DISSERTATION

VALIDATING AND IMPLEMENTING THE INFORMAL LEARNING BEHAVIOR SCALE

Submitted by

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ABSTRACT

VALIDATING AND IMPLEMENTING THE INFORMAL LEARNING BEHAVIOR SCALE

The present study developed and tested a measure of informal learning behaviors for the workplace. Informal learning refers to any learning that occurs outside of formal and structured instructional settings. The literature has recently called for validated and reliable measures of informal learning, following a growing body of evidence that informal learning is both extremely prevalent in the workplace and important to high performance at work. Two connected studies were conducted to address this gap in the literature. In the first, a thorough literature review was conducted to identify a subset of informal learning that was intentional and observable at work. Six dimensions of informal learning were proposed to meet these criteria: planning, socializing, reflecting, experimenting, adapting, and scanning. Items were written and reviewed by subject matter experts. Participants were recruited from a research pool and an online MTurk pool to respond to the initial set of items and several additional scales used for convergent and discriminant validation. Analyses found strong support for a 23-item, five-factor model combining the planning and scanning dimensions and strong relationships between the dimensions and metacognition, motivation to learn, learning goal orientation, and a prior informal learning scale. Conversely, there were weak or negative relationships between the dimensions and prove performance goal orientation, as hypothesized. The second study was conducted to confirm the 23 item, five-factor model of the scale in a new, organizational sample and collect additional validity evidence by testing a model linking informal learning to self-regulation, support for learning, and job performance. Participants completed measures of the informal learning behavior scale, sleep quantity and quality, occupational self-efficacy, and support for learning in the organization. Responses were then matched to archival performance data. Analyses confirmed the hypothesized structure of the scale but found only some support for the proposed model. Sleep had no impact on either occupational self-efficacy or informal learning behaviors. Perceived support for learning was not related to informal learning behaviors. Occupational self-efficacy was related to informal learning, and the experimenting dimension predicted both job performance and job potential. The resulting scale is a reliable measure of five informal learning behavioral dimensions with a developing body of validity evidence supporting its use.

ACKNOWLEDGEMENTS

The dissertation represents the capstone to five years of work in a doctoral program. It's difficult to properly reflect on five years. In fact, I waited to write my acknowledgments until after I defended my dissertation and walked for my graduation. I was not quite ready to confront the overwhelming emotionality of it all. I feel incredibly privileged to say that the last five years pursuing my doctorate have been my most enjoyable, challenging, and rewarding years. I left my hometown, friends, and family to move to a new state, without any friends or support network, to study a niche area of psychology that I'm still not certain my family understands. In that time, I dedicated myself to learning and mastering my chosen field, of course, but I also made lifelong friends and colleagues without whom I never would have succeeded or become the person that I am today.

My advisor, Kurt Kraiger, who left Colorado State shortly before I did, still flew back to hood me and his remaining advisees. Since the beginning, Kurt has been an unwavering support. I remember two things clearly about my early days at Colorado State. First, during my first official meeting with him, he casually mentioned that he did not accept students who had not taken industrial or organizational psychology courses in undergrad. I did not take either of those courses in undergrad. They weren't offered at my alma mater, but I did not remind him of that fact in case there had been a mistake. Second, we had a meeting shortly thereafter to discuss my ideas for my first-year project, which is a sort of introduction to the program meant to get a new student's feet wet with research and working with his or her advisor. Despite his busy schedule as department chair, Kurt spent an hour with me in the basement of Clark working out my ideas on a whiteboard. During that time, he was singularly focused on hearing my ideas and providing his own insight. I also have Kurt to thank for connections that would influence my program of research, connections to two formative applied projects, and the connection that would land me my first job out of the program.

I would also like to acknowledge my committee members: Gwen Fisher, Anne Cleary, and Travis Maynard. I was fortunate to have the same committee for my master's thesis, empirical comprehensive exam, and dissertation. I say fortunate because my committee asked tough questions, pushed back against my weaker ideas, and provided all the support they could for my better ideas and for my progress as a student in general. In particular, I would also like to acknowledge Gwen specifically for her larger role in my student experience. As an IO faculty member and program coordinator, she was a great mentor in my roles as a student, researcher, and practitioner.

My cohort. There are few people who know me like Dorey, Alyssa, and Madison, and there is no way I can fully articulate what these three people mean to me. We worked together, shared offices together, made ridiculous game shows together, attended conferences together, traveled to foreign countries together, creeped out every other student in the program in some way at some point together, went to music festivals, concerts, events, anything, really, together. We did it not as cohort members, although we call ourselves *the (best) cohort*, but as friends, and I cannot think of a better way to experience graduate school than to experience it with your closest friends. Although our time in the program might be coming to an end and we are about to embark on our own journeys, we will do it with each other even if distance and time separate us.

It also so happened that I met my best friend and partner, Melanie, in our first semester at Colorado State. I sat behind her in Research Methods and, after some missed signals, I managed to get her to go out with me (with the help of Madison). We've been together ever since. Melanie has been there for me – and me for her – since the beginning. Our relationship has weathered the worst of our stresses, fears, anxieties, and pressures born not only from graduate school but also from simply living five years of life together. We have also had the best moments of our lives, so far, together. We made it through graduate school because of each other (and by withholding sushi from ourselves each semester to ensure we maintained our perfect GPAs, of course). I have no doubt that we can take on everything that is to come with style, assuming our puppy stops putting holes in our clothes.

I am my parent's only child, and my departure for Colorado was tough for them. I am reminded of this often by my mom. Nevertheless, they visited often, were always eager to hear about my latest project, class, or research, and they did everything they could to support me – including shipping me frozen deep-dish pizzas from home. My parents have always been there for me while I explored the world and pursued my degrees. I owe them everything for not only raising me but letting me find my own way to becoming who I am.

The final person I would like to acknowledge is my grandma. She was my biggest cheerleader from the beginning, often to the point of embarrassment, but the pride she took in my work and accomplishments was truly humbling. Unfortunately, she did not make it to see me complete my degree. I wish that were not that case, but all I can do is remember her and her love to the best of my abilities.

All that is left now is to say the words.

DEDICATION

To Elizabeth Ann Groden

&

Rowan, a very good boy

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GENERAL INTRODUCTION

In the organizational setting, learning occurs either formally – in which a learner is assigned to a course with an instructor and fixed material and occurs either in-person or virtually – or informally – in which a learner acquires knowledge, skills, or abilities him or herself organically (often) on the job. Most learning happens in an organization by the second, informal, route, with estimates attributing 70 to 80% of all on-the-job learning to informal learning (Bear, Tompson, Morrison, Vickers, Paradise, & Czarnowsky, 2008; Cerasoli, Alliger, Donsbach, Mathieu, Tannenbaum, & Orvis, 2018; Enos, Kehrhahn, & Bell, 2003). If we take learning to be a naturally occurring human process, formal learning is an attempt to strategically organize some learning (typically complex information) for easier, more reliable consumption and application, and all remaining learning is informal. Consequently, one "approach" should not replace the other but, rather, the two should be supported simultaneously in organizations.

These two approaches to learning are not mutually exclusive and, while research is lacking in exploring the interaction between formal and informal learning (Cerasoli et al., 2018), there is no reason to assume these approaches are nothing but mutually beneficial, with informal and formal learning facilitating each other and both increasing learning performance and future job performance and job satisfaction, and (Cerasoli et al., 2018). Whereas formal learning rightfully has received decades of attention in the organizational science literatures (Aguinis & Kraiger, 2009; Arthur, Bennett, Edens, & Bell, 2003), informal learning has received comparatively little empirical attention. Complicating our ability to understand informal learning, informal learning behaviors are idiosyncratic and range in intentionality (Cerasoli et al., 2018; Wolfson, Tannenbaum, Mathieu, & Maynard, 2018), with many informal learning constructs, e.g., implicit (Eraut, 2004) and tacit learning (Schugurensky, 2000), describing types of learning for which the learner is not consciously aware, making self-reporting and quantitative analysis difficult.

Recent contributions to the learning literature have described a need for a validated measure of informal learning (Cerasoli et al., 2018; Kukenberger, Mathieu, & Ruddy, 2015; Sitzmann & Ely, 2011) following a growing body of evidence that informal learning is positively related to heightened learning and job outcomes equal to or greater than formal learning (Cerasoli et al., 2018), including transfer to job outcomes (Enos et al., 2003), and job attitudes (Bear et al., 2008; Rowden & Conine, 2005). Given the idiosyncratic and, at times, unintentional nature of informal learning, this gap in the literature has lingered.

Informal learning, if it can be reliably measured, can be tracked and developed within individuals across an organization, providing that organization a powerful means of supporting a variety of learning behaviors without requiring formal instruction. Strategically developing informal learning is largely impractical without a means of quantifying informal learning behaviors; therefore, the lack of informal learning interventions within organizations is in part a consequence of the lack of a measure of these behaviors (Wolfson et al., 2018). Organizations are nevertheless interested in developing informal learning as part of their strategic learning initiatives (The Group for Organizational Effectiveness [gOE], 2014; Bear et al., 2008). This document begins by summarizing the development and validation of an informal learning measure (Study One) - the Informal Learning Behavior (ILB) scale. The latter part of this document presents a study (Study Two) to further validate the ILB scale within an organizational context.

STUDY ONE INTRODUCTION

A proliferation of constructs related to learning behaviors at work has emerged over the last three decades. These constructs include, but are not limited to, continuous learning (London & Mone, 1999; Tannenbaum, 1997), self-directed learning (Clardy, 2000), informal field-based learning (Wolfson et al., 2018), deliberative and reactive learning (Eraut, 2004), vicarious learning (Myers & DeRue, 2017), incidental learning (Watkins & Marsick, 1992), implicit learning (Eraut, 2004), and tacit learning (Schugurensky, 2000). Additionally, authors have suggested several taxonomies to categorize informal learning constructs (e.g., Eraut, 2004; Schugurensky, 2000; Watkins & Marsick, 1992). Disentangling these constructs has proven difficult (Noe, Tews, & Dachner, 2010), as new learning constructs (e.g., Myers & DeRue, 2017; Wolfson et al., 2018) continue to be published. Recently, there has been a trend toward defining informal learning around the idea of *intentionality* or the extent of awareness, control, and motivation one has with respect to learning as a behavior (chronologically: Schugurensky, 2000; Tannenbaum, Beard, McNally, & Salas, 2010; Noe, Tews, & Marand, 2013; Cerasoli et al., 2018; Wolfson et al., 2018).

Successful learning, in a broad sense, is known to be driven by motivation and self-regulation (Sitzmann & Ely, 2011; see also Klein, Noe, & Wang, 2006; Noe et al., 2010). Several studies have shown that individuals enact more informal learning behaviors the more motivated and self-regulated they are (Enos et al., 2003; see also Boud & Middleton, 2003; Noe et al., 2013; Skule, 2004; Zambarloukos & Constantelou, 2002). Viewing informal learning as *intentional* lends several advantages to clarifying it as a measurable, stable construct. First, consciously-driven (e.g., self-directed learning) and unconscious (e.g., tacit learning) learning constructs can be separated from one another. Second, with a focus only on consciously-driven or *intentional* constructs, these constructs can be parceled out into their constituent, salient behaviors. Third, the resulting behaviors can be grouped into possible dimensions, drawing support from learning theory and practice. Fourth and finally, these dimensions can be tested with specific, behaviorally-grounded items. In short, a subset of behaviors from all informal learning constructs can fit within the construct development and validation process.

Creating a New Measure

Why is a measure needed? Many authors have called for a comprehensive and validated measure of informal learning due to the growing evidence that informal learning is not only often used to grow job knowledge but also appears to be a critical mechanism of improving a variety of job outcomes (Cerasoli et al., 2018; Kukenberger et al., 2015; Sitzmann & Ely, 2011). These outcomes include, but are not limited to, learning effectiveness; job performance, and job satisfaction; however, informal learning is rarely documented, directly supported, or clearly understood (Cerasoli et al., 2018; Kukenberger et al., 2015; Sitzmann & Ely, 2011). Academic authors are not the only people interested in informal learning. Learning organizations are, likewise, increasingly turning their attention toward learning that occurs on the job (gOE, 2014; Bear et al., 2008) but no instrument has emerged for organizations to use to measure, benchmark, or develop on-the-job learning in the workplace.

Where have other measures fallen short? Many measures of informal learning exist: Composite Informal Learning Scale (Bednall, Sanders, & Runhaar, 2014), Workplace Learning Behaviors (Gijbels, Raemdonck, Vervecken, & Van Herck, 2012), "Informal Learning

Activities"[1] (Lohman, 2006), "Informal Learning" (Noe et al., 2013), and the Self-Directed Learning Scale (Bartlett & Kotrlik, 1999). The principle issue with previous measures is that none have gone through a rigorous design and validation process, meaning that the items of the scales were largely written for a given study, versus drawn from a large pool of items by exploratory and confirmatory factor analyses (CFAs) on many observations, and used for the study, versus independently confirming relationships with other scales. The secondary issue is that none of the measures assess a comprehensive range of behaviors. At three dimensions each, Lohman's (2006) scale and Noe et al.'s (2013) scale each have three items per dimension, totaling nine items in each measure. Even the next-most recently developed scale, Wolfson et al.'s (2018) Informal Field-Based Learning Scale, which has gone through an extensive validation process, also represents three dimensions with nine items. Parsimonious scales are certainly valuable, especially in organizational contexts where time to participate in studies is short, but measuring a representative number of behaviors and dimensions is incredibly important for organizational development purposes.

How do People Learn on the Job?

Many researchers have attempted to organize the literature detailing learning at work through meta-analyses, literature reviews, taxonomies, or proposing new constructs (e.g., Cerasoli et al., 2018; Eraut, 2004; Marsick & Watkins, 1992; Schugurensky, 2000), yet these efforts have had little effect clarifying the field (Skule, 2004). To bring clarity to the informal learning construct for scale development, I focused on constructs that I believed to be indicative of the range of informal learning behaviors and organized them by the intentionality of the

[1] Measures in quotes refer to unnamed ad hoc measures

behaviors. Intentionality is well-supported in theoretical and empirical work on informal learning; hence it is used as the primary organizing characteristic. Noe et al. (2010) argued that informal learning behaviors require an intentional, conscious act by some agent (see also: Cerasoli et al., 2018; Schugurensky, 2000; Tannenbaum et al., 2010).

Figure 1 organizes the learning constructs extant in the literature, distinguishing learning by its formality and intentionality. Autonomous learning (Beier, Torres, & Gilberto, 2017) describes the extent to which an individual pursues any and all learning him or herself, so it tops the figure. Continuous learning is italicized, as it is a special case of learning over time. The figure is intended to capture the most well-established and, in some cases, the most recent additions to the informal learning construct. The literature uncovered in the search also discussed other learning constructs: experiential learning (Kolb, 1984), action learning (Yorks, O'Neil, & Marsick, 1999), voluntary learning (Birdi, Allan, & War, 1997), experience-based learning (Marsick & Watkins, 2001), situated learning (Lave & Henger, 1991), workplace learning (Gijbels, Raemdonck, Vervecken, & Van Herck, 2012; Le Clus, 2011), and self-regulated learning (Bakkenes, Vermunt, & Wubbels, 2010). These other constructs were not included for several reasons, the primary being overlap with constructs in the figure (e.g., voluntary learning, experience-based learning, and self-regulated learning, which resemble self-directed, vicarious, and informal learning, respectively). Some constructs were more related to learning styles (experiential and action learning). Consequently, I focused on the constructs underneath informal learning in the figure to guide my search for informal learning behaviors.

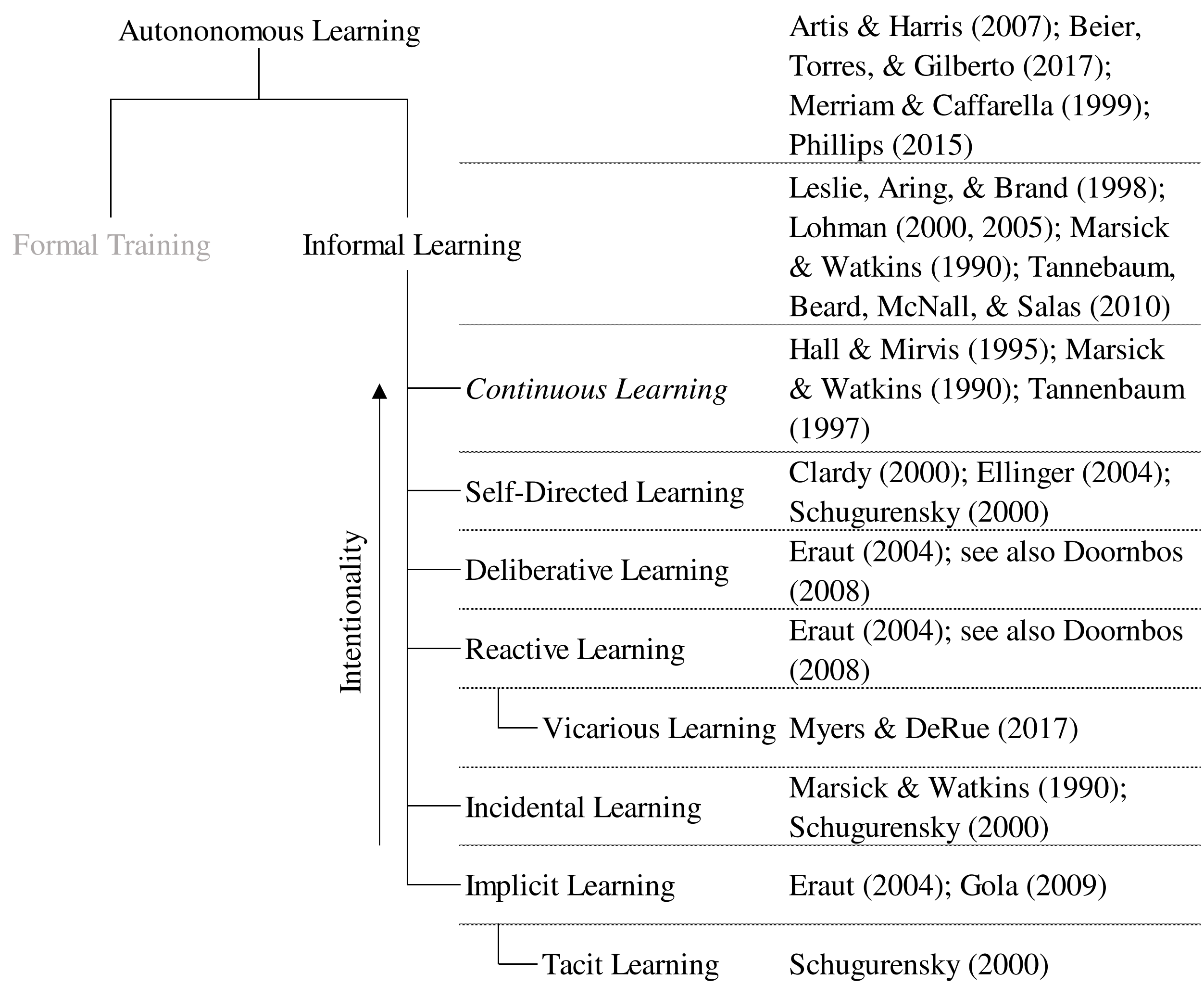

Figure 1. Construct Summary of Informal Learning

Dimensions of Informal Learning Behaviors

I propose that there are six dimensions of intentional informal learning behaviors based on a review of the informal learning literature. These behaviors are planning, socializing, reflecting, experimenting, adapting, and scanning. Many other characterizations of this space exist (e.g., Boud & Middleton, 2003; Lohman, 2000; Wolfson et al., 2018) but my framework is meant to aggregate past conceptualizations rather than add yet another one. Lohman's (2000) taxonomy of informal learning as sharing experiences and knowledge, experimenting with new ideas and processes, and searching for new information remains popular in this space (e.g., Berg & Chyung, 2008; Hoekstra, Brekelmans, Beijaard, & Korthagen, 2009; Noe et. al., 2013). It was, therefore, important to consider her work when building the current framework, while still realizing it misses key aspects of informal learning, notably planning behaviors, adapting behaviors, and conflating socializing and reflecting behaviors. In subsequent paragraphs, I define and provide the rationale for each dimension, stemming from my review of the informal learning literature.

Planning. Planning behaviors are most consistent with the self-directed learning construct (Clardy, 2000; Ellinger, 2005) in that these behaviors involve thinking ahead or preparing in a variety of ways. Thought and preparation are both required when one directs his or her own learning (i.e., creates projects for him or herself). For example, one might determine what learning materials are needed, set learning goals, or rehearse for a future event. These behaviors are highly intentional and can, in some instances, resemble formal instruction in that one prepares materials, sets goals, and evaluates his or her performance, but the key distinction from self-directed learning is that these behaviors remain solely individually-driven and motivated by challenges in an individual's environment and the learning is not the result of some organizationally-sponsored training. Self-directed learning, by contrast, involves both participating in formal training and informal learning.

An important aspect of this behavior, which has received little attention is assessing the veracity of information found primarily online but elsewhere too (Brown & Sitzmann, 2011). An important aspect of most informal learning behaviors appears to be the ability for the learner to assess his or her own learning ability, progress, success, including evaluating materials and feedback as well. Planning behaviors have largely been contained within self-directed learning, but researchers have considered future-oriented informal learning behaviors (e.g., Eraut, 2004) in previous taxonomies of the construct, hence its inclusion.

Socializing. Most authors agree that informal learning is a social process (Enos et al., 2003; Kraiger, 2008; Lave & Henger, 1991; Lohman, 2000; Marsick & Watkins, 1990; Skule, 2004) in which learners share either their experiences with others (Lohman, 2000) or their explicit learning moments (Marsick & Watkins, 1990), and, in organizations, learners interact with others to understand and master processes in the organization, handle politics, and explore novel situations (Boud & Middleton, 2003; Doornbos, Bolhuis, & Simons, 2004). Furthermore, social informal learning at work can come from maintaining relationships, modeling behavior, identifying positive role models, discussing problems as a group, handling conflict, or processing feedback (Cunningham & Hillier, 2013; Doornbos, Simons, & Denessen, 2008). Socializing is crucial to any learning (Lave & Henger, 1991), but it is especially important in informal learning as many learning opportunities derive from natural interactions with peers in addition to more concerted efforts like seeking feedback or participating in learning groups.

