DISSERTATION

WITHIN AND BETWEEN PERSON EFFECTS OF LEARNING AGILITY: A LONGITUDINAL EXAMINATION OF HOW LEARNING AGILITY IMPACTS FUTURE CAREER SUCCESS

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In partial fulfillment of the requirements

For the Degree of Doctor in Philosophy

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Summer 2018

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ABSTRACT

WITHIN AND BETWEEN PERSON EFFECTS OF LEARNING AGILITY: A LONGITUDINAL EXAMINATION OF HOW LEARNING AGILITY IMPACTS FUTURE CAREER SUCCESS

The business environment is highly complex and constantly evolving. Previous research on learning agility has demonstrated support for its use in identifying high potential leaders who can adapt effectively to the evolving business environment. The purpose of this study was to provide further evidence of the construct validity of learning agility and applicability in assessing leadership potential. Learning agility was examined within a broader nomological network of related constructs—a framework developed by DeRue, Ashford, & Myers (2012). It was hypothesized that personality would predict learning agility and learning agility would predict performance and learning *over time*. The results demonstrate partial support for these hypotheses. Several personality variables (e.g., Openness to Experience) were significantly related to learning agility. Further, learning agility was found to predict performance and learning, but not the rate at which these factors changed over time.

ACKNOLWEDGEMENTS

The road to achieve a Ph.D. is paved with perseverance. Thank you to my family who encouraged me to achieve my dreams and taught me the meaning of patience and determination. To my husband, who has been proud of my every accomplishment, regardless of how small, and reassured every time I thought achieving my Ph.D. was unattainable. Finally, to my advisor and dissertation committee who stood by me for what seemed like an eternity. Thank you all for having faith in my ability and supporting me along my journey.

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INTRODUCTION

Learning agility has recently received significant attention from the scientific community due to its use and popularity in organizations for assessing, selecting, and developing high potential leaders. Organizations today are challenged by a business environment that is increasingly complex, highly matrixed, and constantly shifting due to globalization, market changes/uncertainty, virtual interactions, and advancements in technology (Dai, De Meuse, & Tang, 2013; De Meuse, Dai, & Hallenbeck, 2010; Yukl & Mahsud, 2010). It is necessary for leaders to adapt successfully to unknown environments by demonstrating agility through the use of effective leadership behavior (De Meuse et al., 2010; Hogan, Hogan, & Kaiser, 2010; Yukl & Mahsud, 2010). Therefore, critical to a leader's success is learning agility—the willingness and ability to learn from experience and intentionally apply the learning to a novel situation successfully (De Meuse et al., 2010; Lombardo & Eichinger, 2000). To remain successful in the changing business environment, organizations need to identify and retain leaders who are agile and leverage their capabilities as a competitive advantage in the marketplace (Lombardo & Eichinger, 2000).

Prior research on learning agility has demonstrated significant relationships between the construct and leader promotability, potential, and performance; further, learning agility explains variance in these outcomes beyond that explained by cognitive ability (Connolly & Viswesvaran, 2002; De Meuse et al., 2010; Spreitzer, McCall, & Mahoney, 1997). However, there has been little research on the impact that learning agility has on relevant outcomes *over time,* specifically on the direction and trajectory of learning and performance over multiple points in time (Dai et al., 2013; Hezlett & Kuncel, 2012; Trathen, 2007). Understanding the effects of learning agility over time has practical and theoretical implications. First, it will allow organizations to target development opportunities for those that are more likely to apply learning in future experiences and roles. Secondly, it will allow researchers to better understand the construct of learning agility—what it is and what it is not.

