. First, the LBM gives participants the choice of the level of challenge they want to take on in the learning task. Second, it provides them with learning materials and measures the extent to which they engage with those materials. Third, it gives the option to put that information into meaningful context by providing hyperlinks to contextual information. Fourth, the LBM provides a way to continually practice with access to immediate and relevant feedback. Finally, it provides instructions on how to critically reflect and gives participants the option to reflect on their learning. While the LBM in this dissertation used the topic of facial recognition, the methodology can be applied to just about any learning topic.

As such, the LBM provides many avenues for new research. Because it measures each behavior on its own within a single task, further research could examine the individual differences and situational conditions that impact each of the five learning behaviors. It could further determine if there are some traits or circumstances that motivate multiple behaviors or, as the LABS model suggests, if there are some drivers that motivate one behavior but undermine another. Three particularly promising areas of research are applying construal level theory to the process of learning, testing the role implicit theories play in adult learning, and examining how different types of goals impact each of the learning behaviors.

Construal Level Theory

While I argue in Chapter 2 that the learning behaviors are independent, there are some behaviors that seem more alike than others. From the perspective of construal level theory (Trope & Liberman, 2003), some behaviors seem more concrete and detail-focused while others seem more reliant on abstract, big picture thinking (Reyt, Wiesenfeld, & Trope, 2016). Construal level theory suggests that individuals differ in how they attend to and process information based on their psychological distance from it (Trope & Liberman, 2010). Those who are close to it focus more on details and concrete aspects of new situations, while those who can hold distance from it tend to view situations more abstractly. Therefore, both individual differences in construal and prompting individuals to think one way or the other may drive engagement in the learning behaviors.

Specifically, paying attention requires focus on detailed information to gather basic facts and avoid distractions. In addition, particularly early in learning, repeated practice with feedback seems to require focusing and attending to what goes well, and what goes wrong to make corrections to performance. Alternatively, forming meaningful connections seems an exercise in big-picture thinking because it is defined through making connections beyond the information at hand. Likewise, critical reflection means putting together vast amounts of information to abstract patterns of underlying principles. The LBM could be used to empirically examine if differences in construal level, induced or inherent, draw people to engage in different learning behaviors or make achieving the outcomes of certain learning behaviors easier (or more difficult) for some.

Implicit Theory of Intelligence

The implicit theory of intelligence asserts that individuals differ in how they approach learning tasks based on the degree to which they associate effort with intelligence (Dweck, 1986). Individuals who believe they can get smarter by engaging in learning are more likely to take on challenges and respond productively to feedback than individuals who believe intelligence is innate (Dweck & Leggett, 1988). While this work serves as the basis for measures of learning orientation, the results from Chapter 1 showed that learning orientation only predicts taking on a challenge and not the subsequent learning behaviors. However, Chapter 1 also argued that current scales of learning orientation do not adequately represent implicit theories, a claim supported by Payne's (2007) meta-analytic review. Therefore, it remains unclear the degree to which implicit theories of intelligence impact learning behavior in working adults.

The LBM is particularly suited to address this question. First, it allows for examination of the impact of any driver on each behavior. Second, the current version of the LBM presents a learning task that could easily be construed as either requiring innate ability or extensive training. While the ability to read basic facial expressions is universal, the results from Chapter 1 show that reading compound expressions is very difficult. Therefore, either of these facts could be emphasized to manipulate implicit theories experimentally. Specifically, participants could believably be told that only certain people have the ability to read compound expressions, and just as believably be told that everybody has the ability to read compound expressions but that it takes training and practice.

In addition, participants could be asked about their beliefs, both in general and specifically towards a given topic. Asking about implicit beliefs would require a different measure than current scales of learning orientation. Although some scales do exist, it would be worthwhile to develop scales specific to working adults for both general and specific use. With these scales, the LBM could be employed in an observational study to examine the impact of different levels of implicit beliefs on learning. Understanding how these beliefs affect both learning and performance for working adults could shed light on how implicit beliefs differ for students and working adults. These differences could lead to better scale development and interventions for how to encourage more adaptive approaches to learning at work.

An additional line of research is examining whether implicit beliefs differ for each learning behavior. In other words, do some adults believe they will learn more from some behaviors than others? Adults have a rich history of learning and, due to a variety of factors, may believe that they have 'styles' of learning that are more effective for them; this belief could serve as a self-fulfilling prophesy. The LBM could be utilized to see if differences in adult's learning history impact their self-efficacy in each of the learning behaviors. For example, an individual who did particularly well in school due to her ability to memorize quickly may be more drawn to attending to information, but resist seeking a deeper understanding of it. The individual who may have struggled in academics but excelled at more practical tasks working with their hands may believe she can only 'really' learn through practice. Further research could use the LBM to see if adults hold these varying beliefs and the impact of those beliefs on the full learning process.