Reflecting. Reflection is vital to self-improvement and awareness, and it can happen both in natural and structured settings (Maurer, Leheta, & Conklin, 2017). Additionally, there may be significant differences in how individuals reflect as well as the outcomes of those reflections (Maurer et al., 2017). Although reflection is a relatively recent concept in the organizational sciences literature, it has been a frequently studied behavior in informal learning. Reflective behaviors include maintaining awareness of one’s organization, goals, and coworkers (Leslie, Aring, & Brand, 1998), reflecting on what one has learned at work (Cunningham & Hillier, 2013; Hoekstra et al., 2009), reviewing performance reviews and feedback (Berg & Chyung, 2008; Eraut, 2004; Van Woerkom, Nijhof, & Nieuwenhuis, 2002), and reflecting on daily activities and routine (Bednall et al., 2014). In short, reflective activities can draw from any work experience that might promote learning.

Experimenting. Per Lohman (2000), individuals frequently experiment to augment their learning. Experimenting involves trial-and-error behaviors, e.g., trying a new idea or process (Berg & Chyung, 2008, Cseh, Watkins, & Marsick, 1999, Van Woerkom et al., 2002), taking risks or taking on new, challenging tasks, producing alternate solutions to problems, and assessing consequences (Cseh et al., 1999). Experimenting includes considering future consequences (i.e., hypothesizing) and testing an action, idea, or process, but it broadly means trying something new. Naturally, other behaviors may cooccur with experimenting, such as planning, but experimenting includes the behaviors involved in doing an action that stimulates learning rather than the preparation (i.e., planning).

Adapting. Adapting refers to the set of actions an individual performs in response to a new or unanticipated event. A large proportion of learning behaviors discussed in the literature (Boud & Middleton, 2003; Doornbos et al., 2014; Doornbos et al., 2008) involve responding to novel events at work, so these behaviors have been grouped into an adapting dimension. Past studies have how individuals address ambiguous or novel situations at work (Bednall et al., 2014; Cseh et al., 1999; Doornbos et al., 2004; Doornbos et al., 2008; Hoekstra et al., 2009; Leslie et al., 1998), including adapting to challenges, making decisions about a situation, or handling conflict with others. Adapting and experimenting behaviors appear to share many similarities but unlike experimenting, which refers to actions taken to try something new, adapting is reactive whereas experimenting is proactive. Of course, one might adapt to something experimental; for example, one might learn from a mistake or learn to continue with a new process or idea.

Scanning. Searching for new information, also referred to as scanning (e.g., Artis & Harris, 2007) involves reading professional publications, attending conferences, or sourcing information from websites (Lohman, 2000). Scanning shares some similarities with the sourcing and evaluating materials aspect of planning, but scanning refers to a broader notion of staying current with one's field, answering specific questions, clarifying concepts or issues, or putting oneself in a setting to experience new or updated ideas. In this sense, scanning differs from preparing materials in that the search for information is the goal itself rather than a means to a larger goal (e.g., a learning project).

This taxonomy will be tested with a confirmatory factor analysis, which will specify six factors, representing the six proposed dimensions, composed of behavioral items written from the behaviors found in the literature review. The first hypothesis is as follows:

Hypothesis 1. *The best-fitting model of the data will be a six-factor solution representing the six-factors proposed, including planning, socializing, reflecting, experimenting, adapting, and scanning dimensions.*

Learning in the Workplace

There is a broader organizational context that affects the display of informal learning behaviors. Informal learning behaviors occur in the context of interactions between environmental stimuli and personal characteristics (Johns, 2006; Johns, 2018). These environmental and individual variables then provide a foundation for testing the validity of the informal learning behavior scale. Individuals' personal characteristics, e.g., motivation to learn (Colquitt, LePine, & Noe, 2000), self-efficacy (Geijsel, Sleegers, Stoel, & Krüger, 2009; Maurer, Weiss, & Barbeite, 2003; Runhaar, Sanders, & Yang, 2010; Sitzmann & Ely, 2011), learning goal orientation (Klein et al., 2006; Runhaar et al., 2010; Sitzmann & Ely, 2011) metacognition (Schmidt & Ford, 2003) and zest (Noe et al., 2013), influence how individuals respond to their environment via informal learning behaviors. As discussed, informal learning occurs when an individual is motivated and confident and has a clear understanding of his or her own learning abilities and the goals he or she wants to achieve. In short, self-regulation drives informal learning behaviors and, consequently, measuring constructs related to self-regulation alongside informal learning should provide information about the convergent validity of the scale.

To establish the scale's convergent and discriminant validity, four measures of constructs known to be related to learning – a prior ad hoc measure of informal learning (Noe et al., 2013), motivation to learn (Noe & Schmitt, 1986, as used in LePine, LePine, & Jackson, 2004), metacognition (Ford, Smith, Weissbein, Gully, & Salas, 1998), and learning goal orientation (VandeWalle, 1997) were used and one measure of a construct thought to be unrelated to learning – prove performance goal orientation (VandeWalle, 1997) was used. Following traditional logic of convergent and discriminant validity, the hypotheses were as follows:

Hypothesis 2. *The ILB dimensions will be positively and significantly related to a prior (a) measure of informal learning, (b) learning goal orientation, (c) metacognition, and (d) motivation to learn. Evidence of these positive relationships will be indicative of convergent validity.*

Hypothesis 3. *The ILB dimensions will be negatively or non-significantly related to prove performance goal orientation. Evidence of a negative or non-significant relationship will be indicative of discriminant validity.*

STUDY ONE METHOD

Item Generation

To create items for the new scale, a thorough literature review was conducted on informal learning and its constituent constructs. Almost thirty years of papers, beginning with Marsick and Watkins (1990) seminal book on informal and incidental learning in the workplace, were reviewed. Several experts on informal learning were consulted throughout the process for their perspectives on informal learning behaviors and conceptualization. The final stage of this work involved organizing the set of behaviors recorded from the literature review into each proposed dimension. This process yielded anywhere from 10 to 21 unique and specific behaviors per dimension. From these groupings, an initial set of phrases were written to capture the behaviors unique to each dimension. These phrases went through a series of edits and revisions by the author and his advisor to formulate the quasi-final set of 84 items, with 12 to 17 items per dimension. Edits and revisions were conducted to improve the readability, specificity, and relevancy of each item. Following this process, a subject matter expert (SME) panel was assembled to provide a final round of evaluation on the items.

Item Evaluation

Six SMEs, individuals with experience with learning in organizations (Ph.D.s in Industrial/Organizational Psychology with work and research experience in learning and development), were recruited through various professional networks. Each were sent an identical set of materials and tasks: A spreadsheet of the 84 items (randomized to not indicate by ordering their dimensions), rating scales, a construct definition, and instructions. SMEs were asked to complete three tasks: rate each item on its clarity, rate each item on its relevancy to the definition of informal learning, and group each item into a dimension. Clarity and relevancy were rated on a one to three scale, with one indicating not at all clear/relevant and three indicating very clear/relevant. Experts were asked to group items into as few dimensions as possible and assign each dimension a name; otherwise, no other guidance was provided besides the definition of informal learning.

All six SMEs completed each task. Ratings of clarity and relevancy were summarized across experts. Average ratings were categorized into green, yellow, and red bands to describe items that were rated very highly (≥ 2.67), decently (< 2.67, ≥ 2.17), and poorly (< 2.17). In other words, to be rated highly, an item had to be rated 90% or better to be green, 72% or better to be yellow, or 71% or worse to be red. Items that either scored red on either clarity or relevancy or yellow on both clarity and relevancy were revised. 23 items were identified in this manner (two items were red on one dimension and 21 items were yellow on both). The final task, grouping each item into a dimension, was the most difficult task for the experts. The number of dimensions proposed ranged from four to 17, with the average number of dimensions being 8.3. Dimensions were listed and reduced to determine the number of unique factors and the number of mentions per dimension. Twenty-one relatively unique dimensions were identified, of these, 12 received more than one mention. Notably, the most-mentioned dimensions aligned well with the proposed dimensions: reflecting, researching (planning/scanning items), socializing, and adapting each received three to five mentions.

Items were revised to improve on the clarity and relevancy feedback provided by the subject matter experts. No changes were made based on the dimensional grouping at this point to the items. The final set of 84 items are produced in Appendix A.

Participants

616 undergraduate psychology students were sampled from a psychology research pool. An additional 562 full- or part-time workers were sampled online via MTurk. Undergraduate participants signed up to participate in the study via an online research pool portal. Similarly, participants on MTurk signed up for the study (a Human Intelligence Task; HIT) on the MTurk website. 1,178 total participants were collected, exceeding the recommended guidelines of five

to ten participants per item for sample size (Floyd & Widaman, 1995). Unless specifically mentioned, the two subsamples were analyzed together. The combined sample was predominantly female (56.3%; 42.6% male, 0.4% other, 0.7% prefer not to say), white (63.9%; 14.3% Asian or Pacific Islander, 9.9% Hispanic, 5.7% Black or African American, 3.8% Multiracial, 0.9% Native American or American Indian, 1.5% Other), employed (59.1%; 35.4% student, 5.5% unemployed), and high school (or equivalent) educated (61.5%; 31.4% bachelor's degree, 6% master's or professional degree, 0.9% doctorate, 0.2% no high school education). The average age of participants was 26.83, which ranged from 18 to 69. Of employed participants, the average amount of hours worked was 33.12 (38.23 in a busy week), and participants reported being with their employer an average of 4.46 years and in their current role 3.96 years.

Quality item responses. Quality responses, assessed by the attention a participant pays to survey items, are a concern when collecting responses online. Multiple methods are available to prevent and assess for poor responses in survey design (Curran, 2016; Maniaci & Rogge, 2014; Meade & Craig, 2012). Here, three methods were used. First, three attention check items, such as, "Rate this item, 'Highly characteristic of me'," were inserted into the measures to check whether participants were reading the items (Curran, 2016; Maniaci & Rogge, 2014). Second, the intra-individual response variability index (IRV index; Dunn, Heggestad, Shannock, & Theilgard, 2018) was assessed. Participants should, assuming different intrinsic levels of constricts, rate items belonging to different constructs with some variability; for example, rating an item representing construct "A" a 5 and rating an item representing construct "B" a 3. The IRV index is an extension of the long string index (Dunn et al., 2018) in that both methods are used to detect the extent to which a participant uses the same response option regardless of the construct he or she is rating; whereas the long string index is formed by counting the number of times a single response option is used consecutively, the IRV index is formed by calculating the standard deviation of responses across all item responses from a given participant. Very low IRV index values (standard deviations) indicate insufficient effort responding. Third, the time to complete the was recorded for each participant and compared to how quickly the survey's creator could complete the survey while reading every item (Curran, 2016; Maniaci & Rogge, 2014).

Per recommendations by Huang, Curran, Keeney, Poposki, and DeShon (2012), respondents who failed more than one attention check were flagged to be removed from the analyses to improve data quality. Similarly, participants who used the same response scale indicator for every or nearly every item were flagged (Dunn et al., 2018). Participants with mostly or entirely missing data were also considered for removal. Finally, participants who completed the survey substantially faster than the creator could were considered for removal. An index variable was constructed to indicate whether a participant failed one or more of these criteria. In total, 718 participants passed all criteria. Preliminary data analyses were conducted to determine whether removal of the remaining participants improved data quality (as indicated by model results of the proposed six factor solution on all 84 items). Despite creating two additional versions of the quality index (version two only checked missing attention checks and total invariance and version three only checked invariance), model fit was best when all participant data was included (which is consistent with past research, e.g., Kraiger, McGonagle, & Sanchez, under review; Michel, O'Neill, Hartman, & Lorys, 2018). Using every data point has the added advantage of increasing generalizability and reducing the arbitrariness of decisions about data inclusion. Therefore, all subsequent analyses were conducted on all data collected.

Procedures

Participants completed the survey online via Qualtrics. They first consented to the use of their data and then read short instructions to orient themselves to the survey. MTurk participants read the following instructions: “The following statements describe different ways to approach learning at work. Please rate how much each statement describes how you typically approach learning at work.” Directions were extended for the undergraduate psychology participants. These participants may not have had work-related experience but still possess the learning behaviors the scale is intended to measure. Consequently, the instructions were reworded to guide them to use their education experience when necessary. The instructions read: “The following statements describe different ways to approach learning at work. Please rate how much each statement describes how you typically approach learning at work. For this study, please consider your "colleagues" to be friends, classmates, or coworkers. Similarly, if you have not had work-related experience, imagine your class-related experience.”

All participants first completed the informal learning scale items, then the secondary measures, and finally completed the demographic questions. The secondary measured and demographic questions were randomized within each section to prevent ordering effects from influencing the ratings of the items.

Measures

Demographics. Participants were asked to report their age, gender, ethnic background, education, organizational and job tenure, job type, and hours worked per week.

Informal Learning Behaviors. Informal learning behaviors were measured with 84 items written to tap the six proposed dimensions of informal learning behaviors. Participants rated how characteristic each behavior was of them on a five-point Likert-type scale (*1 = Not at* *all characteristic of me*; *5 = Highly characteristic of me*). Please see Appendix A for a list of the items.

Metacognition. Metacognition refers to one's knowledge of and control over his or her thinking (Ford et al., 1998). Metacognitive activities were measured with twelve items to assess the extent to which they engaged in metacognition throughout the day (Ford et al., 1998). The items were developed to assess behaviors related to self-monitoring of learning, learner choice in practice, and self-evaluations of the rater's progress. Modifications were made to the items to remove references to training programs and change the tense of the item. An example of an original item is, "During this training program, I thought about what skills needed the most practice," which was edited to read, "I think about what skills need the most practice". Participants will rate their metacognition on a five-point Likert-type scale *(1 = strongly disagree, 5 = strongly agree*). Ford et al. reported an internal consistency of .83. Coefficient α in the present study was .92. Please see Appendix B for a list of the items.

Motivation to Learn. Motivation to learn refers to the extent to which one is energized and engaged in learning (Noe & Schmitt, 1986). Motivation to learn was measured with three items based on the work of Noe and Schmitt (1986) as used in LePine et al. (2004) with slight modifications for this study. The items were, "I exert considerable effort to learning new materials," "I try to learn as much as I can" and "I am motivated to learn new skills". In this study, these items will be modified to drop "my courses" to emphasize the informal learning context and "in general" to increase the saliency of one's momentary motivation. Responses were provided on a five-point Likert-type scale (*1 = strongly disagree, 5 = strongly agree*) with higher scores representing higher motivation to learn. LePine et al. reported an internal consistency of .71. Coefficient α in the present study was .85. Please see Appendix C for a list of the items.

Learning Goal Orientation. Learning goal orientation, or the desire to gain competence by learning new skills and familiarizing oneself with new situations, was measured with six items developed by VandeWalle (1997). An example item is, "I often look for opportunities to develop new skills and knowledge". Participants rated their learning goal orientation on a six-point Likert-type scale (*1 = strongly disagree; 6 = strongly agree*). VandeWalle reported an internal consistency of .89. Coefficient α in the present study was .89. Please see Appendix D for a list of the items.

Informal Learning (ad hoc). Noe et al. (2013) developed a nine-item scale to assess the frequency of informal learning behaviors representative of learning from oneself, learning from others, and learning from non-interpersonal sources. Noe et al. directed participants to consider the prior three months and rate how frequently they engaged in a behavior. An example item is, "Interacting with my supervisors". Participants rated the frequency of their informal learning behaviors on a five-point Likert-type scale (*1 = never; 5 = all the time*). Noe et al. reported an internal consistency of .71. Coefficient α in the present study was .82. Please see Appendix E for a list of the items.

Prove Performance Goal Orientation. Prove performance goal orientation, or the desire to prove one's personal competence and gain positive regard for it, was measured with four items developed by VandeWalle (1997). An example item is, "I'm concerned with showing that I can perform better than my coworkers". Participants rated their prove performance goal orientation on a six-point Likert-type scale (*1 = strongly disagree; 6 = strongly agree*). VandeWalle reported an internal consistency of .85. Coefficient α in the present study was .85. Please see Appendix F for a list of the items.

Analysis

A confirmatory factor analysis, various item-level analyses, and a structural equation model were conducted to test the following study hypotheses:

Hypothesis 1. The best-fitting model of the data will be a six-factor solution representing the six factors proposed, including planning, socializing, reflecting, experimenting, adapting, and scanning dimensions. See Figure 2.

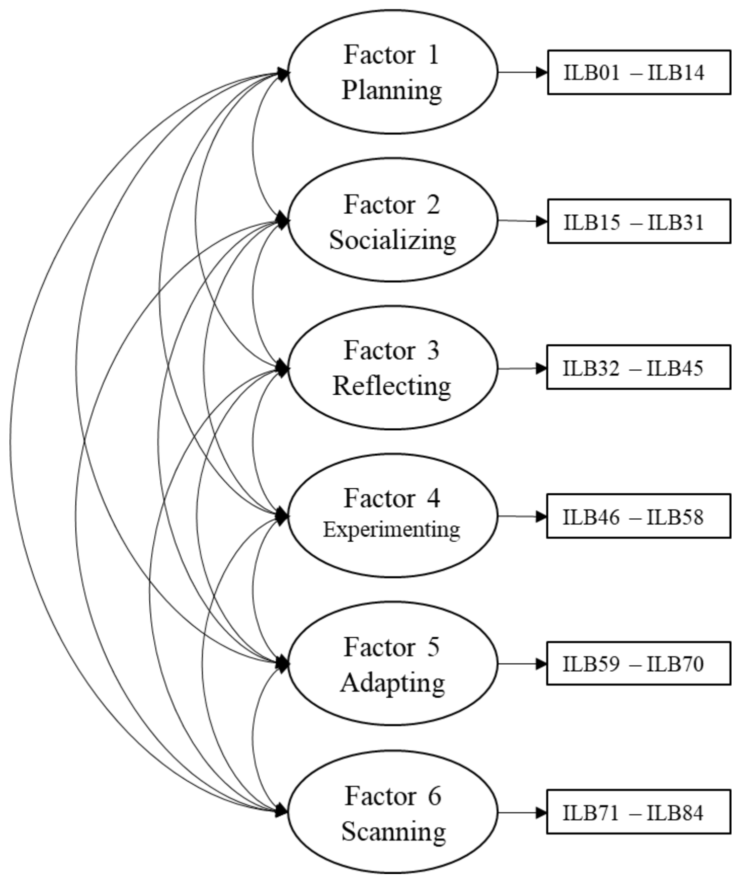

Figure 2. Proposed Dimensional Structure of Informal Learning Behaviors

Hypothesis 2. The dimensions of the informal learning behaviors scale will be positively and significantly related to a prior measure of informal learning, learning goal orientation, metacognition, and motivation to learn. Evidence of these positive relationships were indicative of convergent validity.

Hypothesis 3. The dimensions of the informal learning behaviors scale will be negatively or insignificantly related to prove performance goal orientation. Evidence of a negative or non-significant relationship were indicative of discriminant validity.

All variables were scored on a continuous scale and were normally distributed. The proposed path model is presented in Figure 3. Analyses were conducted using MPlus 8.0 (Muthén & Muthén, 1998–2017). Informal learning behavioral dimensions were modeled as latent variables, composed of their respective item-level indicators, and, when applicable,

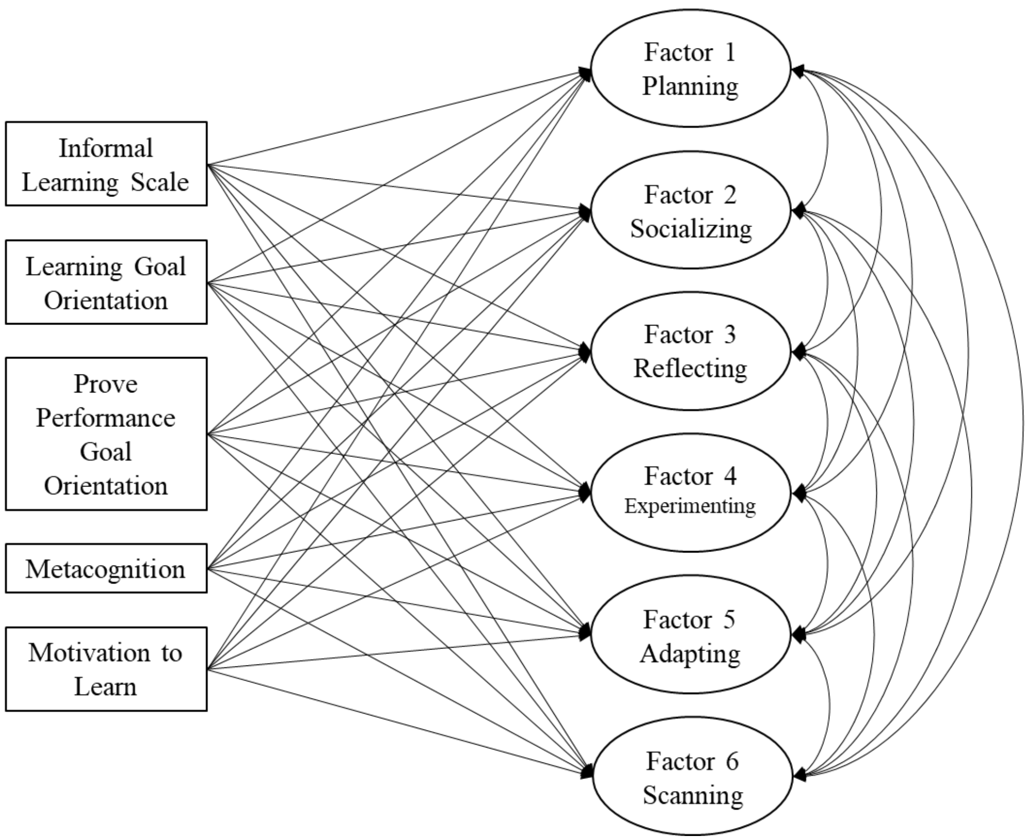

Figure 3. Proposed Path Model for Validation Constructs and Informal Learning Behavior Dimensions

informal learning, learning goal orientation, metacognition, motivation to learn, and prove performance goal orientation were modeled as observed variables.