Although several research studies demonstrate the impact of learning agility on outcomes contributing to an individual's career success (i.e., performance), there remains a lack of research demonstrating a direct relationship between learning agility and learning (Hezlett & Kuncel, 2012). Being able to demonstrate that an individual's career success is a result of the relationship between learning agility and learning would provide further support for the use of learning agility. Specifically, it would provide organizations with clarity regarding individuals most likely to gain procedural knowledge and acquire new cognitive strategies when provided with learning and development opportunities on the job (Hezlett & Kuncel, 2012). Finally, there is an opportunity to continue to explore relevant individual difference variables related to learning agility. By exploring individual differences related to learning agility and outcomes of learning agility over time, the construct validity of learning agility can be assessed and understood further.

The purpose of the present study is threefold: (1) To investigate the construct validity of learning agility by examining it within a broader framework developed by DeRue, Ashford, & Myers (2012); (2) to examine the relationship of individual differences (personality dimensions of Openness to Experience and Conscientiousness) and learning agility; and (3) to measure the longitudinal relationship between learning agility and two outcome variables (performance and learning)—providing evidence that learning agility predicts both performance and learning, two key enablers of future career success.

By integrating new perspectives regarding the construct of learning agility (DeRue, Ashford, et al., 2012) with foundational research and measure of learning agility developed by Lombardo and Eichinger (2000), learning agility will be examined within a broader framework to examine the following hypothesis: personality dimensions (i.e. Openness to Experience and Conscientiousness) will predict a leader's level of learning agility, which will impact performance and learning over time (see Figure 1).

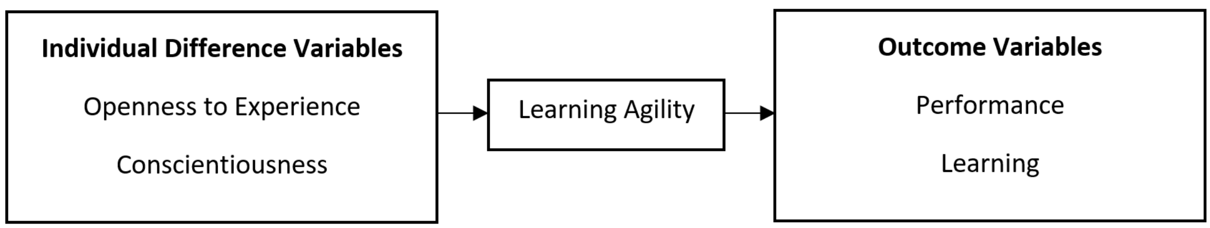

Figure 1. *Proposed Conceptual Framework*

Specifically, I believe that learning agility needs to be better understood conceptually and empirically. One way to do this is to examine it within a broader framework and draw conclusions about the connections with individual difference variables and outcome variables. DeRue, Ashford, et al. (2012) propose a broader framework, but not a measure of learning agility to test within the broader framework. In this study, an existing measure of learning agility is used to examine learning agility within DeRue et al.'s broader framework. One can assume that learning agility, despite being measured using different tests/assessments, is measuring the same foundational construct (willingness and ability to learn from experience).

I will first provide an overview of the construct of learning agility, followed by a summary of the previous research conducted on learning agility. Based on previous research and the need to gain additional insight into the construct of learning agility, a broader framework to explore learning agility and its construct validity is presented. As part of this proposed framework, both individual difference variables (personality—i.e., Openness to Experience and

Conscientiousness), and outcome variables (i.e., performance and learning) will be reviewed and relevant research discussed.

Learning Agility

The construct of learning agility was first measured in the practitioner world as a solution to a growing need by organizations to identify individuals with potential to advance. Learning agility, as a construct, was introduced to the academic community by Lombardo and Eichinger in the early 2000s. Lombardo and Eichinger (2000) defined learning agility as the "ability and willingness to learn from experience, and subsequently apply those lessons to perform successfully in new or first-time situations" (p. 323). According to Lombardo and Eichinger, individuals with high learning agility are able to learn from experience and apply the learning in novel situations, demonstrating potential for success in future roles. They argued that potential cannot be determined strictly from current performance; but rather, assessing potential requires insight on how individuals apply newly acquired skill to novel situations. It is thus the ability and motivation —cognitive and emotional elements of learning from experience — that differentiate high potential leaders (De Meuse et al., 2010; Lombardo & Eichinger, 2000; McCall & Morrison, 1988).