Goal-setting

Decades of research have shown that specific challenging goals lead to better learning and performance outcomes than easy goals, or 'do your best' goals (Locke & Latham, 2002). Further research has examined the impact of distal learning goals versus proximal performance goals on learning strategies, knowledge acquisition, and performance in complex tasks (Chen & Latham, 2014; Seijts & Latham, 2001). However, little has been done to examine the impact of goal-setting on any of the five key learning behaviors. Using the LBM, studies could build upon this rich body of research to examine both dimensions implied by Latham & Locke's (2002) findings that specific challenging goals lead to better outcomes during the learning process. Namely, the LBM could test the impact of specific/challenging, specific/easy, broad/challenging, and broad/easy goals on each of the learning behaviors. In addition, previous research in goal-setting tends to use 'do your best' as the broad goal. This makes sense in academic settings where doing your best is associated with learning. However, in organizational settings doing your best likely means high performance, even at the expense of learning. Therefore, further research could also examine if 'learn the most you can' has an impact on the behavior of working adults.

Reflection

Chapter 3 raised two new questions in the research on reflection as an individual self-directed learning behavior. First, what is the role, if any, of repeated reflection on learning in re-categorizing everyday work experiences as learning opportunities? Second, how can we motivate working adults to engage in this repeated reflection? While the large-scale field experiment shed some light on these questions, there is much more work to be done. First, the relationship between re-categorization and awareness needs further study. Second, there are likely many ways to motivate reflection. Third, it is still unclear the mechanisms through which the manipulation of viewing previous reflections impacted the motivation to reflect.

Re-categorization and Awareness

One of the most difficult psychological phenomena to overcome is unconscious bias (De Martino, Kumaran, & Seymour, 2006; Tversky, 1981). These biases emerge from both conscious and unconscious associations of events that form implicit categories. These categories serve a critical role in human functioning - they allow humans to face new situations without having to relearn every aspect of the situation. However, this ability comes with a cost. Once categorized, these associations often go unexamined and even when examined are resistant to change. In Chapter 3, the crux of my argument was that if categories are formed through association, then explicitly making new associations could get people into the habit of making new associations, thereby changing their categories. Specifically, when work events are repeatedly associated with learning, employees might re-categorize those events as learning opportunities. While I did not find statistically reliable support for this hypothesis, results were in the expected direction. It seems likely that reflection is only one way, and perhaps not the most efficient way, to induce this repetitive association. Studies that specifically target repeated re-categorization by explicitly having participants make new associations with existing categories could examine this as a mechanism for longer-term change.

Whether reflection is the most efficient way to re-categorize events or not, it is still key to individual self-directed learning. Understanding how to motivate busy working adults to reflect would make a strong contribution to the fields of both learning and management. Surprisingly, this question has received little, to no, attention. Drawing on expectancy value theory (Vroom, 1964), research could examine ways to both increase the value of reflection and individuals' expectations that they are able to achieve the learning outcomes of reflection.

One way to start is to be specific about those learning outcomes. While the study in Chapter 3 examined one concrete proximal outcome (raising awareness), there are other both short and long-term effects of reflection that could be made salient to learners. Reflection may be a way to unload distracting thoughts and free up cognitive resources for more productive work (Gortner et al., 2006). Reflection may help learners build a narrative of their learning and be more purposeful in their learning efforts over the long-term. As suggested in Chapter 2, critical reflection could reveal underlying patterns and principles within a domain, so experts are better able to deal with novel situations. In each of these cases, learners may value reflection more because they find value in the outcomes.

Finally, providing employees with resources to aid reflection may be critical to the expectation that they will be able to achieve these valued outcomes. The biggest barrier to reflection seems to be time. Managers could allocate specific time to reflect in either individual or group settings. However, Chapter 3 also revealed that access to previous reflections is particularly useful for motivating ongoing reflection. Therefore, organizations could put simple systems in place for individuals to write and track their reflections. Reflection is both time-consuming and worthwhile. Once organizations accept these parameters, they may be able to find creative ways to motivate this critical learning behavior.