The hypotheses were tested in the following manner:

Hypothesis 1. A CFA was conducted to assess whether the hypothesized six factor solution fit the data. To evaluate overall model fit, model fit criteria suggested by Hu and Bentler (1999) were used: the comparative fit index (CFI) > .95, Tucker–Lewis Index (TLI) > .95, root mean square error of approximation (RMSEA) < .06, and standardized root mean square residual (SRMR) < .08. In addition, the Chi-square test of model fit, where a non-significant test indicates perfect fit of the model to the data, was evaluated. Two models were developed using the following criteria to reduce the total number of items and final, best-fitting models, were selected using the model fit indices described above. Both models will be reported in the results section.

Item-level Analyses. Classical item indices of difficulty and discrimination, along with item-factor loadings, discrepancies between items and factor loadings and items with other items, and factor reliability were calculated and assessed to make decisions about item retainment in the final factor structure.

Difficulty. Item difficulty refers to the mean of a given item. Difficulty indicates how difficult it is for a respondent to strongly endorse an item. Ideally, difficulty ranges across the items of a dimension, as a range indicates that the breadth of the construct is being measured. Difficulty does not indicate if an item should be retained but, taken together with the other item-level analyses, difficulty can be a useful index for evaluating a set of items.

Discrimination. Item discrimination is conceptualized as the correlation between an item score and the total score of a factor. The resulting value indicates the extent to which a given item provides information about the construct as a whole; larger discrimination values mean a specific item provides more information about a respondent's standing on a given construct than smaller discrimination values. A low discrimination value ($r < .1$, per Varma, 2006) indicates that the item does not provide useful of information about participants' level of the construct of interest. A high value ($r > .4$, per Varma, 2006), on the other hand, provides useful information about the participants' level of the construct of interest: mathematically, there is a large relationship between the item and the total score on the measure. Items with discrimination values below 0.1 were dropped, and items with discrimination values below 0.4 were considered for dropping.

Factor loadings. The value of an item's loading on a specified factor approximates its relationship to the factor given the correlations between latent factors in the model. Items with small factor loadings (loadings < 0.3, per Raykov & Marcoulides, 2011) are typically suppressed, meaning those items are removed from the analysis. Consequently, small factor loadings were used as another indicator of which items to drop from the model.

Modification indices. Items may correlate with one another and/or with another factor. While this is expected (and encouraged) to some extent (e.g., for reliability), if these relationships are larger than the relationships with the parent factor (with respect to item-item correlations) or exceed the small factor loading value (0.3) on two or more factors (i.e., cross loading), these relationships can be very detrimental to model fit. The MPlus modindices function provides modification indices for both item-item and item-factor relationships. Modification indices are Chi-square values that indicate the amount the Chi-square value would decrease (an improvement to model fit) if the problematic relationship was removed. By default, MPlus reports all modification indices above 10. Items from problematic relationships were removed from the model in a top-down manner, prioritizing the removal of items that produced the most model fit improvements across all their problematic relationships.

Reliability. Coefficients alpha and omega were computed to provide indications of internal consistency, or the extent to which a set of items are related. Internal consistency is not synonymous with unidimensionality, however (see Raykov & Marcoulides, 2011), so omega, which is computationally based on factor structures, was also calculated. Raykov and Marcoulides recommended that reliability estimates greater than .80 are preferable for both alpha and omega but highlighted that the validity of the scale must also be considered. Generally, items were removed to maximize reliability estimates while overall reducing the number of items in each factor (which generally reduces reliability estimates).

Hypotheses 2 & 3. Hypotheses two and three were tested by adding structural covariance paths between the convergent and discriminant validity variables and the informal learning behavior latent variables. Like the confirmatory factor analysis, model fit was evaluated with the same criteria suggested by Hu and Bentler (1999). DeVellis (2012) differentiated between convergent and discriminant validity in terms of the magnitude of the estimate of the relationship and significance (i.e., convergent variables should have high relationship estimates and remain significant and discriminant variables should have low relationship estimates and be non-significant). Pertaining to discriminant validity, significance is often subject to increases in sample size, which are often large in initial validation studies. That is, it is easier to a find a small effect with a larger sample size, rendering non-significance difficult to achieve in these cases. Although DeVellis (2012) did not provide cutoff values to assess the differences in correlations that would separate convergent and discriminant relationships, the relative size between the correlation sizes can be assessed with his prior criteria. Only paths from a good- or excellent-fitting model were interpreted.

STUDY ONE RESULTS

Item Reduction

Initial Overall Model Fit. The measurement model specifying six latent variables and the covariance between them comprised of 84 items resulted in poor to good fit depending on the fit statistics. The Chi-Square test of model fit was significant ($\chi^2(3{,}387) = 11{,}267.099$, $p < .01$). Overall fit indices were all in the poor to good range (RMSEA = .044 [.044, .045], $p = 1$; CFI = .821; SRMR = .052). The factor loadings for all items ranged from .387 to .774 and were significant. Due to the promising initial fit and desire to retain the theorized structure, the analyses proceeded to item reduction step to improve model fit rather than conduct an exploratory factor analysis to find a better factor structure.

Item-level Analyses. Classical item indices of difficulty and discrimination, along with item-factor loadings, discrepancies between items and factor loadings and items with other items, and factor reliability were calculated and assessed to make decisions about item retainment in the final factor structure. See Table 1 for a summary of the item-level analyses conducted.

Difficulty. An index of difficulty was computed by dividing the mean score of an item by the highest possible numeric response scale option (5) to create a range of values from zero to one. Overall, items were easy for participants to endorse. Mean item difficulty was .77, and item difficulty ranged from .59 to .87. On average, participants used the upper end of the distribution to rate items. Item score frequencies were also calculated to assess whether any item responses were non-normally distributed. While items responses tended to use the higher end of the response scale, no item was non-normally distributed (using the +/- 2.0 cut-off for skewness and kurtosis recommended by George & Mallery, 2010). Please see Table 1 for a summary of the score frequencies, including response option use histograms for each item.

Discrimination. Discrimination values were calculated by summing individual factor total scores less a given item to create remainder scores (that is, for each item, a remainder total score of its parent factor was calculated). Remainder total scores were calculated so the correlation between an item score and the total score was not inflated by the inclusion of the given item in its total score. Mean item discrimination was .53, and discrimination values ranged from .35 to .66. All items fell above Varma's (2006) lower .1 cut-off and all but four items fell above the higher .4 cut-off, indicating that every item provided good information about an individual's standing on its respective factor. Consequently, discrimination values were not used to make item retention decisions.

Factor loadings. As reported in the initial overall model fit, no factor loadings were below .3 and consequently factor loadings were not used to remove items from the model.

Modification indices. Items from problematic relationships (e.g., the scanning item, "Maintain a network of peers who learn from each other" cross-loaded on the socializing factor, and the experimenting item, "Anticipate possible consequences of your actions at work" cross-loaded on reflecting and adapting factors) were removed iteratively such that batches items that contributed the most to misfit were removed, analyses were rerun, the most problematic remaining items were removed in similar batches, and so on. In total, 14 iterations of item removal were initially conducted. In total, 61 items were removed in this manner to produce a five-factor, 23-item final scale.

Reliability. Reliability, estimated by coefficients alpha and omega, was calculated for the five-factor solution. Alpha estimates for informal learning dimensions ranged from .72 to .81 and omega estimates ranged from .72 to .81 across the five factors, with overall scale alpha being .92 and omega being .94.

Confirmatory Factor Analysis: Overall Model Fit

Six-factor model fit. Following the steps taken to reduce the number of items and improve model fit, an excellent-fitting model emerged from a comprise between removing 54 items with high modification index values while preserving dimensional reliability. This model solution included 30 items evenly spread across the six proposed factors of the informal learning behavior scale. The measurement model specifying six latent variables and the covariance between them comprised of 30 items resulted in good to excellent fit. The Chi-Square test of model fit was significant ($\chi^2(390) = 1063.912$, $p < .01$). Overall fit indices were all in the good to excellent range (RMSEA = .038 [.036, .041], $p = 1$; CFI = .948; SRMR = .032). While these indices indicated good to excellent fit, factors one (planning) and six (scanning) were very highly correlated with one another ($r = .948$), which is strong evidence that the latent factors are identical. A second CFA was conducted on the same items except a second-order factor composed of factors one and six was also included. This model resulted in the same model fit as the six-factor solution, so the reduction of items by modification indices and reliability steps were redone to produce a five-factor solution in which items from the original first and sixth factors were combined into a single factor.

Five-factor model fit. A 23-item, five-factor solution was produced by removing 61 items with high modification index values. See Table 2 for a list of the items, factors, and dimensional internal consistency. The resulting measurement model specifying five latent variables and the covariance between them comprised of 23 items resulted in excellent fit. Chi-Square test of model fit was significant ($\chi^2(220) = 573.438$, $p < .01$). Overall fit indices were all in the excellent range (RMSEA = .037 [.033, .041], *p* = 1; CFI = .962; SRMR = .028). Please see Figure 4 for the path diagram of this measurement model.

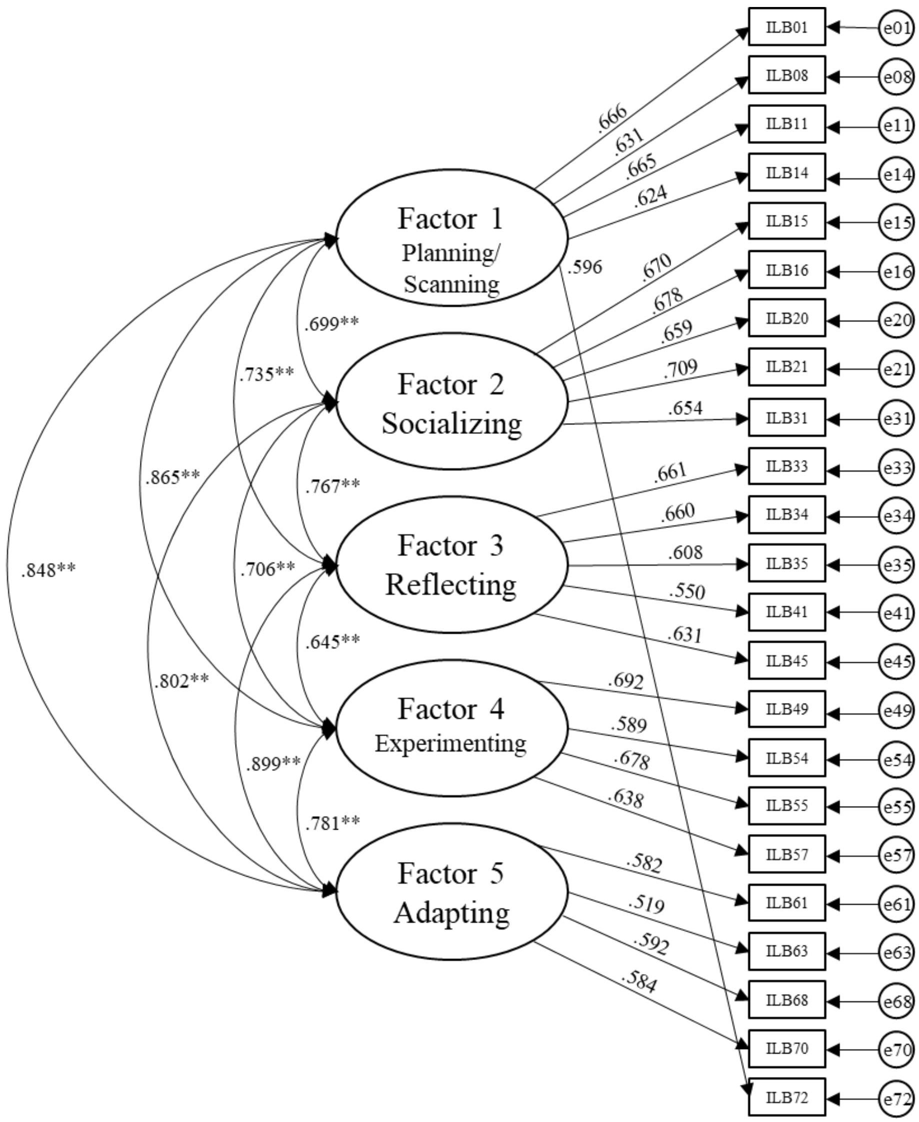

Figure 4. Path Diagram of the Five-Factor Measurement Model

Structural Equation Modeling: Overall Model Fit

Structural covariance paths were added between the five latent factors of the informal learning behavior scale and the convergent and discriminant validity variables informal learning, learning goal orientation, metacognition, motivation to learn, and prove performance goal orientation. This model resulted in excellent fit. The Chi-square test of model fit was significant ($\chi^2(310) = 817.477$, $p < .01$). Overall fit indices were all in the excellent range (RMSEA = .038 [.035, .042], $p = 1$; CFI = .952; SRMR = .029).

Structural Equation Modeling: Path Estimates

The following results are summarized in Table 3.

Convergent validity. Convergent validity was assessed with the relationships between the five factors and the following criteria:

Informal learning. Informal learning (measured by the Noe et al. 2013 scale) was positively and significantly related to planning/scanning ($b = .42$, $SE = .08$, $p < .01$), socializing ($b = .50$, $SE = .07$, $p < .01$), and experimenting ($b = .51$, $SE = .08$, $p < .01$). Informal learning was not significantly related to reflecting or adapting.

Learning goal orientation. Learning goal orientation was positively and significantly related to planning/scanning ($b = .62$, $SE = .07$, $p < .01$), socializing ($b = .20$, $SE = .05$, $p < .01$), reflecting ($b = .17$, $SE = .06$, $p < .01$), experimenting ($b = 1.14$, $SE = .09$, $p < .01$), and adapting ($b = .45$, $SE = .07$, $p < .01$).

Metacognition. Metacognition was positively and significantly related to planning/scanning ($b = 1.13$, $SE = .11$, $p < .01$), socializing ($b = .54$, $SE = .08$, $p < .01$), reflecting ($b = 1.18$, $SE = .09$, $p < .01$), experimenting ($b = .43$, $SE = .10$, $p < .01$), and adapting ($b = 1.21$, $SE = .12$, $p < .01$).

Motivation to learn. Motivation to learn was positively and significantly related to planning/scanning (b = .34, SE = .08, p < .01), socializing (b = .41, SE = .07, p < .01), reflecting (b = .54, SE = .07, p < .01), and adapting (b = .60, SE = .09, p < .01). Motivation to learn was not significantly related to experimenting.

Discriminant validity. Discrimination validity was assessed with the relationships between the five factors and prove performance goal orientation:

Prove performance goal orientation. Prove performance goal orientation was negatively and significantly related to socializing (b = -.08, SE = .03, p < .01) and reflecting (b = -.09, SE = .03, p < .01). Prove performance goal orientation was not significantly related to planning/scanning, experimenting, or adapting.

Trimmed model results. A final structural equation model was produced by removing prove performance goal orientation, which was mostly unrelated to the rest of the variables in the model and any other specific non-significant relationships while allowing the criteria variables to correlate. This model resulted in excellent fit. The Chi-square test of model fit was significant ($\chi^2(295) = 779.86$, p < .01). Overall fit indices were all in the excellent range (RMSEA = .037 [.034, .041], p = 1; CFI = .956; SRMR = .028). This final model path diagram is produced in Figure 5.

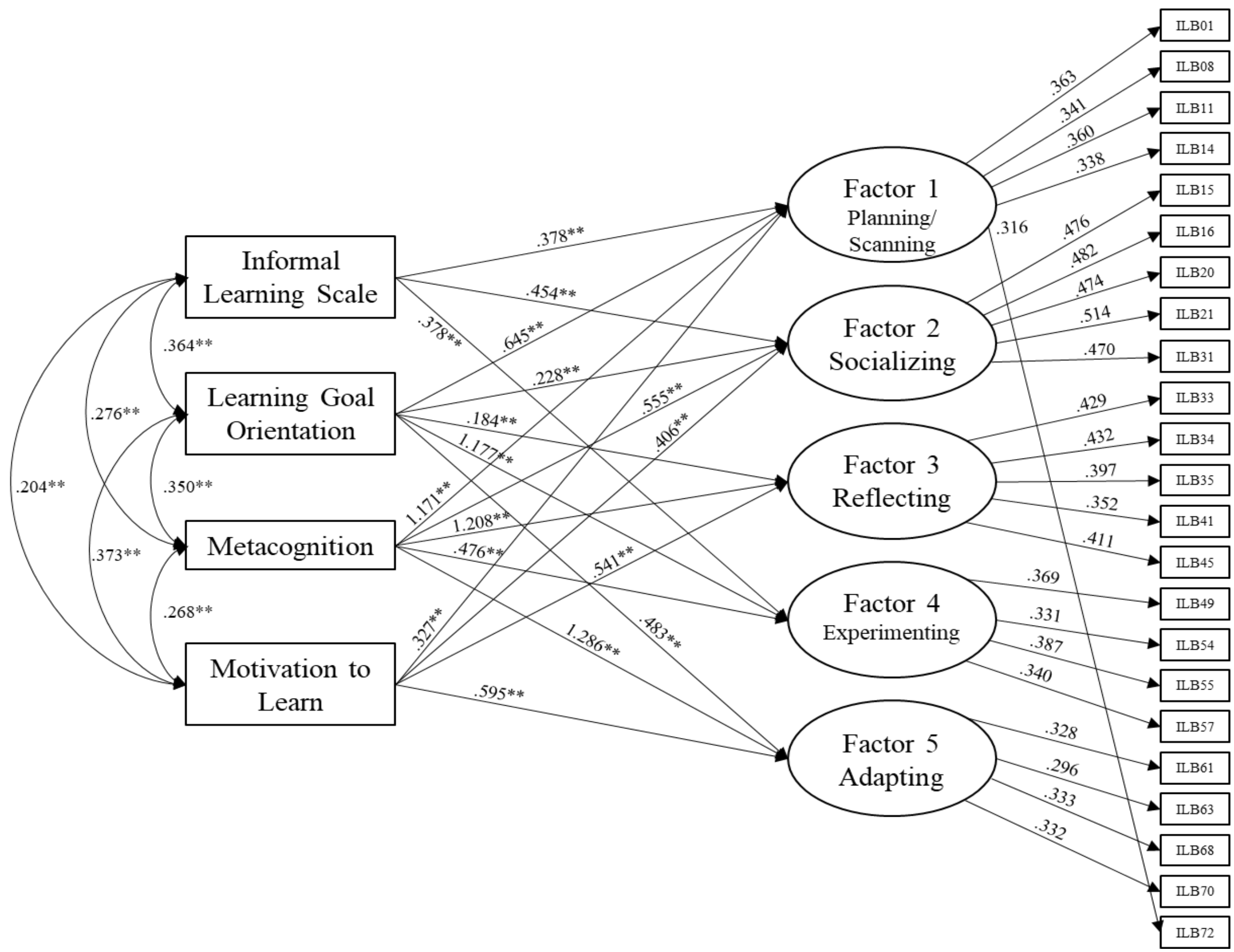

Figure 5. Trimmed Path Model for Significant Relationships Among Constructs and Informal Learning Behavior Dimensions

STUDY ONE DISCUSSION

The purpose of the present study was to develop a reliable and valid measure of informal learning behaviors to be used by both researchers and practitioners. Despite a well-developed theoretical space around informal learning, no formalized measure of the construct exists, and research interest in the construct is steadily growing (Cerasoli et al., 2018; Kukenberger et al., 2015; Sitzmann & Ely, 2011). Previous measures of informal learning typically identified three dimensions – planning, reflecting, and socializing (e.g., Lohman 2000, 2005; Noe et al., 2013) – but many other similar constructs have been suggested (e.g., Eraut, 2004; Schugurensky, 2000), leading one to wonder what the full range of informal learning dimensions might be. The Informal Learning Behaviors measure, developed in this study, is an attempt to provide a reliable and valid measure to the literature and consolidate our knowledge about informal learning.

Development, Refinement, and Content Validity of Informal Learning Behaviors

The existing informal learning literature and measures of informal learning were used to develop 84 potential items. Due to the construct proliferation in the literature, related constructs were reviewed and organized by their primary shared characteristic, intentionality (Cerasoli et al., 2018). From this review, a set of six dimensions were proposed, the extant literature was reviewed for definitions and behavioral examples of informal learning, and these behaviors were grouped into the most relevant dimension. SMEs then provided further content validity by reviewing all 84 proposed items. SMEs were asked to rate each item on its relevance to the parent construct (informal learning), its clarity, and finally assign each item to a dimension of his or her own creation, using as few dimensions as possible. SMEs tended to over-create dimensions compared to the six proposed dimensions, but the most frequently suggested dimensions aligned well with the proposed dimensions. 23 items did not meet criteria for a quality item (an average agreement about relevancy and clarity that was within the top 10% of the rating distribution). These items were rewritten using feedback collected from the SMEs.

Confirmatory Factor Analysis

Hypothesis 1, which proposed that a six-factor solution representing the six dimensions would fit the data well, was partially supported. Items were removed from the proposed model to improve model fit and retain intra-dimensional reliability (which are often competing interests, Raykov & Marcoulides, 2011) After item reduction, a six-factor solution did fit the data well but two factors, planning and scanning, were very highly correlated with one another. A modification was made to the model, allowing a second order factor to load on those factors, and the ensuring model fit the data identically to the original model. Consequently, the two factors were treated as one (i.e., all items from the two factors were loaded onto one new factor), and items were then further removed to improve model fit and reliability. 23 items across five factors (planning/scanning, socializing, reflecting, experimenting, and adapting) were retained, and this model solution fit the data excellently.