Although Lombardo and Eichinger (2000) were the first to formally name the construct of learning agility, many researchers contributed to its early development and advancement through the examination of similar constructs (e.g., learning from experience; Dai et al., 2013; De Meuse et al., 2010). For example, learning agility is rooted in a series of executive research studies conducted by the Center for Creative Leadership (CCL) in the 1980s that examined the impact of learning from experience on leadership success (Dai et al., 2013; De Meuse et al., 2010; Lombardo, Ruderman, & McCauley, 1988; McCall & Lombardo, 1983; McCall & Morrison, 1988).

In their research on learning from experience, CCL interviewed executives regarding the key events they believed shaped the development of their leadership capabilities. The researchers reviewed over 600 key events described in the executive interviews and coded these events into types of career experiences, e.g., turning around a business. The authors found that successful executives had more variability in their experiences than the less successful counterparts (McCall & Lombardo, 1983). CCL researchers inferred that what differentiated successful executives was the intention and persistence they exhibited in learning from each experience, demonstrating that simply experiencing something does not lead directly to learning (Dai et al., 2013).

Additional research conducted by CCL, which also contributed to the conceptualization of learning agility, involved comparing successful versus derailed executives (De Meuse et al., 2010; Hogan et al., 2010). They found that all executives examined were bright, identified as high potential early in their career, strong performers, and ambitious. However, the successful (versus derailed) executives differed on their ability to adapt and change to the environment. The derailed executives relied too heavily on a narrow set of skills and failed to learn from their mistakes (De Meuse et al., 2010; Hogan et al., 2010). Aligned with these findings, Lombardo et al. (1988) found that factors differentiating successful (versus derailed) leaders was a result of how they handled business complexity, described as "the ability to handle the intellectual demands of tough business problems. Being able to learn quickly, think strategically, and absorb technical knowledge" (Lombardo et al., 1988, p. 210). More recently, Eichinger and Lombardo (2004) found that derailment of leaders is most impacted by emotional intelligence and learning agility, concluding that success may be a result of interpersonal strengths and adaptability to change.

The importance of leaders learning from experience has been reinforced in other research. Spreitzer et al. (1997) examined competencies related to the potential of aspiring international executives and found that certain competencies (e.g., Seeks Learning Opportunities and Flexibility) related to performance, potential, and on-the-job learning. Here, competencies refer to characteristics and/or attributes in individuals that contribute to and predict future performance (Shippmann, et al., 2000). Spreitzer et al. concluded that these competencies, if assessed in leaders, can assist in the early identification of individuals who are more likely to be successful as international executives in the future.

Despite previous research demonstrating significant relationships between learning agility, constructs that share a nomological network with learning agility (i.e., learning from experience), and measures of career success, little is known about individual differences that predict learning agility. It is suggested that not all leaders would be agile in a learning environment (Beck, 2012; DeRue, Nahrgang, Hollenbeck, & Workman, 2012; Spreitzer et al., 1997). McCall (2010) concluded that learning from experience is not guaranteed and there remains an opportunity to explore individual difference variables that predict learning agility.

In summary, the willingness and ability to learn from experience, defined as learning agility, is important when determining the potential of a leader and likely subsequent career success. Previous research has concluded that learning agility is a distinct construct that predicts career success, yet it resembles, and is related to, other variables found in theories of adult learning (e.g., learning from experience, learning ability, adaptability, adaptive performance, motivation to learn, leadership agility, learning goal orientation, etc.; Colquitt & Simmering, 1998; De Meuse et al., 2010; DeRue, Ashford, et al., 2012). It is my intent in this paper to clarify the construct of learning agility as well as examine the individual differences and outcomes related to the construct. The next section introduces two perspectives of learning agility that have evolved from previous research on the construct.