The barriers to reflection were demonstrably evident in the findings in Chapter 3. Even though all participants agreed to participate in the study, attrition rates were extremely high. The minor intervention of viewing previous reflections significantly decreased these rates, but it still unclear why. Pivoting off this field study, lab research could examine the two mechanisms proposed in Chapter 3. First, lab research could observe or experimentally manipulate the degree to which individuals find reading recent reflections pleasurable, and then test the extent to which that pleasure motivates them to reflect again. If the reflections are repeated frequently, future research could test whether viewing previous reflections reminds individuals of these positive feelings and whether that translates into further action. Alternatively, future research could target narrative building as a mechanism for motivation. Prompting individuals not just to reflect, but also to build meaningful connections between reflections, could determine if the chance to create and maintain this narrative gets people into the habit of reflection.

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Appendix 1

Chapter 1: Study 3 Measure Checks

Taking on a challenge

Reason for choosing challenge level 0 or 1	%
low self-efficacy	26
avoid difficulty	15
avoid bad performance	10
avoid unknown	10
unwilling to spend time	8
seek good performance	5
Total	100

Reason for choosing challenge level 4-5	%
wanted challenge	42
more interesting	18
wanted moderate challenge	15
seek good performance	6
try best	6
high confidence	6
curious	3
wanted to learn	3
Total	100

Clicking on Hyperlinks

Reason for clicking on hyperlinks	%
would help with task	3
other	3
was told to	4
interested	5
to understand better	7
to compare faces	14
curious	19
to learn more	44
Total	100

Reason for NOT clicking on hyperlinks	%
not interested	3
didn't think would help	5
didn't want distraction	5
didn’t want to	5
other	7
took too much time	8
didn't need to	66
Total	100

Repeated Practice with Feedback

Reason	Minimum number attempts (percentage)	More than minimum (percentage)
didn't like task	1	2
didn't want to over practice	1	
wanted to do more than minimum		2
to get feedback	4	
fun		4
to get it right	2	27
thought it would help with task	1	4
to improve	16	29
wanted to keep trying		2
to learn pattern		2
low self-efficacy	13	12
other	9	8
needed the practice	1	
it was required	16	
see if could do it	1	
see progress	2	
test self	1	
to learn	7	6
too hard	1	
too much time	3	
was enough	21	2
Total	100	100

Reflection

Reason for Reflecting	%
because was asked to	1
curious	1
was a good thing to do	1
to process information better	1
to reflect on task	1
to realize strategies	2
learn by reflection	3
to learn	3
to remember better	4
for future use	5
task was interesting	5
other	7
was surprised at difficulty	7
to understand better	10
to improve	11
to share thoughts	16
to process feedback	23
Total	100

Reason for NOT reflecting	%
did poorly on practice	2
didn't learn from exercise	2
was frustrated	2
hard to reflect	2
unprepared	2
would be distracting	2
task was pointless	6
other	9
too much time	11
wouldn't help	11
nothing to say	13
didn't want to	14
didn't need to	25
Total	100

Appendix 2

Chapter 1 Study 3 Excluded Reflections

It was very difficult to identify combined emotions. I tried very hard, but was not able to get better. Not sure if I learned anything
I had a tough time matching the compounded emotions to faces. I thought that it would be easier.
I could not figure it out and only got 1 expression correct. I had to give up sadly.
|All of these tasks were much more difficult that I expected. I didn't get any right the first time, and only got 1 right. |
It is hard to figure out combined emotions

Chapter 1 Study 3 Examples of Included Reflections

I feel like the happy faces and the disgusted faces and any combination with those in it were the easiest to identify. Other ones were more nuanced and more difficult to pinpoint.
The happy faces were harder to distinguish, as were the surprised ones. The anger and fear ones were more easily recognized, probably because those are more essential to survival.
I find it difficult to distinguish sadness when associated with anger
Disgust was easy to detect due to the wrinkled nose. It was sometimes hard to identify what other emotions were with it, harder than I expected.
The disgusted and angry ones were more confusing. Just different people can express these emotions a little differently and make it look similar to another emotion
I think the faces that were disgusted and fearful are hard to judge when surprised is added to them. my idea of surprised is different i guess and to be that and disgusted or fearful is somehow difficult for me to discern for some reason.
I definitely struggle with anything other than happy. It would help if I could have seen more example pictures or could go back and review the examples given. I think I just don't correctly remember when the mouth should be opened vs closed for different expressions. I also can't always detect when the lines in the forehead and eyebrow are in a specific setting. I learned that I am really bad with visual tasks!
Alot of the facial expressions seemed to be linked together and it's harder to distinguish between disgusted and angry, or even combining both expressions to make one. There is more than one way to read a person, not everything is straightforward.