Construct Validity Evidence

Construct validity was established by the strength of the beta weights between the five dimensions of informal learning behaviors and other theoretically related (Hypothesis 2; convergent validity) and an unrelated measure (Hypothesis 3; discriminant validity) in a structural equation model. The results support large and positive associations between informal learning behaviors and other learning constructs, including a previous measure of informal learning, learning goal orientation, metacognition, and motivation to learn. As levels of informal learning behavior endorsement increases, the greater one endorses other learning behaviors, thoughts, and motivations.

It is challenging to establish whether a hypothesized nonsignificant effect (as is common in discriminant validation) is a result of a true lack of relationship between two variables or some methodological deficiency. The analyses revealed small and negative associations between informal learning behaviors and prove performance goal orientation, which was hypothesized to have no relationship to learning behaviors based on past research (VandeWalle, 1997). Due to the sample size used in this study, it is not surprising that the relationships between prove performance goal orientation and some informal learning behaviors were significant. The strength and direction of the coefficients provides a clearer indication of discriminant validity than statistical significance alone. As levels of informal learning behaviors increased, prove performance goal orientation mostly stayed the same or decreased slightly, supporting Hypothesis 3.

Construct Coverage

An ancillary goal of this study was to organize and consolidate the constructs within the learning space. The literature and expert review conducted suggested three more dimensions (experimenting, adapting, and scanning) than the often discussed three (planning, reflecting, and socializing). While two factors did collapse into each other (planning and scanning), there was evidence for the existence of the two additional new factors, experimenting and adapting. The specific relationships between the factors and other learning constructs provide useful information here.

Learning goal orientation and metacognition were significantly and positively related to all informal learning behavior dimensions with some particularly large effects. For example, a one-unit increase in experimenting scores was associated with a 1.145 increase in learning goal orientation (on a 1 – 5 scale); however, a one-unit increase in reflecting only led to a .17 increase in learning goal orientation, indicating a high degree of differentiability between factors. Planning/scanning, reflecting, and adapting had similarly large relationships with metacognition. Motivation to learn, on the other hand, was only moderately related to four of the factors and not related at all to experimenting behaviors.

Interestingly, reflecting was not related to the informal learning scale (Noe et al., 2013), which includes a reflection dimension. The item content between the two dimensions is different, however. Noe et al.'s items largely refer to experimenting behaviors (e.g., "Experimenting with new ways of performing my work," and "Using trial and error strategies to learn and better perform") whereas the items on the Informal Learning Behavior scale more closely correspond to reflection (e.g., "Reflect on feedback you have received from colleagues," "Reflect on challenging moments you have experienced at work").

Together, the results indicated that the five-factor solution, a more diverse range of constructs than any other informal learning measure, also provides a finer-grained range of behaviors and relationships to related factors.

Limitations

Comprehensiveness. A scale can be limited in comprehensiveness in both the number of dimensions and the representativeness of a dimension's items. With respect to the dimensionality of the informal learning behavior scale, much effort was exerted to review and include as much of the documented construct space as possible. Nevertheless, informal learning includes quasi-behavioral aspects that are difficult, if not impossible, to measure with a traditional set of items. Specifically, informal learning theoretically encompasses unintentional behavior, such as tacit learning, which an individual should not be aware of ever, or if they are, only after the learning has occurred. Since this aspect of informal learning is unintentional, an individual cannot accurately report whether he or she engages in the behavior. It is the prerogative of the future researcher to determine whether this aspect of informal learning is of theoretical interest, as this scale and, arguably, any informal learning scale, cannot consistently measure this facet of informal learning.

Creating a practical measure of a construct necessarily demands selecting as few items as possible to approximate the facets of the construct. This scale began with 84 items meant to measure six dimensions and ended with 23 items to measure five dimensions. The original 84 items were created after a thorough review of the literature and SME analysis, but this effort does not mean the resulting items necessarily capture the entire range of the construct. Rather, this effort is merely a documented best attempt to do so. Likewise, the resulting 23 items are the best items from those 84 but neither the only nor the absolute best; they are, rather, the best relative to the original 84 items and to the efforts taken to develop those 84 items and should, therefore, be judged on the merits of the foundational efforts to review, understand, and articulate, in terms of behavioral statements, the literature on informal learning. Based on the results of the study, these 23 items constitute reliable and valid (with respect to concurrently measured, theoretically related constructs) dimensions of informal learning behaviors.

Predictive validity. Responses to several measures of theoretically related and unrelated constructs were collected alongside responses to the informal learning behavior scale. Analyses indicated encouraging results with respect to convergent and discriminant validity, suggesting the dimensions of informal learning measured by these items relate as expected to other constructs in the literature. The data collected in this study do not, however, indicate whether or how informal learning behaviors predict levels of a theoretically-related construct in the future (e.g., does informal learning, as operationalized by this scale, predict training performance or job performance?) This is a limitation of the current study; however, this study is the beginning of a multi-phase project, and questions around predictive validity will be addressed in future steps.

Next Steps

This study was part of a larger endeavor to develop the informal learning behavior measure. The work conducted here was meant to move the understanding of informal learning from the theoretical space to a reliable and valid measure. The preliminary results reported here are very encouraging. The results indicate, for example, a great deal of evidence that informal learning behaviors can be measured with latent variables, these variables have strong and varied relationships across other learning constructs, and these variables have small and negative relationships with a theoretically unrelated measure. Evidence additionally suggests that the measure provides more information about the construct than previous measures.

Study Two will test the final measure and factor structure in new samples and collect additional information to test criterion-related validity. Interest in informal learning is driven in part by promising indications of boosted learning outcomes and job performance equal or greater to formal training (Cerasoli et al., 2018). These criteria make natural variables to measure as predictive outcomes of scores on this scale. Given the possibility that developing one's ability to perform informal learning behaviors leads to heightened learning success and job performance, future research might consider growing the scale into a developmental tool for organizations to use to measure informal learning and provide feedback to employees.

Conclusion

The present study aimed to develop a valid and reliable measure of intentional ILBs present in the workplace. This effort started with clarifying the informal learning construct by reviewing the constructs that have proliferated within this space, organizing them by intentionality, and producing a set of dimensions to capture the range of behaviors a learner could self-report. Items were developed to tap each dimension and reviewed by a panel of subject matter experts. Respondents across two samples completed a survey including measures of an initial 84-item scale measuring six proposed dimensions of ILBs, learning goal orientation, prove performance goal orientation, metacognition, motivation to learn, and a prior informal learning scale. These data were used to confirm the factor structure of ILBs via a confirmatory factor analysis and test convergent and discriminant validity through relationships between each informal learning behavioral dimension and the other constructs via structural equation modeling. A five-factor model, representing 23 items, was found to fit the data best. Relationships between the ILB dimensions and other constructs largely occurred as hypothesized, with dimensions related positively to other learning constructs and either negatively or not at all to prove performance goal orientation. Following work will confirm the 23-item, five-factor version of this scale with new samples and continue to test its validity.

STUDY TWO INTRODUCTION

Confirming the Structure of the Scale

The next stage of establishing the ILB-23 as a reliable and valid scale is to collect additional responses to the final form of the scale, test the hypothesized factor structure, and test more relationships between the scale's dimensions and related criteria. Study One found that five factors of informal learning behaviors fit the data excellently. The ILB-23 will be administered to a new sample (of employees) to confirm the proposed factor structure. Following the results of Study One, four of the six hypothesized factors representing informal learning behaviors remained and two factors were combined into one: planning/scanning (combined), socializing, reflecting, experimenting, and adapting. It is expected, therefore, that a new set of responses will indicate the five-factor structure found in Study One.

Hypothesis 1. *The underlying structure of the ILB-23 corresponds to a five-factor model of informal learning behaviors; the five factors include planning/scanning, socializing, reflecting, experimenting, and adapting.*

Informal Learning in an Organization

Insight into employee informal learning is valuable to organizations. Informal learning is not easily tracked within formalized organizational systems (e.g., human resource information systems or learning management systems) because informal learning behaviors (e.g., reflecting on one's performance) are personal and may go unobserved by supervisors or peers. Consequently, for an organization to track informal learning, individuals must self-report their learning behaviors, which presents an issue of cost (time taken from employees) and benefit (what can be learned from knowing how or to what extent an employee learns informally?) for an organization. Previous literature has described the benefits of informal learning in terms of better transfer of training content to one's job (Enos et al., 2003), improved job performance (Cerasoli et al., 2018; Wolfson et al., 2018), and increased satisfaction with one's job (Bear et al., 2008; Rowden & Conine, 2005). Cerasoli et al. additionally found that informal learning improved job performance above and beyond formal training, which receives significant resources from organizations to strategically improve job performance. Informal learning is, therefore, critically important to organizations.

The costs of measuring informal learning to an organization can be justified by using the information gained to support and develop informal learning in the organization, given that improving informal learning improves job performance. Within this perspective, informal learning is a criterion of change within the organization or, in other words, a measure of success of an intervention to improve employee outcomes (be they learning, performance, attitudes, etc.). The ILB-23 helps justify this cost to organizations, as it provides a validated and comprehensive measure of informal learning behaviors to use as criteria of change and as predictors of performance, when before there was no such measure. The results of study one indicated that the ILB-23 is strongly related to several motivation and self-regulation constructs, supporting the inclusion of informal learning within a self-regulation and motivation framework as was hypothesized.

Testing a model of informal learning within a single organization can provide insight into the construct space around informal learning in ways study one could not. The proposed study comes with a collaboration with a partner organization. This organization offered to support data collection in return for an assessment of the overall learning environment and individual feedback on learning behaviors. Partnering with this organization allows the collection of cohesive learning culture information and consistent job performance criteria and the ability to situate these elements within a model of self-regulation and informal learning. This model, in general, includes antecedents to informal learning, environmental moderators of the relationships between these antecedents and informal learning, and outcomes of informal learning.

Antecedents of informal learning. Maurer et al. (2003) proposed and tested a model for antecedents to participation in developmental activities. They integrated three theoretical frameworks, measures of attitudes and motivation, self-efficacy, and expectancy theory to explain whether someone intended to participate in training and whether they participated in training. While the model specifically explored formal training, the scope of the model is applicable to workplace learning in general; that is, measuring specific antecedents, motivational and affective components, and behaviors related to the learning process. My study uses a similar framework. The use of specific self-regulation measures in the previous study to test the convergent validity of the scale will be expanded upon to test whether informal learning behaviors are related to individual characteristics other than the ones previously tested (i.e., motivation to learn, learning goal orientation, and metacognition). Whereas the study one variables had clear links to workplace learning, making them ideal candidate variables for testing convergent validity, the antecedent variables in this study were chosen to expand the theoretical space around informal learning in the workplace. Two new variables, sleep quality and self-efficacy, were implemented in this study.

Sleep is an attractive antecedent variable for several reasons. Informal learning and sleep are thought to share a common mechanism, self-regulation, by which sleep affects self-regulation (Barnes, 2012) and self-regulation affects informal learning (Sitzmann & Ely, 2011). Thus far, no study has tested these three constructs together, which allows this study to contribute not only to the learning literature, in the form of the ILB scale, but also to the sleep literature by testing the effects of sleep on novel work-related variables. Moreover, sleep, unlike other antecedents of informal learning such motivation to learn or learning goal orientation, is not obviously related to informal learning behaviors. Thus, including sleep as an antecedent of informal learning behaviors provides a fairly robust explanatory variable for validating the scale.

The sleep literature often discusses negative outcomes due to sleep restriction and poor-quality sleep via the self-regulation theoretical framework (Barnes, 2012). Sleep is known to be a critical phase of brain repair and maintenance and disruptions to this bodily function can have significant downstream effects in the workplace (Barnes, 2012). Sleep is operationalized both in terms of quantity, or the amount of sleep one gets a night, and quality, or the extent to which an individual struggled to fall asleep and stay asleep (Watson et al., 2015). Impairment due to sleep restriction, or, in other words, detrimental effects due to not getting enough sleep in terms of both quantity and quality, has negative consequences for working individuals. Poor sleep has been shown to decrease alertness, directing or focusing one's attention, and working memory (Barnes, 2012). Poor sleep also leads to negative affect in the form of hostility, frustration, anxiety, and depression (Barnes, 2012). Notably, poor sleep is also associated with poor motivation (Baranski, Cian, Esquievie, Pigeau, & Raphel, 1998). These findings suggest a broad connection between lack of sleep, reduced self-regulation, and secondary consequences.

Restricted and poor quality sleep has been linked to several poor work outcomes, including presenteeism and absenteeism (Kessler, Berglund, & Coulouvrat, 2011; Leger, Bayon, Laaban, & Philip, 2012), work limitation and accidents (Leger et al., 2012), poor cognitive performance (Watson et al., 2015) including reduced self-regulation, low alertness, and impaired attention (Barnes, 2012); lower performance (Barnes, Jiang, & Lepak, 2016); and poor supervisory behavior (Barnes, Lucianetti, Bhave, & Christian, 2015). Sleep, therefore, is a critical influence on a person's work. Given that sleep impacts both self-regulation and motivation, it is expected that sleep is a significant – but so far unstudied – antecedent to learning performance at work. This represents a gap in the literature that may provide additional evidence for the importance of sleep and the necessary components for learning on the job.

Occupational self-efficacy, or the extent to which one feels confident in his or her abilities to perform well, handle challenges, and develop on the job (Schyns & Von Collani, 2002), represents motivation and self-regulation in the model. Self-efficacy is a commonly used construct to represent one’s motivation and self-regulation (Schyns & Von Collani, 2002), including in a learning context (Sitzmann & Ely, 2011). Consistent with prior studies (e.g., Enos et al., 2003; Noe et al., 2013; Sitzmann & Ely, 2011) supporting the link between motivation, self-regulation and informal learning behaviors, it is expected that occupational self-efficacy will be related to informal learning behaviors.

Occupational self-efficacy is likewise expected to be the mechanism by which impairment due to sleep impacts informal learning behaviors. Barnes (2012) reviewed several studies which found: a) sleep-related impairment disrupted both self-regulatory cognition and behavior; and b) accumulated sleep impairment, referred to as sleep debt, additionally disrupted self-regulation. Occupational self-efficacy, therefore, is expected to be impacted by impairment due to sleep restriction. Specifically, as impairment due to poor sleep increases, occupational self-efficacy is expected to decline. Given that sleep directly impacts several workplace variables, it is also expected that as impairment due to poor sleep increases, informal learning behaviors will also decline.

Hypothesis 2. *Sleep quality will be (a) positively related to occupational self-efficacy and (b) informal learning behaviors. Additionally, occupational self-efficacy will be (c) positively related to informal learning behaviors.*

Informal learning behaviors largely stem from one's ability to self-regulate (Sitzmann & Ely, 2011). Therefore, it is expected that occupational self-efficacy will act as a mediating mechanism between sleep quality and informal learning behaviors such that the influence of sleep quality on occupational self-efficacy will add to the effect sleep quality has directly upon informal learning behaviors.

Hypothesis 3. *Occupational self-efficacy will partially mediate the relationship between sleep quality and informal learning behaviors. That is, poor-quality sleep will lead to reduced occupational self-efficacy, which will in turn lead to reduced informal learning behaviors above and beyond the direct effect of poor-quality sleep on informal learning behaviors.*

Finding support for these hypotheses supports the two goals of this study. First, finding an expected direct and mediated effect of poor-quality sleep on informal learning behaviors contributes validity evidence for the scale by way of predicting informal learning in a manner consistent with sleep and self-regulation theory. Second, the results would contribute new knowledge to both the learning and sleep literatures. It is not currently known whether poor-quality sleep impacts informal learning although it is theoretically expected to do so by disrupting self-regulation.

Environmental factors moderating the relationship between self-efficacy and informal learning. Watkins and Marsick (1992) argued that informal learning is embedded in the organizational context. Per Leslie et al. (1998), many organizational factors influence informal learning. These include being aware of the organization’s goals, one’s external market, and the requirements within the organization as well as the development of individual employees in their acquisition of new skills and knowledge. It is no surprise, then, that many authors have argued that the workplace is a rich environment for learning (Le Clus, 2011; Noe et al., 2010; Tannenbaum et al., 2010). No doubt the collection of many individuals working on similar or shared goals provides ample room for sharing learning with one another. Moreover, informal learning behaviors are often driven by an immediate need or desire to respond to the environment. Often these stimuli can provide for experiences the learner is not aware he or she has had; for example, a change in attitude about the organization following a change in policy.

Informal learning behaviors occur because of interactions between environmental stimuli and personal characteristics. Learning occurs anytime an individual interacts with his or her environment; in the workplace, this happens nearly constantly as learning is integrated into everyday work routines (Marsick, Volpe, & Watkins, 1999). Ongoing learning is said to be influenced by the learning environment, or the extent to which the workplace supports learning (e.g., Tannenbaum, 1997), through a variety of factors including cultural and leadership commitment to learning (Ellinger, 2005; Reardon, 2010; Skule, 2004), sharing learning among peers (Ellinger, 2005; Lohman, 2006; Tannenbaum, 1997), exposure to changes, challenges, and demands (Skule, 2004; Tannenbaum, 1997), and availability and accessibility of resources (Ellinger, 2005; Lohman, 2006; Tannenbaum, 1997). There is a large body of evidence that both formal and informal learning can be promoted via these contextual factors (e.g., Jeon & Kim, 2012; Klein et al., 2006; Maurer et al., 2003; Reardon, 2010; Skule, 2004; Tannenbaum, 1997), suggesting that learning at work is generally supported in the environment via individual demands, social support, and access to resources.

How an individual perceives his or her work environment is referred to as psychological climate (James, 1982). Aggregating individual psychological climate ratings, a topic of some debate (James, Choi, Ko, McNeil, Minton, Wright, & Kim, 2008), forms a conceptualization of organizational climate, or the shared perceptions of the work environment. The learning organization model (Marsick & Watkins, 2003) describes dimensions of a climate for learning thought to influence strategic and informal learning. These dimensions include support for continuous learning opportunities, support for inquiry and dialogue, encouragement of collaboration and team learning, maintaining systems to support learning, empowering a collective vision, connecting to organization to its environment, and strategic leadership for learning. Marsick and Watkins (2003) provided evidence that these dimensions influence employee knowledge and organizational performance.

It is expected that these dimensions will likewise be related to informal learning behaviors. Empirically linking climate perceptions to informal learning requires valid climate measures however, and operationalizing climate in a meaningful way can be challenging. Joyce and Slocum (1984) suggested that organizational climate could be operationalized by statistical clustering, or using a statistical process of optimizing within-group homogeneity and between-group heterogeneity, to create groups from response patterns in the data. Since this process produces groups solely on responses to a set of dimensions, it is an attractive process for creating compelling aggregates of individual responses without relying on outcome data to delineate the groups. This process, however, has drawn criticism for similar reasons. If the groups are not formed from meaningful outcome criteria, it is unclear how many groups there should be or why the resultant groups are composed in a certain manner (Young & Parker, 1999).

Latent profile analysis (LPA) is a statistical technique the addresses the clustering issue. LPA creates profiles from continuous data that represent a fixed number of response patterns and determines the probability that any individual belongs to one profile or another. Past research has determined several criteria for determining an appropriate number of profiles based on the statistical results of the technique (Muthén & Muthén, 2000; Nylund, Asparouhov, & Muthén, 2007). Past research has applied latent profile analyses to organizational-level variables with robust results (e.g., Morin, Morizot, Boudrias, & Madore, 2011, who found different profiles of workplace affective commitment) LPA is, therefore, a rigorous and appropriate technique for extracting organizational climate groupings from individual climate ratings.

To assess the meaningfulness of the profiles, this study followed the recommendations of Joyce and Slocum (1984) and Payne (1990) to determine the predictive validity of the profiles. Namely, it is expected that the dimension scores of the learning organization model (Marsick & Watkins, 2003) aggregate into a finite number of climate profiles. These profiles will be evaluated for meaningfulness and relevancy in addition to the statistical evaluation criteria above. A likely outcome of the profiles, for example, would be if two groups formed from individuals who rate the climate items high (they perceive a positive learning environment) and individuals who rate the climate items low (they perceive a negative learning environment). If the profiles satisfy both statistical and conceptual criteria, they will be investigated as moderators of the relationship between occupational self-efficacy and informal learning behaviors. It is expected that each profile will interact significantly with occupational self-efficacy to influence informal learning behaviors.

Hypothesis 4. *Psychological learning climate will cluster into a finite set of profiles, or latent manifestations of response patterns to continuously-scored climate items. These clusters will broadly represent types of organizational learning climate.*

Hypothesis 5. *Each organizational climate profile will significantly moderate the relationships between occupational self-efficacy and informal learning behavior dimensions such that the relationship between occupational self-efficacy and informal learning behavior dimensions will be stronger under one cluster than another cluster.*

Outcomes of informal learning. Recent findings have indicated that informal learning leads to the acquisition of knowledge, skills, and attitudes equal to and above formal training (Cerasoli et al., 2018), contentment, job satisfaction, and self-rated job performance (Rowden & Conine, 2005), supporting decades of theory consistent with these findings (e.g., Marsick & Watkins, 1990; Marsick & Watkins, 2003). Specifically, Cerasoli et al.'s meta-analysis found several positive main effects for relationships between informal learning and job outcomes. These included job attitudes (ρ = .29), knowledge and skill acquisition (ρ = .41), and job performance (ρ = .42). Additionally, the main effect of informal learning on job performance exceeded the main effect of formal training on job performance found by Arthur et al. (2003); Cerasoli et al. reported that those who engage in informal learning behaviors could expect a 9% greater increase in job performance than those who engage in formal training. It is not clear, however, whether those effects are additive or mutually exclusive.

Given that learning follows from motivation and self-regulation, it is therefore unsurprising that informal learning is highly effective: motivation and discipline are key components of successful learning. The partner organization rates its employees' performance and potential for job growth (i.e., promotion or additional responsibilities). With these ratings, it is therefore possible to assess the predictive validity of the ILB-23 on a well-established criterion relationship, job performance, and a novel criterion relationship, job potential. Job potential, or career growth, was not a criterion directly assessed in Cerasoli et al.'s (2018) meta-analysis although it is closely related to job performance. Several informal learning constructs, e.g., continuous learning (Hall & Mirvis, 1995) and self-directed learning (Clardy, 2000), refer to informal learning, specifically by pursuing learning opportunities, social networks, and maintaining awareness of their job and skills, as *the* construct by which individuals can growth in their careers. Consequently, it is expected that informal learning behaviors will positively predict job performance and job potential.

Hypothesis 6. *The five dimensions of informal learning behaviors will broadly predict job performance such that higher levels of any dimension will be associated with higher performance ratings. Evidence of these positive relationships will be indicative of predictive validity.*

Hypothesis 7. *The five dimensions of informal learning behaviors will broadly predict job potential such that higher levels of any dimension will be associated with higher ratings of potential. Evidence of these positive relationships will be indicative of predictive validity.*

Evidence of positive relationships specified in Hypotheses 6 and 7 provide evidence of the predictive validity of the ILB-23.

Conceptual Model of Informal Learning in an Organization

Please see Figure 6 for a summary of the model being tested. The proposed relationships will be tested in a field study within the partner organization as part of an assessment of the organization's learning climate.

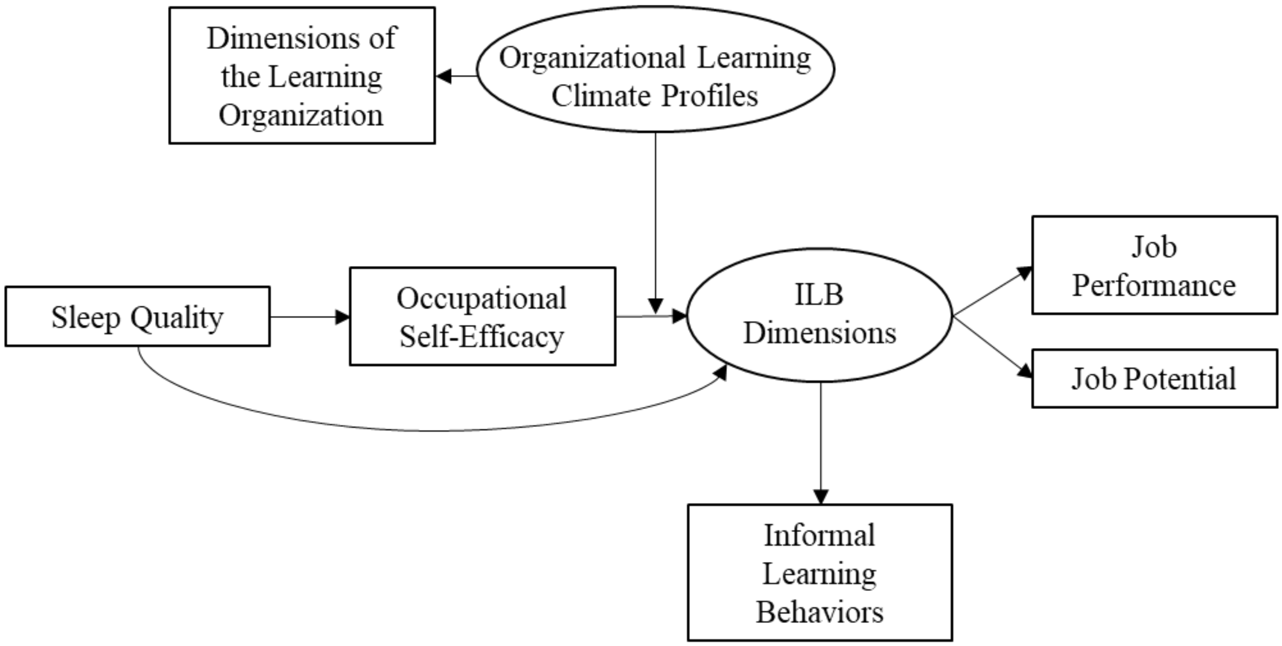

Figure 6. Conceptual Model of Informal Learning in an Organization

STUDY TWO METHOD

Participants

2,169 individuals were contacted in a single, large, technology-focused organization based on the East Coast to participate in the study. To be eligible to be contacted, individuals must have been non-executives and employed full-time for at least six months. 167 individuals completed enough of the survey to be included in the following analyses (response rate = 7.7%); see the data quality section for additional details. This number of participants was lower than targeted but still met Floyd and Wildman's (1995) criteria for a sufficient sample size to conduct a confirmatory factor analysis on 23 items. Other sources recommend a minimum of 100 participants (Anderson & Gerbing, 1984) but, more recently, researchers have recommended at least 200 participants for similar models (Bandalos, 2014; Muthén & Muthén, 2002). Too few participants can lead to models that do not converge or underpowered findings (Hu & Bentler, 1999). The CFA model and SEM both converged, so analyses proceeded but with the caveat that a lack of power might be a concern.

Most participants were male (68.1%), white (90%), and had a bachelor's or higher degree (92.3%). Participants were on average 44.07 years old (*SD* = 10, ages ranged from 21 to 71). Average organizational tenure was 6.71 years (*SD* = 4.77), average job tenure was 4.53 years (*SD* = 5.44), and participants reported working 43.3 hours per week on average (*SD* = 7.97) and 51.23 hours during a busy week (*SD* = 11.14).

Nonresponse Analyses

Given the low response rate, analyses were conducted to determine how, if at all, respondents (n = 167) differed from non-respondents (n = 1,921), following recommendations from Rogelberg and Stanton (2007). Rogelberg and Stanton indicated that response rate by itself is not a useful indicator of nonresponse bias and suggested several possible analyses to detect bias. The organization was willing to share some archival data about all respondents, so archival analyses were conducted to detect nonresponse bias. The organization shared the following data about non-respondents: training participation (whether or not the individual had participated in at least one training course provided by the organization), region (North America, Europe and the Middle East, Latin America, or Asia-Pacific), leadership level (individual contributor, manager, director, vice president), business unit (the type of business organization the employee works for), and days on the job.

To test for differences in the proportions of training participation, region, business unit, and leadership level, chi-square tests of independence were conducted by response type. The chi-square test for training participation by response type was significant, $\chi^2(1) = 23.204$, $p < 0.01$. More training participants responded than expected (72 vs 45.4) and fewer non-participants responded than expected (95 vs 121.6). The chi-square test for region was significant, $\chi^2(3) = 17.255$, $p < 0.01$. Fewer employees from the Asia-Pacific Island (APAC) region responded than expected (18 vs 33.4) and more North American employees responded than expected (91 vs. 72.8). The chi-square test for leadership level was significant, $\chi^2(3) = 12.597$, $p < 0.01$. Fewer individual contributors responded than expected (101 vs 119.7) and more managers responded than expected (54 vs 39.9). The chi-square test for business unit was significant, $\chi^2(15) = 70.316$, $p < 0.01$. Fewer consultants responded than expected (1 vs. 5.9), more people team employees responded than expected (17 vs. 4.1), and fewer research and development employees responded than expected (13 vs. 21.4).

To test for differences in the number of days on the job, a one-way analysis of variance (ANOVA) was conducted to detect mean differences in days on the job by response type. The ANOVA was significant, respondents have been on the job (M = 2,453.86, SD = 1,686.07) for fewer days than non-respondents (M = 3,860.34, SD = 8,208.99), $F(1) = 4.766$, $p < 0.05$.

These analyses indicate that, at least among the variables provided by the organization, that the respondent sample differs in several ways from the sampling population. By themselves, these differences are not necessarily indicators of bias in the responses. The respondents were more likely to have participated in training, come from North America, be managers, work on the people team, and have less tenure with the organization than the sampling population; likewise, respondents were less likely to come from APAC, be individual contributors, and work on either the consulting or research & development organizations.

To determine whether these differences between the sample and sampling population could bias the results, analyses were conducted to determine whether the archival information were related to the survey topics (Rogelberg & Stanton, 2007). To test whether days on the job was related to the survey topics, days was regressed onto the scale scores for each survey measure. No scale score was significantly related to days on the job. To test whether training participation, region, job title, or business unit were related to any measure, ANOVAs were conducted for each archival variable. Only one difference was significant: Those who participated in training reported significantly high reflecting scores (n = 72, M = 4.16, SD = 0.55) than those who did not (n = 95, M = 3.93, SD = 0.64), $F(1) = 5.957$, $p < 0.05$. Past training participants are overrepresented in this sample (likely due to some level of interest in the topic of the study), and these individuals reported higher reflecting scores than individuals who have not gone through training.

There does not appear to be a concerning amount of bias in the responses of participants based on the archival data shared by the organization. This does not mean, however, that there is no bias in the responses due to the response rate, but the analyses have exhausted the criteria to check for bias based on the information shared by the organization. Reflecting scores are the only scale measure that appears to be influenced by the low response rate. There is some elevation in those scores related to prior training experience and, therefore, any results dealing with reflecting scores should be interpreted with this caveat. Otherwise, the low response rate does not appear to have influenced the interpretability of the results.

Data Quality

As in study one, survey responses were assessed for quality. Due to the participant population (no incentives, known population) and concerns about survey length, attention checks were omitted from the survey. Completely or nearly completely missing data from 73 participants (e.g., a respondent opened the survey, clicked through the consent page, and did not complete the rest of the survey) were removed. Three individuals did not consent to the survey and five individuals chose to withdraw their data after completing the survey, so these eight respondents were also removed. 171 responses were retained for quality assessment. Data quality was then assessed two strategies: the IRV index (Dunn et al., 2018) and the time to complete the survey. Four responses had completely invariant data and were removed per the recommendations of Dunn et al. (2018). No further responses were removed - all participants used an appropriate amount of time to complete the survey - so the analyses were conducted with 167 responses.

Procedures

Participants completed the survey online via Qualtrics. The survey contained measures of informal learning behaviors, organizational learning culture, and demographics. Survey responses were linked to archival ratings of job performance and job potential. Scale and item order were randomized to prevent ordering effects in survey responses (demographics, however, appeared at the end of all surveys to prevent perceptions that demographics were related to scale responses). The survey was distributed into two two-part waves. Each wave had a US and global distribution in order to send the survey out during working hours. The second wave was distributed after the data collection of the first wave closed.

Measures

Demographics. Participants reported their age, gender, ethnic background, education, organizational and job tenure, job type, and hours worked per week. Demographic questions appear in Appendix M.

Informal learning behaviors. Informal learning behaviors were measured with 23 items previously derived from the CFA in study one. These 23 items represent five dimensions of informal learning behaviors. An example item is, “Complete ambiguous tasks by first finding clarifying information.” Participants rated how characteristic each behavior is of him or herself on a five-point Likert-type scale (*1 = Not at all characteristic of me; 5 = Highly characteristic of me*). Coefficient α in study one for the overall scale was .92, with specific dimension-level subscale internal consistencies ranging from .72 to .81. In study two, coefficient α was .87 for the overall scale, with specific dimension-level subscale internal consistencies ranging from .7 to .78. Please see Appendix G for a list of all the items. After they rated items on the five-point scale, participants indicated, by dimension, how many of the behaviors they performed in the last seven days in a new section of the survey.

Occupational self-efficacy. Occupational self-efficacy was measured with eight items from the short form of the Occupational Self-Efficacy Scale (OCCSEFF; Schyns & Von Collani, 2002), the OCCSEFF-8. An example item is, “If I am in trouble at my work, I can usually think of something to do.”. Participants rated the extent to which these statements are true of themselves on a six-point Likert-type scale (*1 = Not at all true; 6 = Completely true*). Schyns and Von Collani found an overall internal consistency of .88 for the OCCSEFF-8. Coefficient α in study two was .87. Please see Appendix H for a list of all the items.

Sleep quality and sleep quantity. Sleep quantity was assessed with a single item self-report measure that asked participants to report the hours of sleep they had in the previous night. Sadeh (2011) reported that self-reports of sleep quantity had good agreement with objective measures of sleep quantity, specifically actigraphy. To measure sleep quality, the PROMIS Sleep Disturbance scale developed by Yu et al. (2012) was used. The items were developed to assess the extent to which a rater experienced high- or low-quality sleep in the previous seven days. An example item is, “My sleep was restless”. Participants rated these items on a five-point Likert-type scale (1 = Never, 5 = Always). As with sleep quantity, subjective measures are considered valid measures of sleep quality. Yu et al. reported validity evidence for the PROMIS Sleep Disturbance scale in the form of correlations with established sleep scales (i.e., the Pittsburgh Sleep Quality Index and the Epworth Sleepiness Scale, as cited in Yu et al., 2012) and an internal consistency of .90. Study two found an internal consistency of .89. Please see Appendix I for a list of all the items.

Job performance. Job performance, or the extent to which an employee performs his or her current job well, was measured on a three-point scale, using preexisting in-house appraisals by the partner organization. Performance was rated “A,” “B,” or “C,” with A indicating excellent performance; these ratings were converted into numbers such that A = 3, B = 2, and C = 1. These ratings are sourced from archival performance data. Performance ratings are conducted on the extent to which associates of the organization completed or supported assigned objectives and demonstrated behaviors consistent with organizational expectations. The most recent evaluation was used in the following analyses. Please see Appendix J for definitions of the performance criteria.

Job potential. Job potential, or the extent to which an employee can continue to develop into more challenging roles, will be measured on a five-point scale, using a method also developed by the partner organization. Potential was rated “High,” “Growth,” “Well Placed,” “Not Well Placed,” potential or “Performance Issue,” with High indicating best future job potential; these ratings were converted into numbers such that High potential = 5, Growth potential = 4, and so on. These ratings are sourced from archival performance data. Potential is assigned after evaluating three criteria: capability, engagement, and aspiration. These criteria are assessed by reviewing an individual’s performance, scope of responsibility, and engagement with the organization's culture. The most recent evaluation was used in the following analyses. Please see Appendix K for definitions of the potential criteria.

Organizational learning culture. Organizational learning culture, or the extent to which the organization supports continuous learning and development, was measured with 21 items from the Dimensions of the Learning Organization Questionnaire (DLOQ; Watkins & Marsick, 1992; Marsick & Watkins, 2003). The 21 items are taken from the DLOQ-A, the short-form DLOQ, tested and validated by Yang (2003). An example item is, "In my organization, people help each other learn.". Participants rated the extent to which these attributes are true of their organization on a six-point Likert-type scale (*1 = Almost never; 6 = Almost always*). Yang found an overall internal consistency of .91, with specific dimension-level subscale internal consistencies ranging from .68 to .83. Coefficient α in study two was .93, with specific dimension-level subscale internal consistencies ranging from .71 to .87. Please see Appendix L for a list of all the items.

Analysis Plan

Several techniques were used to test the following hypotheses, including confirmatory factor analysis (H1), latent profile analysis (H4), and path analysis (H2, H3, H5-H7).

All variables besides job performance and job potential were scored on a continuous scale. Both job performance and job potential were scored on an ordinal scale and were analyzed accordingly. Analyses were conducted using MPlus 8.0 (Muthén & Muthén, 1998–2017). Informal learning behavioral dimensions were modeled as latent variables, composed of their respective item-level indicators, to test the first hypothesis. Following the test of the first hypothesis, the informal learning items were averaged by dimensions and used as observed variables in the larger model. Sleep quality, occupational self-efficacy, job performance, and job potential were modeled as observed variables. Learning climate items were modeled as latent profiles which were stored and treated as a categorical variable for moderation analyses.

The hypotheses were tested in the following manner:

Confirmatory factor analysis. A CFA was conducted to assess whether the hypothesized five factor solution fit the data (Hypothesis 1). To evaluate overall model fit, model fit criteria suggested by Hu and Bentler (1999) was used: the comparative fit index (CFI) > .95, Tucker–Lewis Index (TLI) > .95, root mean square error of approximation (RMSEA) < .06, and standardized root mean square residual (SRMR) < .08. In addition, the Chi-square test of model fit, where a non-significant test indicates perfect fit of the model to the data, was evaluated.

Latent profile analysis. A latent profile analysis (LPA) was conducted to discern distinct profiles of individuals' reports of perceived learning climate responses (Hypothesis 4). Models were run until the best-fitting number of profiles was found. Model fit statistics are based on recommendations from a Monte Carlo study that determined the most appropriate fit indices for LPA (Nylund et al., 2007) and four recommended criteria (Muthén & Muthén, 2000).

The first criterion was the Lo-Mendell-Rubin likelihood ratio test of model fit (LMR; Lo, Mendell, & Rubin, 2001). The LMR compares a model with k classes to a model with k-1 classes. The LMR statistically tests the probability that the data have been generated by the model with k-1 classes (i.e., a significant p-value indicates that the k-class model is an improvement over the k-1-class model). The second criterion was the Bayesian Information Criterion (BIC; Schwarz, 1978). The BIC maximizes the likelihood ratio statistic while rewarding parsimony. Lower values indicate better model fit, and the model with the lowest BIC is generally preferred (Muthén & Muthén, 2000). Third, entropy values provided an index of model classification quality. Values range from 0 to 1; higher values indicate better classification quality (Celeux & Soromenho, 1996). Values greater than 0.80 are generally considered to have adequate classification quality (Jung & Wickrama, 2008). The fourth criterion was the average latent class probabilities for the most likely latent class membership by latent class discrimination. Values close to 1 in the primary diagonal and values close to 0 in off-diagonal represent good fit. These values provide an index of how likely the individuals within a latent class belong in that class. The usefulness of the LPA classes to differentiate participants on the variables of interest was also considered. Final model selection was based on goodness of model fit indices, parsimony, and substantive interpretability of the model.

Multilevel path analysis. Multilevel path analysis modeling was conducted to test the remaining hypotheses. These hypotheses were tested by first adding structural covariance paths between predictor and outcome variables as summarized in Figure 6 in a piecewise manner. Like with confirmatory factor analysis, model fit was evaluated with the same criteria suggested by Hu and Bentler (1999). Once adequate model fit was established, each hypothesis was evaluated by assessing its respective predicted effects in the model.

Hypothesis 2. The direct effect of sleep quality on occupational self-efficacy was assessed. All variables were scored on a continuous scale. Unstandardized regression coefficients (i.e., *b*) are an index of effect size, with values of smaller than .2, .2 through .4, and .4 or greater being considered small (33rd percentile or lower), medium, and large (67th percentile or higher), respectively for attitudinal or perceptual relationships (Bosco, Aguinis, Singh, Field, & Pierce, 2015). The percentiles indicate the distribution of effect sizes gathered across four decades of empirical articles published in *Personnel Psychology* and *Journal of Applied Psychology* (*n* effect sizes = 14,493). When evaluating regression coefficients, unstandardized regression coefficients, standard errors, p-values, and overall r^2 will be evaluated.

Hypothesis 3. The indirect effect of sleep quality on informal learning behaviors via occupational self-efficacy was tested by specifying a mediation relationship between these variables. The product of two regression slopes is not normally distributed, making the interpretation of the strength of the indirect relationship difficult. The violation of the normality assumption results in a loss of statistical power for many traditional approaches to testing mediation (e.g., the Sobel Test). To circumvent this issue, the best practices approach is to assess asymmetrical confidence intervals (ACIs) that best represent the true distribution of the product of coefficients (Hayes & Scharkow, 2013). ACIs that do not contain zero are considered to be statistically significant. The indirect effects of each predictor variable on informal learning will be examined by using bias-corrected bootstrapped estimates (Efron & Tibshirani, 1993) based on 1,000 bootstrapped samples, which provides a powerful test of mediation (Fritz & MacKinnon, 2007). Statistical significance was determined by 95% bias-corrected bootstrapped confidence intervals that do not contain zero.

Hypothesis 5. The interaction between organizational learning climate profile and occupational self-efficacy on informal learning behaviors was assessed by specifying a moderation relationship in the model. The organizational learning climate profiles was treated as a categorical variable. The relationships between occupational self-efficacy and informal learning behaviors was specified as random slopes at the within level of the model and regressed onto the profile variable at the between level, using the Random Coefficient Prediction (RCP) moderation method (Preacher, Zhang, & Zyphur, 2016).

Hypotheses 6 & 7. The direct effects of informal learning behaviors on job performance (Hypothesis 6) and job potential (Hypothesis 7) was specified to test the final hypotheses. As both criteria are ordinal variables, the measure of effect size is not a regression coefficient but an odds ratio. For both hypotheses, it is expected that there is a positive relationship between ILB dimension ratings and membership in higher job performance (“A” category) and potential (“high” category) categories. Significant odds ratios greater than one are indicative of a positive relationship between a predictor and a category.

STUDY TWO RESULTS

Descriptive statistics for each scale are summarized in Table 4. As part of the descriptive statistics analysis, the normality of the scales was examined. No scale exhibited skewness, but three scales exhibited some amount of positive kurtosis, according to George and Mallory’s (2010) +/- 2.0 value cut-off for skewness and kurtosis. Positive kurtosis refers to heavily weighted tails in the distribution, meaning that more respondents used either high or low responses than would ordinarily be expected. Positive kurtosis was observed for the adapting dimension of informal learning, occupational self-efficacy, and sleep quality. For each scale, a single outlier value was observed affecting the distribution (each outlier came from different participants, however, so it was not a case of a single, abnormal response pattern). For adapting, a participant rated him or herself a one on all items, which was almost two points lower than the next lowest adapting score. For occupational self-efficacy, a participant rated him or herself a 1.88 out of six on the scale which was again nearly two points lower than the next lowest score. Finally, for sleep quantity, a participant reported sleeping on average 12 hours a night, which was over three hours more than the next highest sleep amount. These data did not appear to affect the following analyses and were retained rather than lower the sample size.

Hypothesis 1

Confirmatory factor analysis. The 23-item, five-factor solution found in study one was tested again in study two. The resulting measurement model specifying five latent variables and the covariance between them comprised of 23 items resulted in good to excellent fit. Chi-Square test of model fit was significant ($\chi^2(243) = 361.891$, $p < .01$). Overall fit indices were all in the good to excellent range (RMSEA = .054 [.042, .065], $p = .274$; CFI = .888; SRMR = .071). Please see Figure 7 for the path diagram of this measurement model.

Due to the interrelated conceptual nature of informal learning behaviors, a CFA with correlated residuals was specified. According to Brown (2015), correlating residuals (that is, allowing the error terms of some or all of the item-level indicators to correlate) is an accepted way to improve model fit without substantially changing the model, provided that the following conditions are present: sound theoretical reasoning for correlating the residuals, a consistent rule for specifying the correlations, and no substantial changes to the relationships between the parameters of interest.

Informal learning behaviors should be related to one another across dimensions to some extent. A correlation matrix was used to analyze the relationships between all ILB-23 items; items that correlated with one another outside of their constituent factors above 0.3 were allowed to correlate. The results of this model were compared to a model without correlated residuals. Besides improved fit, which strengthens the interpretability of the model, parameter estimates were not considerably different from one another, so the model with correlated residuals was used to test the hypotheses in study two. The resulting measurement model specifying five latent variables and the covariance between them comprised of 23 items resulted in excellent fit. Chi-

Square test of model fit was nonsignificant ($\chi^2(176) = 199.443$, $p = 0.11$). Overall fit indices were all in the excellent range (RMSEA = .039 [0, .054]; CFI = .978; SRMR = .061).

Overall model fit. A structural equation model was conducted to test the remaining hypotheses. A fully-specified model resulted in excellent fit. The Chi-Square test of model fit was significant ($\chi^2(212) = 322.564$, $p < .01$). Overall fit indices were all in the excellent range (RMSEA = .043 [.028, .07], CFI = .958, SRMR = .073).

Hypothesis 2

Direct effects of sleep quality on occupational self-efficacy and learning behaviors. The direct effect of sleep quality on occupational self-efficacy was assessed. Occupational self-efficacy was not significantly associated with sleep quality ($b = .15$, $SE = .11$), thus hypothesis 2a was not supported. Next, the direct effect of sleep quality on the informal learning behavior dimensions was assessed. No learning behaviors were significantly related to sleep quality (effect sizes ranged from -.15 to .01); hypothesis 2b was not supported.

Direct effects of occupational self-efficacy on learning behaviors. Finally, the direct effect of occupational self-efficacy on the informal learning behavior dimensions was assessed. Planning/Scanning behaviors were positively and significantly related to occupational self-efficacy ($b = .48$, $SE = .27$, $p < .05$; $R^2 = .18$), as were socializing behaviors ($b = .459$, $SE = .26$, $p < .05$; $R^2 = .1$), experimenting behaviors ($b = 1.03$, $SE = .36$, $p < .01$; $R^2 = .24$), and adapting behaviors ($b = .67$, $SE = .31$, $p < .05$; $R^2 = .17$). Reflecting behaviors were not related to occupational self-efficacy ($b = .01$). Hypothesis 2c was therefore partially supported.

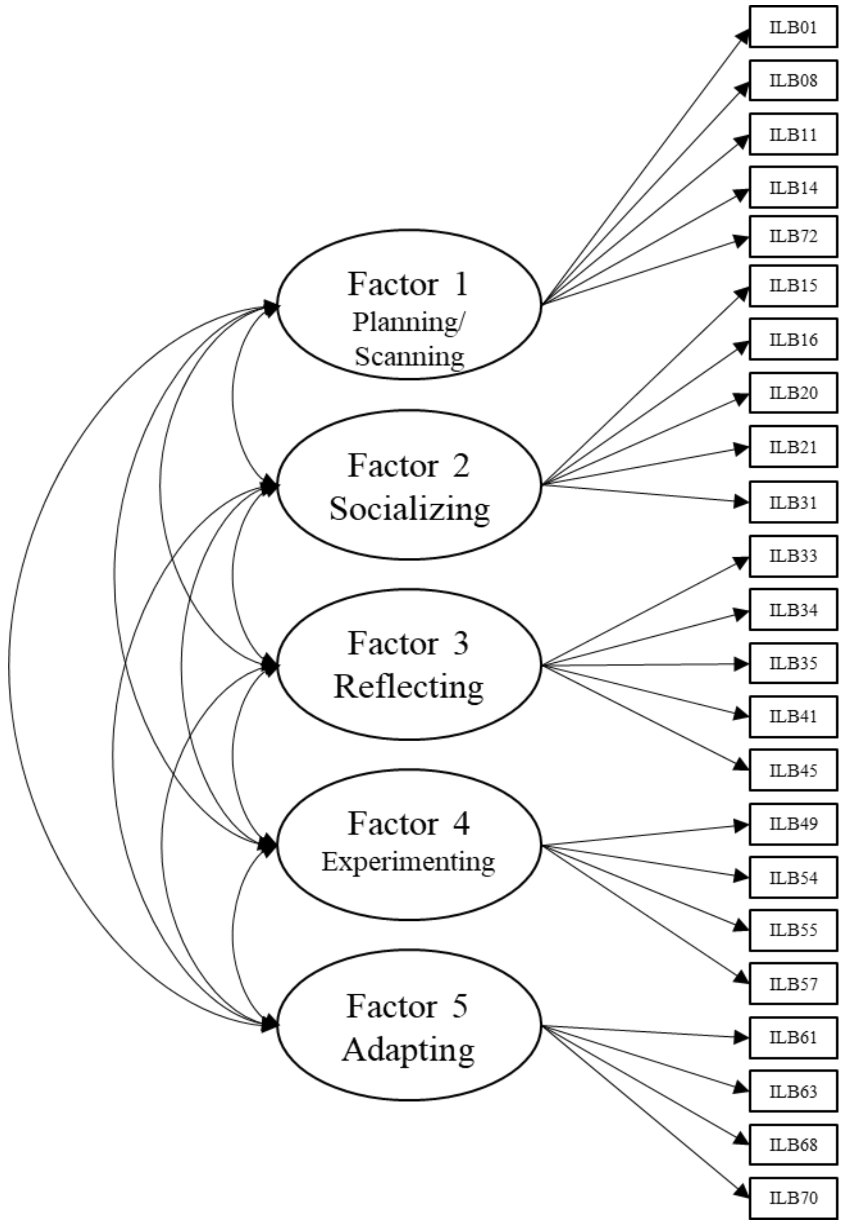

Figure 7. Measurement Model of the ILB-23

Hypothesis 3

Indirect effects of sleep quality on learning behaviors. Asymmetrical confidence intervals (ACIs) were used to evaluate the indirect effects of sleep quality on informal learning behaviors. Examination of the bias-corrected bootstrapped confidence intervals revealed that the indirect effects were generally positive but not statistically significant. From sleep quality via occupational self-efficacy to: planning, *b* = 0.07, 95% CI [0, 0.24], socializing *b* = 0.07, 95% CI [0, 0.22], reflecting, *b* = 0.03, 95% CI [0, 0.21], experimenting, *b* = 0.15, 95% CI [0, 0.49], and adapting, *b* = 0.10, 95% CI [0, 0.29]. Hypothesis three was not supported.

Hypothesis 4

Latent profiles of organizational learning culture. One- through four-profile models were conducted.

Overall model fit. The three-profile solution provided the best overall model fit to the data. Specifically, the three-profile solution had the lowest BIC (8949.312), the highest entropy (.923), and the highest average latent class probabilities (.972, .964, .961). The examination of the LMR tests indicated that the two-profile solution was an improvement over the one-profile solution and the three-profile solution was an improvement over the two-profile solution. The four-profile solution resulted in an unstable model fit and could not be evaluated. The breakdown of the three-profile solution was reasonable, with profile one matching 16% of the sample, profile two matching 52% of the sample, and profile three matching 32% of the sample.

Description of the best fitting model. The three profiles can be described as "weak perceptions of learning culture" (DLOQ-W), "positive perceptions of learning culture" (DLOQ-P), and "strongly positive perceptions of learning culture" (DLOQ-SP).

The DLOQ-W profile was associated beliefs that the organization supports learning no more often than it does not. In particular, the DLOQ-W profile was associated with a perceived lack of support for rewarding learning, tracking time and resources spent on training, and listening to recommendations from individuals.

The DLOQ-P profile was associated with beliefs that the organization supports learning more often than not but not always. Two items emerged as key negative perceptions that ran contrary to other perceptions in this profile: respondents belonging to this profile do not believe that the organization measures gaps between current and expected performance and do not think that the organization measures the time and resources spent on training.

The DLOQ-SP profile was associated with beliefs that the organization supports learning frequently or almost always. In particular, members of the DLOQ-SP profile believe that the organization almost always supports employees to think globally (above and beyond their other, high ratings). Members of the DLOQ-SP profile share the same doubts about tracking training and performance as the DLOQ-P profile, but they still rated these items favorably although less favorably as the other items. Hypothesis four was supported.

Hypothesis 5

The relationships between occupational self-efficacy and informal learning behaviors were specified as random slopes at the within level of the model and regressed onto the three learning culture perception profiles (dummy coded as two variables) at the between level, using the RCP moderation method (Preacher et al., 2016). The direct effects of the dummy-coded profile variables on the informal learning behaviors were not significant and there was large variability in the effect sizes (effects ranged from -.37 to 2.8 for the comparison between the DLOQ-W and DLOQ-SP profiles for example). The effects of the interaction terms, specified as the products of the profile dummy variables and occupational self-efficacy, on the informal learning behaviors were also assessed. The interaction terms were not significantly related to informal learning behaviors (with the exception of planning (.21), the effects were negative and ranged from -.18 to -.44), so the simple slopes were not interpreted. Hypothesis five was not supported.

Hypothesis 6

Direct effects of learning behaviors on job performance. An ordinal logistic regression was conducted to determine whether learning behaviors predicted job performance ratings. Experimenting behaviors were positively and significantly related to occupational self-efficacy (b = .605, SE = .21, $p < .01$; log odds ratio = 1.832); no other learning behaviors were predictive of performance. For a one-unit increase in experimenting behaviors, the log odds of having a higher performance rating was 83.2%. That is, for an increase in one standard deviation (SD = 0.66 for the scale score of experimenting), the likelihood that an individual had a higher performance rating (from either one to two or two to three) increased by 83.2%. Hypothesis six was partially supported.

Hypothesis 7

Direct effects of learning behaviors on job potential. An ordinal logistic regression was conducted to determine whether learning behaviors predicted job potential ratings. Experimenting behaviors were positively and nearly significantly related to occupational self-efficacy (log odds = .348, SE = .09, p = .06; log odds ratio = 1.416); no other learning behaviors were predictive of potential. For a one-unit increase in experimenting behaviors, the log odds of having a higher potential rating was 41.6% although this result is not significant. Hypothesis seven was not supported.

STUDY TWO DISCUSSION

Learning informally on the job is a critical process linking together one's motivation and self-regulation to on-the-job results (Enos et al., 2003; Noe et al., 2013). Study one conceptualized the informal learning construct as a multifaceted set of intentional behaviors. Study one provided an initial validation of a scale measuring those behaviors, but additional validation was necessary. Study two continued the validation process of the new scale. A concurrent validation design was employed to determine antecedents and outcomes of informal learning. To that end, data about participants' sleep (Yu et al., 2012), self-regulation, and perceptions about the organizational learning culture (Marsick & Watkins, 2003) were collected to test antecedent hypotheses: It was hypothesized that sleep quality and occupational self-efficacy would directly and positively impact informal learning.

Information about participants' occupational self-efficacy (Schyns & Von Collani, 2002) was collected to operationalize self-regulation in the organizational setting. Self-regulation is a well-established antecedent to informal learning in both the general literature (Enos et al., 2003; Sitzmann & Ely, 2011) and in study one. Occupational self-efficacy was additionally used in study two to test indirect mediation and moderation effects. It was hypothesized that sleep quality would indirectly affect informal learning behavior via occupational self-efficacy, following from previous work that established the effect of sleep on self-regulation (specifically poor-quality sleep disrupting self-regulation; Barnes, 2012).

It was also hypothesized that organizational learning culture would interact with occupational self-efficacy to heighten or dampen informal learning behaviors based on how individuals perceived the learning culture. To that end, group-level perceptions of culture were delineated from individual responses via latent profile analysis, and these profiles were used as moderating variables. Additionally, the partner organization provided archival performance data to use as criteria for the informal learning behaviors. It was hypothesized that informal learning would be directly related to performance ratings.

The purpose of study two, therefore, was to continue the validation process of the Informal Learning Behaviors scale started in study one, specifically to confirm the structure of the scale in a new sample and collect data to determine the predictive validity of the scale. Data were collected from a single organization to test the factor structure of the ILB-23 and a subsequent predictive model centered on the ILB-23 learning behaviors. Data analyses proceeded in three main steps: 1) confirming the factor structure, 2) developing a path model of direct, predictive effects toward and from the learning behaviors, and 3) adding complexity to that model, in terms of mediation and moderation effects, to determine whether any additional within or between person mechanisms predicted learning behaviors.

Study one found that a five-factor, 23-item solution best fit the data. Study two, then, aimed to confirm whether the same factor structure and set of items fit new data excellently. Latent structures can be an artifact of the specific dataset used to create them, so collecting new data and testing the same structure again is a necessary component of scale validation (DeVellis, 2012). Initial model fit was acceptable: CFI was below the excellent range (.89 observed vs. $> .95$ target) but both RMSEA and SRMR were above their respective excellent ranges (.05 vs. $< .06$ and .07 vs. $< .08$). Following guidance from Brown (2015), error terms between indicators in different factors were allowed to correlate in order to improve model fit and to test the remaining hypotheses with a latent model rather than an observed model.

Correlating residuals is a common practice in latent variable modeling and should be conducted only when sound theoretical reasoning, a consistent method of allowing correlations, and no significant impact to the parameter estimates are all present (Brown, 2015). All three conditions were present in study two: informal learning behaviors are expected to relate to one another, only residual correlations between items in a correlation matrix greater than a certain threshold (.03) were then specified in the model, and the parameter estimates were compared to a model without correlated residuals and no large differences were present. The ensuing model fit was excellent for all criteria for the measurement model and structural equation model, supporting the first hypothesis and alleviating any concerns that fit to the data might impair tests of the remaining hypotheses.

Finding that the factor structure found in study one was consistent in new data was a critical component of study two and has major implications for the project generally. No previous measure of informal learning includes more than three dimensions. Lohman (2006) and Noe et al. (2013) described reflecting, socializing, and scanning behaviors although their reflecting dimensions included both reflecting and experimenting behaviors. Wolfson et al. (2018) described experimenting, reflecting (on feedback), and vicarious learning behaviors in their recent measure. The present results indicate that more than three dimensions represent informal learning and, therefore, previous measures may insufficiently represent the construct domain. The ILB-23 thus represents a more comprehensive measure of informal learning and should be used in future research.

The second aim of study two was to establish direct effects of two variables, sleep quality and occupational self-efficacy, on informal learning (antecedents) and direct effects of informal learning behaviors on two criteria, job performance and job potential (outcomes). As discussed earlier, most of these outcomes – self-efficacy, job performance, and job potential - are used frequently in informal learning research (e.g., Cerasoli et al., 2018) and were therefore included to test the validity of the ILB-23 within the confines of the established literature. Sleep quality was added to the study as a predictor to link together a nonwork variable with on-the-job informal learning via self-regulation, a mechanism both literatures (Barnes, 2012; Enos et al., 2003; Noe et al., 2013).

Contrary to expectations, sleep quality was related neither to occupational self-efficacy (not supporting hypothesis 2a) nor to informal learning behaviors (not supporting hypothesis 2b). Occupational self-efficacy was, as expected, related to most informal learning behaviors (reflecting behaviors were not related to occupational self-efficacy and, therefore, hypothesis 2c was partially supported). Hypothesis two, then, was partially supported. These results were inconsistent with the extant literature supporting the link between sleep quality and self-regulation (Barnes, 2012) and consistent with self-regulation and informal learning (Enos et al., 2003; Noe et al., 2013), which supports the notion that this informal learning behavior scale relates to its established antecedents as expected. The direct effect of sleep quality on informal learning was not supported, but this finding will be discussed later with the test of the indirect effect of sleep quality on informal learning.

Turning to the relationships between informal learning and performance criteria, experimenting behaviors, but not other behaviors, were significantly related to an increased chance of a higher performance rating (partially supporting hypothesis six). No behaviors were related to job potential ratings (hypothesis seven was not supported). This result is surprising given that prior research has established robust links between informal learning and job performance (Cerasoli et al., 2018). The discrepancy between the current study and previous research is possibly due to issues with the criterion. Both job performance and job potential are supervisor ratings, and the ratings are done on an ordinal scale. A better criterion would have been an objective interval or ratio scale variable. This type of criterion was not available in the present study. Another possibility is that there was a mismatch between how informal learning was measured (as a personal characteristic) and when performance was measured (the most recent performance rating was used). A stronger concurrent design would have collected performance criteria contemporaneously with the predictor variables (informal learning). The current design, therefore, possibly results in weaker relationships than are true and reported in the literature.

Informal learning behaviors did not, in general, predict performance or potential; however, experimenting behaviors were an exception. Experimenting behaviors were significantly and strongly related to job performance and almost significantly related to job potential. Experimenting behaviors are well-represented in previous scales (Lohman, 2006; Noe et al., 2013; Wolfson et al., 2018) and, therefore, experimenting behaviors may be a narrow driver of the connection between informal learning (as a broad construct) and job performance. Experimenting behaviors include trying new things, taking on stretch tasks, taking risks, and coming up with new ideas. These are visible behaviors that are attractive to an organization (Berg & Chyung, 2008, Cseh et al., 1999), so it is perhaps unsurprising that these behaviors are related to performance ratings.

The third aim of study two was to examine mediating and moderating effects of group- and individual-level factors to the proposed model. First, it was hypothesized that occupational self-efficacy would mediate the relationship between sleep quality and informal learning as both variables were linked by self-regulation. Inconsistent with expectations, sleep quality was not indirectly related to informal learning (hypothesis three was not supported); while nearly significant, the effect sizes were quite small. The study likely lacked the power to find these effects but, even if it did have the power, the potential findings do not appear to be practically meaningful.

The lack of support for mediation (hypotheses 2a, 2b, and 3) were arguably due to a methodological issue rather than a theoretical one: Sleep quality was measured as a temporarily-sensitive variable (i.e., report your sleep quality from the past seven days) whereas informal learning behaviors and occupational self-efficacy were measured as a personal characteristics (i.e., report how like you this behavior is). Sleep quality in the previous seven days could be related to occupational self-efficacy or informal learning behaviors in the previous seven days, whereas sleep quality in the previous seven days may not be related to one's general self-efficacy or informal learning attributes. If the study had found an effect for sleep quality on informal learning or occupational self-efficacy, the obvious explanation would be that the study had sufficient power to find a true effect of sleep quality on the variables of interest. It did not, and the corollary to the previous explanation is that the study lacked the power to find those effects. A competing explanation, however, could be that the effect would have been due to the effect of sleep on survey responding rather than any true relationship between the survey variables (Barber, Barnes, & Carlson, 2013). Barber et al. found systematic differences in response patterns in surveys attributable to restricted sleep. Consequently, future research should 1) more carefully operationalize variables along the same timeframe to rule out temporal differences in measures and 2) account for any variances in responses due to predictable patterns of responses due to sleep restriction.

At the group-level, perceptions of the learning climate were used as moderating variables to test whether the relationship between occupational self-efficacy and informal learning behavior varied as a function of how the learning culture was perceived. Awareness of and reaction to the environmental is a key theoretical component of informal learning (Leslie et al., 1998; Watkins & Marsick, 1992). For example, one might be very confident in his or her professional abilities but not exert effort to learn on the job if he or she believed that such learning would not be rewarded. Some researchers have gone as far as to suggest that informal learning occurs because of the interaction between environmental and personal characteristics (Marsick, Volpe, & Watkins, 1999; Tannenbaum, 1997), hence I examined climate as a moderating variable in this study.

The moderator was created with latent profile analysis, a data exploration technique that classifies respondents into groups based on their shared response patterns (Morin et al., 2011). In short, this technique took individual responses, or perceptions, to the dimensions of the learning organization questionnaire (Marsick & Watkins, 2003), thereby creating grouping of shared psychological climate (James, 1982). Three profiles emerged from the data, with one profile describing individuals with fairly negative attitudes toward the organization's support for learning, a second describing fairly positive attitudes, and a final profile describing very positive attitudes. These profiles fit the data excellently, were interpretable, and had a reasonable number of individuals belonging to each profile, satisfying both the statistical and theoretical criteria for deriving latent profiles from the participants' responses (Muthén & Muthén, 2000; Nylund, Asparouhov, & Muthén, 2007). Hypothesis four was therefore supported.

The analyses did not find a direct effect of the climate profiles on informal learning behaviors. More importantly, the profiles did not moderate effects on informal learning behaviors (hypothesis five was not supported). Unlike the prior discussion about sleep quality, these variables were measured in a similar manner to occupational self-efficacy and informal learning; in short, there is not a competing methodological limitation that could explain the lack of support for this hypothesis. Moderating relationships have been previously established in the informal learning literature (e.g., Jansen, Van Den Bosch, & Volberda, 2006; Wolfson et al., 2018) but these studies had far larger sample sizes. Given the large variability in the profile effects, it is likely that the analyses were too underpowered to find the hypothesized effects if they were there.

It is risky to interpret effect sizes that are not statistically significant, but the results showed evidence of large effect sizes and a pattern of estimates that suggest planning behaviors could operate differently under certain climates than the other behaviors. In short, there is a strong possibility that the study was underpowered to find these effects (Bandalos, 2014) especially considering the previous research supporting the effects of moderating variables on informal learning (Wolfson et al., 2018) and for climate specifically on organizational variables (Morin et al., 2011).

Limitations

Study two collected data from fewer participants than planned. 300 responses were targeted to ensure enough observations to confirm the factor structure of the ILB-23 and test the study's hypotheses in a latent model (following Floyd & Wildman's, 1995 criteria and consistent with minimum suggested sample sizes by Bandalos, 2014 and Muthén & Muthén, 2002). However, my response rate was 7.7%, yielding 167 only responses. The low final N raises potential problems of nonresponse bias and lack of power. Although related, these are two different issues with different possible consequences. Before diving into both issues tactics around response facilitation bear mentioning.

Response facilitation refers to the tactics employed to increase response rate (Rogelberg & Stanton, 2007). Data collection in study two was conducted with a partner organization employing nearly 11,000 individuals globally. Over 20% of the employee population was contacted, and several techniques were used to ensure that the response rate was a high as possible. The survey was designed to be as brief and clear as possible, and feedback from internal stakeholders was solicited and used at every step of the survey design process. Two waves of data collection were planned, and the waves were further stratified by global location to ensure that the majority of participation received survey links and reminders during work hours. Most participants were pre-notified by internal stakeholders that a survey was inbound from an outside researcher and that both the study and survey link were vetted by the organization. Each survey wave was open for two weeks and three reminders were sent to participants. The study was introduced as research into how learning functions in the organization and data would be used for academic purposes and to present suggestions to the organization for how to support learning. Finally, all participants were offered an individualized report about their survey results in return for their time and responses.

The first wave of data collection was met with some resistance. The research team did not pre-notify participants about the study and survey link, so several individuals raised the concern that the study could be a phishing attack. The team addressed each of these individuals directly. All potential respondents in this wave were then contacted by the internal stakeholders, who stated that the study was real and the survey link was vetted by the organization. Despite the prenotification in the later wave, individuals still vocalized their resistance to clicking on the survey link due to phishing concerns. A few individuals also withdrew their data after completing the survey. In short, at all stages of the data collection process the research team followed the best practices of response facilitation (Rogelberg & Stanton, 2007) but the response rate was quite low. Whether this was due strictly to the phishing concerns or for additional reasons (disinterest in the study, distrust in the research, busy schedules, etc.) is difficult to say. Organizations are increasingly offering information security training (warning against phishing attacks, social engineering, etc.) and future researchers should be mindful that potential participants may resist online surveys from unfamiliar sources.

To address whether the survey respondents were substantively different in some way to the nonresponse population, the organization provided some archival data about the sampling population which was used to conduct archival nonresponse bias analyses (Rogelberg & Stanton, 2007). Some differences between the two groups were found, but follow-up analyses did not find any concerning relationships between the differences and the survey topics. It did not appear that nonresponse bias was a concern in this study.

The next concern was whether the model was underpowered. Power refers to the likelihood that a statistical test can find a true effect given a certain sample size (Muthén & Muthén, 2002). As the data analyses used fewer participants than planned, it was less likely that the model would find true effects should they exist. A small sample size can also cause models to not converge or have poor fit to the data (Bandalos, 2014; Muthén & Muthén, 2002). Fortunately, the small sample size in study two did not cause many problems with the interpretation of the results. Both the measurement model and structural equation model met the excellent criteria for model fit to the data (Hu & Bentler, 1999). Not all hypotheses were fully supported or supported at all, however, but not all these unsupported hypotheses can be attributed to an underpowered model.

Specifically, the components of hypothesis two related to sleep and hypothesis three were more likely due to faulty methodology (see earlier discussion) than an underpowered model. That said, hypothesis five and seven were likely underpowered. The test of hypothesis five, the moderation hypothesis, found some large, direct effects of the climate profiles and profile x occupational self-efficacy interaction terms on informal learning behaviors. Due to the number of direct effects and interaction terms that were added to test this hypothesis, it is very possible that there were too many parameters for the sample size. In other words, testing five to ten direct effects for climate profile and interaction terms required a larger sample size than was present in the study. Similarly, hypothesis seven, the job potential hypothesis, was nearly partially supported. Experimenting behaviors had a strong effect on job potential ratings, but this result was almost significant.

In sum, a low response rate resulted in a smaller sample size than targeted, both of which could limit the scope of the study's results. Fortunately, nonresponse bias did not appear to be an issue. It is the researcher's opinion that the small sample size contributed to a lack of power to find certain hypothesized effects, however. A methodological issue concerning the operationalization of sleep, which has a different time reference than the other measures, likely also contributed to the lack of support of the sleep-related hypotheses.

Conclusion

Several researchers have called for a validated measure of informal learning (Cerasoli et al., 2018; Kukenberger et al., 2015; Sitzmann & Ely, 2011) and confirming the structure of the scale found in the prior study was essential for providing a validated scale to the literature.

Construct validation, or the extent to which a measure measures what it purports to measure, is an on-going process where evidence is continually collected over successive studies including a measure of interest. Thus far, studies one and two have collected evidence that the scale developed across these two studies measure five broad dimensions of informal learning: planning and scanning behaviors, socializing behaviors, reflecting behaviors, experimenting behaviors, and adapting behaviors. Additionally, the dimensions of the scale largely exhibit convergent, discriminant, emerging evidence of concurrent validity consistent with the theoretical space around informal learning.

GENERAL DISCUSSION

Unsurprisingly, informal learning has been the subject of study for several decades but only recently have well-developed measures of the construct (e.g., Wolfson et al., 2018) begun to emerge in the literature, following calls for these types of scales (Cerasoli et al., 2018; Kukenberger et al., 2015; Sitzmann & Ely, 2011). The breadth and idiosyncrasy of informal learning has challenged researchers who conceptualize the construct in the literature: There are numerous taxonomies (Eraut, 2004; Marsick & Watkins, 1992; Schugurensky, 2000) and ad hoc scales (e.g., Bednall et al., 2014; Gijbels et al., 2012; Noe et al., 2013) describing not only informal learning but its subconstructs and related constructs. This project was designed to address the calls for a validated, comprehensive measure of informal learning.

The two present studies have largely achieved their goal of creating and validating a measure of informal learning behaviors. The content of the scale reflects the literature's current understanding of intentional behaviors conducted by the learner across several well-defined behavior types. The foundation to study one was a thorough review of the literature, which culminated in a framework describing the construct space around informal learning and an exhaustive list of the behaviors, documented by the literature, thought to be indicative of intentional informal learning (Noe et al., 2010). The present scale development drew upon these findings to hypothesize the existence of six dimensions that broadly represent how individuals consciously engage in learning activities. These dimensions were planning, socializing, reflecting, experimenting, adapting, and scanning. Study one found and study two confirmed a five-factor structure to the scale, in which planning and scanning items merged to indicate a single factor.

The dimensionality of the ILB-23 is a key strength of the scale and differentiates it from other scales in the literature. Study one found good support for the proposed six-factor solution, but two dimensions were nearly identically related to one another: planning behaviors and scanning behaviors, which both largely involve accumulating and assessing learning content, with planning being more proactive (setting goals) and scanning being more passive (staying current). This finding contradicted the structure of previous scales (Lohman, 2006; Noe et al., 2013) who both included scanning dimensions but not planning dimensions. The evidence from study one suggested that the content of these two dimensions approximated the same latent structure and, after item reduction, that mostly planning behaviors were the best indicators of the shared dimension.

Previous work has documented the effect of informal learning on job performance (Cerasoli et al., 2018; Wolfson et al., 2018) but the results of study two suggested a more fine-grained take. Specifically, experimenting behaviors were the behaviors most related to job performance and job potential. No other behavior was related to job performance; interestingly, previous measures of informal learning include experimenting behaviors, suggesting perhaps that informal learning as a unidimensional construct may not be directly related to job performance.

There is significant amount of conceptual literature supporting all five of the ILB-23 dimensions, but no other scale includes more than three dimensions and nine items (e.g., Lohman, 2006; Noe et al., 2013; Wolfson et al., 2018). Study two found that all five dimensions fit the data well. The results of these studies, therefore, are both *consistent* with informal learning theory and *inconsistent* with previous scales used in the literature. An underlying goal of this project was to clarify the informal learning construct and bring a common language of informal learning to the literature. By expanding the dimensionality of informal learning to include adapting dimensions, clarifying the distinction between reflecting and experimenting behaviors, and condensing planning and scanning behaviors, this scale presents a nuanced but comprehensive set of informal learning dimensions.

Future Directions

Future research should continue to validate the scale, test the generalizability of the scale to other settings (e.g., other industries), use this scale to develop the theoretical space around informal learning, and consider applications to applied problems.

Construct validation is an ongoing process (DeVellis, 2012); therefore, while the evidence collected in study one and two constitute very promising results, future research should continue to develop our understanding of the ILB-23's validity. This process involves reconfirming the factor structure of the scale with new data, linking it to other variables thought to be related to informal learning (e.g., personality, organizational support), and collecting evidence of concurrent and predictive validity.

Second, the ILB-23 should be used in new settings. The scale has so far been validated using student, online, and technology-focused organizational populations. Future research could consider other industries (e.g., manufacturing, healthcare, finance, etc) to use the scale. The types of learning behaviors individuals typically use may vary by industry; for example, experimenting behaviors may be more suited to white-collar fields in which employees have more autonomy over their jobs.

From a theoretical perspective, understanding antecedents to informal learning should be a primary concern, particularly variables under the control of the individual or organization. For example, training departments might explore improving informal learning by targeting antecedents to informal learning. Goal-setting theory (Locke & Latham, 2006) could be used to leverage the motivational antecedents to informal learning by creating specific learning goals that require extending one's current learning tactics. Organizational learning climate may also be an antecedent to informal learning (Tannenbaum, 2010); consequently, supporting informal learning could be another reason to measure and address climate concerns.

Study two did not find any effects of sleep on informal learning behaviors as hypothesized. These hypotheses were included in order to expand the theory around sleep and its influence on learning, but methodological issues likely dampened the ability to find the hypothesized effects. Future research might consider exploring these relationships using time-controlled study designs, like diary or experience sampling designs, which could control for the effect of time while exploring how sleep processes might boost or inhibit how or when people engage in informal learning behaviors (similar studies have been suggested by Cerasoli et al., 2018 and Sitzmann & Ely, 2011). Outside of directly developing learning abilities, understanding how situational or biological variables affect on-going learning is arguably the best way of improving informal learning in an organization.

Research can also inform how informal learning is encouraged in practice. Learning is highly valued in organizations (Bear et al., 2008), but most organizational resources for learning are dedicated to supporting formal instruction (Sitzmann & Ely, 2011). Formal instruction has an undeniable place in the organization, but these studies and past studies have shown that informal learning also has a place (Cerasoli et al., 2018). Developing informal learning as a set of behaviors is consistent with the growth mindset of learning, lends itself to easier competency modeling around learning, and gives tools to employees that they can transfer to any future project, course, job, or career. Research on how to design, implement, and evaluate informal learning training could open a door to a new set of core courses for organizations. The work done in these studies can serve as a framework for the content, topics, and evaluation of informal learning.

Conclusion

The ILB-23 is a reliable and developing as a valid measure of informal learning, providing information about the planning, socializing, reflecting, experimenting, and adapting behaviors individuals consciously engage in on the job. These dimensions were found to be related to several other learning constructs, motivation constructs, and self-regulation constructs. Additionally, experimenting behaviors were found to predict job performance. Future research should consider exploring the antecedents to informal learning that can be influenced by practitioners and researchers to support and develop informal learning in organizations.

TABLES

Table 1. *Item Level Analyses*

Dimension	Item	*M*	95% CI	*SD*	Difficulty	Discrim-ination	Loadings	Skewness	Kurtosis	Response Frequency					Histograms
										1	2	3	4	5	
1	ILB01	3.90	[3.84, 3.96]	1.05	0.78	0.62	0.682	-0.886	0.177	33	108	174	465	371	
1	ILB02	3.90	[3.84, 3.96]	1.09	0.78	0.45	0.558	-0.887	0.036	38	114	170	421	401	
1	ILB03	3.36	[3.29, 3.43]	1.15	0.67	0.49	0.636	-0.3	-0.79	69	220	283	383	196	
1	ILB04	4.11	[4.05, 4.15]	0.84	0.82	0.55	0.534	-0.995	1.169	11	47	147	545	395	
1	ILB05	3.73	[3.67, 3.79]	1.08	0.75	0.53	0.630	-0.669	-0.281	39	139	217	451	302	
1	ILB06	3.74	[3.68, 3.8]	1.03	0.75	0.52	0.606	-0.655	-0.128	33	118	249	467	287	
1	ILB07	3.89	[3.83, 3.94]	0.99	0.78	0.60	0.697	-0.872	0.399	27	93	189	514	328	
1	ILB08	3.84	[3.79, 3.9]	0.96	0.77	0.54	0.615	-0.821	0.426	25	92	208	545	285	
1	ILB09	3.97	[3.92, 4.02]	0.94	0.79	0.53	0.573	-0.9	0.583	19	75	184	516	359	
1	ILB10	3.58	[3.51, 3.64]	1.17	0.72	0.52	0.632	-0.524	-0.695	61	189	210	411	282	
1	ILB11	3.99	[3.94, 4.05]	0.94	0.80	0.59	0.646	-0.93	0.597	19	76	175	505	378	
1	ILB12	3.73	[3.67, 3.79]	1.07	0.75	0.56	0.684	-0.684	-0.159	44	120	243	449	300	
1	ILB13	4.00	[3.95, 4.06]	0.94	0.80	0.53	0.582	-0.964	0.671	18	81	157	522	375	
1	ILB14	3.50	[3.44, 3.57]	1.11	0.70	0.50	0.636	-0.467	-0.571	54	183	259	440	215	
2	ILB15	4.01	[3.95, 4.06]	0.93	0.80	0.55	0.590	-0.961	0.749	19	70	170	515	377	
2	ILB16	3.85	[3.79, 3.9]	1.00	0.77	0.59	0.656	-0.833	0.288	30	99	199	509	310	
2	ILB17	3.60	[3.54, 3.67]	1.17	0.72	0.57	0.732	-0.597	-0.569	63	174	199	434	281	
2	ILB18	3.52	[3.45, 3.59]	1.18	0.70	0.61	0.774	-0.524	-0.652	75	179	223	420	252	
2	ILB19	3.85	[3.79, 3.91]	1.06	0.77	0.44	0.539	-0.844	0.079	36	116	181	473	350	
2	ILB20	3.95	[3.89, 4.01]	1.05	0.79	0.55	0.647	-1.027	0.524	40	93	152	474	398	
2	ILB21	3.77	[3.71, 3.83]	1.04	0.75	0.66	0.743	-0.768	-0.003	36	125	197	498	294	
2	ILB22	3.38	[3.32, 3.45]	1.18	0.68	0.54	0.727	-0.327	-0.862	74	228	251	388	216	
2	ILB23	3.31	[3.24, 3.37]	1.14	0.66	0.54	0.660	-0.368	-0.788	78	235	240	445	152	
2	ILB24	2.93	[2.85, 3]	1.24	0.59	0.45	0.577	0.055	-1.05	160	311	258	288	129	
2	ILB25	3.64	[3.59, 3.71]	1.07	0.73	0.53	0.627	-0.662	-0.174	48	135	238	484	244	
2	ILB26	3.48	[3.41, 3.55]	1.20	0.70	0.56	0.735	-0.447	-0.756	81	184	249	378	261	
2	ILB27	3.81	[3.75, 3.87]	1.01	0.76	0.61	0.687	-0.866	0.233	31	125	158	549	286	
2	ILB28	3.62	[3.55, 3.68]	1.06	0.72	0.60	0.696	-0.663	-0.127	52	130	250	488	226	
2	ILB29	4.04	[3.99, 4.1]	0.94	0.81	0.45	0.521	-0.992	0.747	19	69	166	493	409	
2	ILB30	3.77	[3.7, 3.83]	1.13	0.75	0.60	0.724	-0.777	-0.198	52	132	185	439	338	
2	ILB31	3.90	[3.84, 3.95]	0.96	0.78	0.54	0.610	-0.918	0.625	27	84	184	539	317	

Table 1. *Item Level Analyses*

Dimension	Item	*M*	95% CI	*SD*	Difficulty	Discrim-ination	Loadings	Skewness	Kurtosis	Response Frequency 1	2	3	4	5	Histograms
3	ILB32	4.11	[4.05, 4.15]	0.88	0.82	0.58	0.575	-1.188	1.737	20	48	127	553	404	
3	ILB33	4.04	[3.99, 4.09]	0.93	0.81	0.57	0.602	-1.041	1.049	22	58	165	514	393	
3	ILB34	4.20	[4.14, 4.25]	0.91	0.84	0.62	0.624	-1.227	1.413	18	48	134	439	509	
3	ILB35	4.00	[3.94, 4.05]	0.93	0.80	0.60	0.624	-0.984	0.78	17	82	146	546	360	
3	ILB36	3.98	[3.93, 4.04]	0.92	0.80	0.53	0.576	-1.022	1.086	24	63	168	554	347	
3	ILB37	3.81	[3.76, 3.87]	0.97	0.76	0.50	0.584	-0.709	0.074	22	105	227	509	289	
3	ILB38	3.90	[3.85, 3.96]	0.95	0.78	0.55	0.598	-0.913	0.65	24	85	180	553	310	
3	ILB39	4.16	[4.11, 4.21]	0.86	0.83	0.54	0.555	-1.118	1.312	12	51	127	508	451	
3	ILB40	4.03	[3.97, 4.08]	0.91	0.81	0.61	0.611	-1.025	1.111	22	54	171	528	374	
3	ILB41	3.70	[3.64, 3.76]	1.04	0.74	0.44	0.540	-0.681	-0.148	37	138	219	500	258	
3	ILB42	3.84	[3.78, 3.89]	0.99	0.77	0.54	0.620	-0.812	0.312	29	94	213	514	303	
3	ILB43	3.95	[3.89, 4]	0.94	0.79	0.63	0.656	-0.875	0.588	21	69	201	511	347	
3	ILB44	3.91	[3.86, 3.97]	0.96	0.78	0.50	0.559	-0.807	0.254	18	93	195	509	336	
3	ILB45	4.09	[4.04, 4.15]	0.92	0.82	0.66	0.653	-1.087	1.073	19	59	149	490	433	
4	ILB46	3.95	[3.89, 4]	0.91	0.79	0.54	0.575	-0.789	0.392	14	74	205	525	333	
4	ILB47	3.63	[3.57, 3.69]	1.03	0.73	0.57	0.636	-0.525	-0.344	32	146	270	465	235	
4	ILB48	3.87	[3.81, 3.93]	0.98	0.77	0.60	0.652	-0.821	0.277	23	99	193	516	316	
4	ILB49	3.61	[3.55, 3.67]	1.04	0.72	0.58	0.657	-0.486	-0.487	28	169	253	470	227	
4	ILB50	4.02	[3.96, 4.07]	0.91	0.80	0.54	0.596	-0.947	0.791	17	64	173	520	373	
4	ILB51	3.63	[3.57, 3.68]	1.01	0.73	0.55	0.640	-0.627	-0.098	37	135	258	513	210	
4	ILB52	4.11	[4.06, 4.16]	0.86	0.82	0.41	0.446	-1.025	1.148	11	53	139	541	407	
4	ILB53	3.89	[3.83, 3.94]	0.94	0.78	0.62	0.633	-0.771	0.199	14	102	189	540	305	
4	ILB54	3.55	[3.49, 3.61]	1.08	0.71	0.45	0.542	-0.526	-0.452	48	170	252	465	218	
4	ILB55	3.76	[3.7, 3.82]	1.03	0.75	0.55	0.636	-0.756	0.025	33	125	202	514	279	
4	ILB56	3.90	[3.84, 3.96]	0.99	0.78	0.44	0.537	-0.862	0.27	22	107	169	516	335	
4	ILB57	3.93	[3.88, 3.98]	0.95	0.79	0.60	0.615	-0.77	0.157	15	89	204	493	347	
4	ILB58	3.74	[3.68, 3.8]	1.07	0.75	0.55	0.678	-0.697	-0.226	36	142	202	476	296	

Table 1. *Item Level Analyses*

Dimension	Item	*M*	95% CI	*SD*	Difficulty	Discrim-ination	Loadings	Skewness	Kurtosis	Response Frequency					Histograms
										1	2	3	4	5	
5	ILB59	3.93	[3.87, 3.98]	0.95	0.79	0.54	0.592	-0.87	0.474	20	86	185	527	334	
5	ILB60	4.33	[4.28, 4.37]	0.84	0.87	0.53	0.517	-1.348	1.829	9	39	103	413	583	
5	ILB61	3.97	[3.92, 4.02]	0.90	0.79	0.54	0.570	-0.901	0.769	16	68	179	553	334	
5	ILB62	3.75	[3.69, 3.8]	0.99	0.75	0.45	0.557	-0.654	-0.044	25	118	242	508	261	
5	ILB63	3.94	[3.89, 4]	0.96	0.79	0.46	0.536	-0.835	0.335	19	83	198	494	357	
5	ILB64	3.86	[3.81, 3.92]	0.95	0.77	0.47	0.544	-0.831	0.474	25	84	210	532	296	
5	ILB65	3.90	[3.84, 3.96]	0.99	0.78	0.35	0.387	-0.764	0.039	19	101	205	472	352	
5	ILB66	3.73	[3.67, 3.79]	0.98	0.75	0.36	0.416	-0.547	-0.257	19	125	263	485	258	
5	ILB67	4.13	[4.08, 4.18]	0.85	0.83	0.52	0.539	-1.191	1.936	18	40	126	564	407	
5	ILB68	3.98	[3.92, 4.03]	0.89	0.80	0.56	0.563	-0.952	1.064	19	57	180	566	324	
5	ILB69	3.90	[3.85, 3.96]	0.96	0.78	0.47	0.554	-0.919	0.615	25	88	176	547	314	
5	ILB70	3.93	[3.87, 3.98]	0.91	0.79	0.55	0.587	-0.836	0.692	20	59	218	532	318	
6	ILB71	3.50	[3.44, 3.57]	1.13	0.70	0.47	0.618	-0.472	-0.619	62	185	252	429	229	
6	ILB72	4.03	[3.96, 4.08]	1.05	0.81	0.47	0.584	-1.068	0.519	34	91	147	421	462	
6	ILB73	3.51	[3.43, 3.57]	1.25	0.70	0.39	0.521	-0.497	-0.819	93	184	208	373	288	
6	ILB74	4.17	[4.12, 4.23]	0.92	0.83	0.43	0.456	-1.209	1.257	17	62	121	454	495	
6	ILB75	4.06	[4, 4.11]	0.95	0.81	0.47	0.535	-1.035	0.827	20	69	156	485	420	
6	ILB76	4.05	[3.99, 4.1]	0.93	0.81	0.49	0.515	-1.056	1.065	22	59	160	511	398	
6	ILB77	4.14	[4.08, 4.18]	0.88	0.83	0.54	0.530	-1.157	1.511	16	51	126	527	432	
6	ILB78	3.30	[3.23, 3.37]	1.19	0.66	0.38	0.545	-0.251	-0.927	81	250	252	376	191	
6	ILB79	3.91	[3.85, 3.96]	0.96	0.78	0.57	0.656	-0.828	0.396	22	83	206	512	329	
6	ILB80	3.63	[3.56, 3.69]	1.08	0.73	0.46	0.577	-0.551	-0.421	42	154	252	445	258	
6	ILB81	3.95	[3.89, 4]	0.97	0.79	0.47	0.554	-0.855	0.322	21	86	195	485	370	
6	ILB82	4.14	[4.09, 4.19]	0.88	0.83	0.46	0.525	-1.206	1.704	18	50	120	538	435	
6	ILB83	3.55	[3.48, 3.61]	1.15	0.71	0.45	0.579	-0.496	-0.655	58	184	232	415	259	
6	ILB84	3.77	[3.7, 3.83]	1.07	0.75	0.48	0.606	-0.8	0.037	45	118	198	487	301	

Table 2. *Final 23 Items of the Five-Factor Solution*

Factor	Internal Consistency[1] ω	Internal Consistency[1] α	Item (Scale: 1 - 5, 1: Not at all characteristic of me, 5: Highly characteristic of me)
Factor 1 Planning/ Scanning	0.760	0.759	1. Set a learning goal for yourself 2. Pick new topics or skills to learn to enhance your performance 3. Plan to learn something new 4. Research how your job duties could change in the future 5. Search for new information or ideas on the internet (e.g., using a search engine)
Factor 2 Socializing	0.81	0.81	6. Share your knowledge (content, technical process, etc.) with colleagues 7. Discuss challenges with tasks or assignments you have at work with colleagues 8. Work together with a team to complete a task 9. Network with peers at work to exchange ideas or knowledge 10.Assist colleagues with their work as a way to learn more on the job
Factor 3 Reflecting	0.79	0.79	11. Reflect on feedback you have received from colleagues 12. Reflect on feedback you have received from supervisors 13. Reflect on challenging moments you have experienced at work 14. Reflect on the performance of others at work 15. Evaluate your personal performance at work
Factor 4 Experimenting	0.73	0.74	16. Challenge existing assumptions about ideas at work 17. Take calculated risks 18. Take on challenging or stretch tasks at work 19. Come up with new ideas
Factor 5 Adapting	0.72	0.72	20. Respond to a change at work by learning more about the change 21. Start ambiguous tasks by first finding clarifying information 22. Learn about a change that occurred at work 23. Use what you have learned to address the unanticipated consequences of decisions made at work

[1]Overall scale ω = .942, α = .919

Table 3. *Structural Equation Model Results for the 23-Item, Five-Factor Solution*

Scale	Factor	*α*	*ω*	*M*	*SD*	ILS		LGO		PPGO		MC		MTL	
						Beta (Unstandardized)									
						b	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*	*b*	*SE*
Informal Learning Behaviors - Before Trimming	Planning/ Scanning	0.759	0.760	3.86	1.02	0.418**	0.079	0.625**	0.069	-0.010	0.036	1.131**	0.107	0.338**	0.079
	Socializing	0.808	0.807	3.90	0.99	0.503**	0.068	0.195**	0.054	-0.082**	0.031	0.537**	0.083	0.415**	0.067
	Reflecting	0.788	0.792	4.01	0.89	0.083	0.068	0.170**	0.057	-0.094**	0.032	1.181**	0.094	0.539**	0.071
	Experimenting	0.735	0.729	3.72	1.02	0.512**	0.083	1.145**	0.086	0.047	0.037	0.432**	0.102	0.058	0.081
	Adapting	0.715	0.718	3.96	0.91	0.161*	0.081	0.453**	0.070	-0.027	0.038	1.210**	0.118	0.597**	0.086
	Overall	0.919	0.942												
Informal Learning Behaviors - After Trimming	Planning/ Scanning			3.86	1.02	0.378**	0.076	0.645**	0.068			1.171**	0.107	0.327**	0.075
	Socializing			3.90	0.99	0.454**	0.062	0.228**	0.053			0.555**	0.082	0.406**	0.065
	Reflecting			4.01	0.89			0.184**	0.054			1.208**	0.088	0.541**	0.070
	Experimenting			3.72	1.02	0.472**	0.081	1.177**	0.084			0.476**	0.095		
	Adapting			3.96	0.91			0.483**	0.067			1.286**	0.112	0.595**	0.084
	Overall														
						Beta (Standardized)									
						β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*
Informal Learning Behaviors - After Trimming	Planning/ Scanning					0.147**	0.029	0.323**	0.031			0.407**	0.032	0.127**	0.029
	Socializing					0.235**	0.031	0.152**	0.035			0.257**	0.036	0.209**	0.033
	Reflecting							0.111**	0.032			0.505**	0.031	0.252**	0.031
	Experimenting					0.187**	0.031	0.598**	0.029			0.168**	0.033		
	Adapting							0.253**	0.032			0.467**	0.032	0.241**	0.032

$^*p < .05$; $^{**}p < .01$

Table 4. *Descriptive Statistics*

Scale	α	*M*	*SD*	Skewness	Kurtosis
Informal Learning Behaviors	0.87	4.06	0.45	-0.424	0.322
Planning & Scanning	0.68	3.85	0.64	-0.520	0.652
Socializing	0.78	4.25	0.63	-1.171	1.259
Reflecting	0.74	4.02	0.61	-0.802	0.805
Experimenting	0.77	4.08	0.66	-0.987	1.766
Adapting	0.70	4.14	0.61	-1.141	3.204
Dimensions of the Learning Organization	0.93	4.58	0.71	-0.472	0.437
Individual	0.82	4.64	0.77	-0.702	1.419
Team	0.71	4.64	0.82	-0.611	0.210
Organizational	0.87	4.53	0.71	-0.341	0.096
Occupational Self-Efficacy	0.87	4.89	0.62	-1.069	3.102
Sleep Quantity		6.85	1.12	0.260	2.858
Sleep Quality	0.89	3.56	1.02	0.541	0.499
Job Performance				-0.179	-0.881
Job Potential				0.266	-0.419

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APPENDICES

Appendix A. Proposed Informal Learning Behavior Items

The following statements describe different ways to approach learning at work. Please rate how much each statement describes how you typically approach learning at work.

Scale: 1 - 5, 1: Not at all characteristic of me, 5: Highly characteristic of me

1. Set a learning goal for yourself[P]
2. Rehearse for an upcoming presentation, meeting, etc. [P]
3. Assign yourself an extensive project meant to teach yourself something new[P]
4. Practice something you have learned so you can use it well in the future[P]
5. Collect learning materials (tutorials, books, websites, guides, etc.) that you plan to use to learn from[P]
6. Evaluate the accuracy or usefulness of the learning materials (tutorials, books, websites, guides, etc.) you plan to use[P]
7. Think about different ways you could learn something new[P]
8. Pick new topics or skills to learn to enhance your performance[P]
9. Prepare for future events (new tasks, roles, changes, etc.) [P]
10. Make a schedule to plan how much time to commit to learning[P]
11. Plan to learn something new[P]
12. Map out the developmental needs you need to fulfill to advance your career or education[P]
13. Envision your future at work[P]
14. Inform yourself about how your job duties (current or future) might change in the future[P]
15. Share your knowledge (content, technical process, etc.) with colleagues[S]

16. Discuss challenges with tasks or assignments you have at work with colleagues[S]

17. Request feedback about your performance from supervisor(s) [S]

18. Request feedback about your performance from peers or colleague(s) [S]

19. Observe (shadow) peers at work to learn how they complete their work[S]

20. Work together with a team to complete a task[S]

21. Network with peers at work to exchange ideas or knowledge[S]

22. Network with professional peers outside of work to exchange ideas or knowledge[S]

23. Give feedback to colleague(s) about their performance[S]

24. Give feedback to supervisor(s) about their performance[S]

25. Seek out content experts to advise you on particular tasks[S]

26. Seek out a mentor to guide your development[S]

27. Solve problems at work by brainstorming with colleagues[S]

28. Discuss work-related expectations with colleagues[S]

29. Ask questions about work issues[S]

30. Socialize with colleagues[S]

31. Support colleagues in work-related issues[S]

32. Reflect on your past performance[R]

33. Reflect on feedback you have received from colleagues[R]

34. Reflect on feedback you have received from supervisors[R]

35. Reflect on challenging moments you have experienced at work[R]

36. Measure your progress completing tasks[R]

37. Estimate your current knowledge about work-related content[R]

38. Identify barriers that prevent you from performing better at work[R]

39. Remember past experiences that are relevant to your current work[R]

40. Assess the consequences of past work-related events[R]

41. Reflect on the performance of others at work[R]

42. Seek to understand your attitudes toward your work[R]

43. Seek to understand your expectations of your work[R]

44. Note the outcomes of your performance at work[R]

45. Evaluate your personal performance at work[R]

46. Test different solutions to solve a problem[E]

47. Challenge existing assumptions about how to complete work[E]

48. Experiment with new ways to complete your tasks[E]

49. Challenge existing assumptions about ideas at work[E]

50. Apply new ideas you have learned from learning materials (tutorials, books, websites, guides, etc.) [E]

51. Evaluate experimental processes at work[E]

52. Anticipate possible consequences of your actions at work[E]

53. Come up with new ways of completing your work[E]

54. Take calculated risks[E]

55. Take on challenging or stretch tasks at work[E]

56. Make decisions without knowing the likely outcome[E]

57. Come up with new ideas[E]

58. Put yourself in new situations to develop yourself[E]

59. Adapt to challenges at work[A]

60. Improve your performance by learning from your mistakes[A]

61. Cope with change at work by gathering information[A]

62. Consider the context of a work-related change before reacting[A]

63. Complete ambiguous tasks by first finding clarifying information[A]

64. Process unexpected feedback received from colleagues[A]

65. Change your behaviors to avoid friction at work[A]

66. Resist reverting to old ways of completing your tasks[A]

67. Adapt to changes in your tasks or assignments[A]

68. Learn about a change that occurred at work[A]

69. Maintain awareness of your work environment[A]

70. Handle the unanticipated consequences of a decision at work[A]

71. Search for new information or ideas in professional publications[Sc]

72. Search for new information or ideas on the internet (e.g., using a search engine) [Sc]

73. Search for new information or ideas on social media[Sc]

74. Answer questions you had yourself by searching for the answer[Sc]

75. Observe work situations to understand the environment[Sc]

76. Recognize behaviors that others are rewarded for at work[Sc]

77. Keep up with topics in your areas of interest[Sc]

78. Maintain awareness of your work-related knowledge and skills[Sc]

79. Study new ways to learn[Sc]

80. Remain sensitive to how marketable your skills are[Sc]

81. Stay on the lookout for new work opportunities[Sc]

82. Clarify work-related concepts you don't fully understand[Sc]

83. Attend talks, lectures, etc. related to your areas of interest[Sc]

84. Maintain a network of peers who learn from each other[Sc]

Appendix B. Metacognition

Please rate the extent to which you perform the following behaviors when you learn new material.

Scale: 1 - 5; 1: Almost never, 5: Almost always

1. I make up questions to help focus on my learning
2. I ask myself questions to make sure I understand the things I have been trying to learn
3. I try to change the way I learn in order to fit the demands of the situation or topic
4. I try to think through each topic and decide what I am supposed to learn from it, rather than just jumping in without thinking
5. I try to determine which things I don't understand well and adjust my learning strategies accordingly
6. I set goals for myself in order to direct my activities
7. I make sure I sort out any confusion as soon as I can before moving on
8. I think about how well my tactics for learning are working
9. I think carefully about how well I have learned material I have previously studied
10. I think about what skills need the most practice
11. I try to monitor closely the areas where I need the most improvement
12. I think about what things I need to do to learn
13. I carefully select what to focus on to improve on weaknesses I identify
14. I notice where I make mistakes and focus on improving those areas
15. When I practice a new skill, I monitor how well I was learning its requirements

Appendix C. Motivation to Learn

Please rate the extent to which you agree with the following statements.

Scale: 1 - 5, 1: Strongly disagree, 5: Strongly agree

1. In general, I exert considerable effort to learning the materials during training
2. In general, I try to learn as much as I can from training.
3. In general, I am motivated to learn the skills emphasized in training.

Appendix D. Learning Goal Orientation

Please rate how much you agree with each of the following statements that describe how you typically approach your work.

Scale: 1 - 6, 1: Strongly disagree, 6: Strongly agree

1. I am willing to select a challenging work assignment that I can learn a lot from.
2. I often look for opportunities to develop new skills and knowledge.
3. I enjoy challenging and difficult tasks at work where I'll learn new skills.
4. For me, development of my work ability is important enough to take risks.
5. I prefer to work in situations that require a high level of ability and talent.

Appendix E. Noe et al.'s (2013) Informal Learning Scale

Consider the past three months. How often during a typical work week have you engaged in the activities below in order to learn and help you better perform your job?

Scale: 1 - 5, 1: Never, 5: All of the time

1. Reflecting about how to improve my performance
2. Experimenting with new ways of performing my work
3. Using trial and error strategies to learn and better perform
4. Interacting with a mentor
5. Interacting with my supervisors
6. Interacting with my peers
7. Reading professional magazines and vendor publications
8. Searching the internet for job relevant information
9. Reading management textbooks

Appendix F. Prove Performance Goal Orientation

Please rate how much you agree with each of the following statements that describe how you typically approach your work.

Scale: 1 - 6, 1: Strongly disagree, 6: Strongly agree

1. I'm concerned with showing that I can perform better than my coworkers.
2. I try to figure out what it takes to prove my ability to others at work.
3. I enjoy it when others at work are aware of how well I am doing.
4. I prefer to work on projects where I can prove my ability to others.

Appendix G. ILB-23

The following statements describe different ways to approach learning at work. Please rate how much each statement describes how you typically approach learning at work.

Five-point Likert-type scale (1 = Not at all characteristic of me; 5 = Highly characteristic of me)

1. Set a learning goal for yourself
2. Pick new topics or skills to learn to enhance your performance
3. Plan to learn something new
4. Research how your job duties could change in the future
5. Search for new information or ideas on the internet (e.g., using a search engine)
6. Share your knowledge (content, technical process, etc.) with colleagues
7. Discuss challenges with tasks or assignments you have at work with colleagues
8. Work together with a team to complete a task
9. Network with peers at work to exchange ideas or knowledge
10. Assist colleagues with their work as a way to learn more on the job
11. Reflect on feedback you have received from colleagues
12. Reflect on feedback you have received from supervisors
13. Reflect on challenging moments you have experienced at work
14. Reflect on the performance of others at work
15. Evaluate your personal performance at work
16. Challenge existing assumptions about ideas at work
17. Take calculated risks
18. Take on challenging or stretch tasks at work
19. Come up with new ideas

20. Respond to a change at work by learning more about the change

21. Start ambiguous tasks by first finding clarifying information

22. Learn about a change that occurred at work

23. Use what you have learned to address the unanticipated consequences of decisions made at work

Appendix H. Occupational Self-Efficacy

Please rate the following statements based on how true they are of you.

Six-point Likert-type scale (1 = Not at all true; 6 = Completely true)

1. Thanks to my resourcefulness, I know how to handle unforeseen situations in my job.
2. If I am in trouble at my work, I can usually think of something to do.
3. I can remain calm when facing difficulties in my job because I can rely on my abilities.
4. When I am confronted with a problem in my job, I can usually find several solutions.
5. No matter what comes my way in my job, I’m usually able to handle it.
6. My past experiences in my job have prepared me well for my occupational future.
7. I meet the goals that I set for myself in my job.
8. I feel prepared to meet most of the demands in my job.

Appendix I. PROMIS Sleep Disturbance Scale

How many hours did you sleep last night?

Please rate the extent to which you experienced the following in the past seven days.

Five-point Likert-type scale (1 = Not at all, 5 = Very much)

1. My sleep was restless
2. I was satisfied with my sleep
3. My sleep was refreshing
4. I had difficulty falling asleep

In the past 7 days…

Five-point Likert-type scale (1 = Never, 5 = Always)

5. I had trouble staying asleep
6. I had trouble sleeping
7. I got enough sleep

In the past 7 days…

Five-point Likert-type scale (1 = Very poor, 5 = Very good)

8. My sleep quality was…

Appendix J. Job Performance

Overall Performance Rating: A rating comprised of the objectives assessment and demonstrated behaviors that reflect the organization's culture and the expectations of the function or organization.

- "A" Rating: Exceeds expectations and performs at the highest level in the criteria being rated.
- "B" Rating: Consistently meets expectations in the criteria being rated and may occasionally exceed them.
- "C" Rating: Improvement is required in the criteria in order to succeed.

Appendix K. Job Potential

- High Potential: Individual with the capability, engagement, and aspiration to rise to and succeed in positions with broader and deeper responsibilities (usually two levels of greater scope and impact on the organization, with an expectation of performance in the top 25%) Additional responsibility recommended within 12 months. Typically 10% of the organization.
- Growth Potential: Within 18 months, this individual is capable of having one or more assignments with greater scope and responsibility, such as cross functional project leadership, change initiative leadership, company-wide project leadership. Note, typically 40%-50% of associates will fall into this category
- Well Placed: The Performing Professional. An individual who has demonstrated depth and capabilities that reflect their expertise and experience. This individual may move into other positions with additional levels of responsibility, will likely follow a normal career progression for the role. Note, typically 40% - 50% of associates will fall into this category
- Not Well Placed: An individual who has skills, experience and knowledge that are valuable to the organization but who are not performing to their potential in their current role. Possible actions include reassignment of role or separation.
- Performance issue: An individual with documented performance issues. Possible actions include significant performance improvement or separation. These individuals should be on a Corrective Action Plan.
- Too New to Rate: An individual who has been with the company OR in the role for less than 3 months at time of the review

Appendix L. Dimensions of the Learning Organization Questionnaire

Please think about how your organization supports and uses learning at an individual, team, and organizational level. Please respond to each of the following items. For each item, determine the degree to which this is something that is or is not true of your organization.

Six-point Likert-type scale (1 = Almost never; 6 = Almost always)

1. In my organization, people help each other learn.
2. In my organization, people are given time to support learning.
3. In my organization, people are rewarded for learning.
4. In my organization, people give open and honest feedback to each other.
5. In my organization, whenever people state their view, they also ask what others think.
6. In my organization, people spend time building trust with each other.
7. In my organization, teams/groups have the freedom to adapt their goals as needed.
8. In my organization, teams/groups revise their thinking as a result of group discussions or information collected.
9. In my organization, teams/groups are confident that the organization will act on their recommendations.
10. My organization creates systems to measure gaps between current and expected performance.
11. My organization makes its lessons learned available to all employees.
12. My organization measures the results of the time and resources spent on training.
13. My organization recognizes people for taking initiative.
14. My organization gives people control over the resources they need to accomplish their work.

15. My organization supports employees who take calculated risks.
16. My organization encourages people to think from a global perspective.
17. My organization works together with the outside community to meet mutual needs.
18. My organization encourages people to get answers from across the organization when solving problems.
19. In my organization, leaders mentor and coach those they lead.
20. In my organization, leaders continually look for opportunities to learn.
21. In my organization, leaders ensure that the organization's actions are consistent with its values.

Appendix M. Demographics

- How old are you? (enter a number)
- Please indicate your gender:
    - Male
    - Female
    - Other
    - Prefer not to say
- What ethnicity do you most identify with?
    - White
    - Hispanic or Latino
    - Black or African American
    - Native American or American Indian
    - Asian or Pacific Islander
    - Multiracial
    - Other
- On average, how many hours do you work a week?
    - (Must put in a number between 0 – 168)
- During a busy week, how many hours do you work on average
    - (Must put in a number between 0 – 168)
- How many years have you been with your current employer?
    - Years:__ Months:__
- How many years have you been in your current job?
    - Years:__ Months:__

- How many years of education do you have?
    - Did not complete high school
    - High school degree/GED
    - Bachelor's degree
    - Master's or professional degree (e.g., MA, MBA, JD)
    - Other degree beyond a master’s or professional degree (e.g., Ph.D. or MD)
- What is your current occupation?
    - Managerial or professional specialty
    - Executive, administrative, or managerial
    - Professional specialty
    - Technical, sales, or administrative support
    - Technicians or related support
    - Sales
    - Administrative support or incl. clerical
    - Service
    - Private household
    - Protective service
    - Service, exc. protective or household
    - Farming, forestry, or fishing
    - Precision production, craft, or repair
    - Operations, fabrication or labor
    - Machine operation, assembly, or inspection
    - Transportation or material moving
    - Handling or cleaning equipment, help or labor