Perspectives of learning agility: Previous research. Although learning agility has been widely used by practitioners for decades, the construct of learning agility is still debated within the scientific community. For example, much of one 2012 issue of the *Industrial and Organizational Psychology* journal was dedicated to a debate about the state of learning agility theory and research. There remains two perspectives regarding the construct of learning agility: Lombardo and Eichinger (2000) and DeRue, Ashford, et al. (2012). Both perspectives vary in the breadth of the construct and the extent to which empirical evidence has been gathered. Lombardo and Eichinger's measurement of learning agility has been widely used by practitioners and examined by the scientific community. DeRue, Ashford, et al. proposed a broader framework for which to examine learning agility, but in the absence of a measure of learning agility, their framework has not yet been empirically tested (De Meuse, Dai, Swisher, Eichinger, & Lombardo, 2012). A goal of this paper is to further investigate the construct of learning agility as proposed by Lombardo and Eichinger (2000) and measured using Lombardo and Eichinger's (2003) instrument of learning agility within DeRue, Ashford, et al.'s broader framework to provide further conceptual clarity and theoretical grounding of the construct. While examining learning agility, based on Lombardo and Eichinger's (2000) definition, this study will integrate elements of the DeRue, Ashford, et al. model. In the following sections both perspectives will be discussed.

Lombardo and Eichinger (2000) perspective of learning agility. For over 20 years, research has been conducted by practitioners on the construct of learning agility, which has led to the conclusions that learning agility is a defining component of leadership potential and career success (De Meuse et al., 2010). Through their research, Lombardo and Eichinger (2000) constructed a definition of learning agility comprised of four facets: Mental Agility, People Agility, Change Agility, and Results Agility. Mental Agility describes individuals who are comfortable with complexity and able to draw unique connections between items. People Agility describes individuals who are self-aware and able to interact effectively with others in difficult situations. Change Agility describes individuals who are comfortable with ambiguous and changing environments. Results Agility describes individuals who deliver results in new and unique environments (De Meuse et al., 2010). Based on this definition and through factor analysis, the authors developed an instrument for practitioners to assess the potential of leaders in organizations called the CHOICES® *Architect* (De Meuse et al., 2010; De Meuse et al., 2012; Lombardo & Eichinger, 2003). Table 1 provides detailed descriptors of Lombardo and Eichinger's four facets of learning agility as measured through the CHOICES® *Architect* assessment.

The research based on the model proposed by Lombardo and Eichinger (2000) and the development of the CHOICES® *Architect* assessment has led to important conclusions about the construct of learning agility and what it predicts. Research has demonstrated a significant relationship between learning agility and performance, potential, and promotability of individuals and managers (De Meuse et al., 2010; De Meuse, Dai, Hallenbeck, & Tang, 2008; Dries, Vantilborgh, & Pepermans, 2012; Connolly & Viswesvaran, 2002). For example, Lombardo and Eichinger examined learning agility and supervisor ratings of promotability and

Table 1

Four Facets of Learning Agility as Defined by Lombardo and Eichinger (2000)

Facet of Learning Agility	Description
Mental Agility	Comfortable with complexity. Describes people who think through problems from a fresh point of view and are comfortable with complexity, ambiguity, and explaining their thinking to others.
People Agility	Skilled communicator who can work with a diversity of people. Describes people who know themselves well, learn from experience, treat others constructively, and are cool and resilient under the pressure of change.
Change Agility	Like to experiment and comfortable with change. Describes people who are curious, have a passion for ideas, like to experiment with test cases, and engage in skill-building activities.
Results Agility	Deliver results in first time situations. Describes people who get results under tough conditions, inspire others to perform beyond normal, and exhibit the sort of presence that builds confidence in others.

Note: Adapted from: Lombardo and Eichinger (2000) and De Meuse, Dai, Hallenbeck, and Tang (2008).

performance after the promotion and found significant findings to support both relationships. Additionally, Connolly and Viswesvaran (2002) found that learning agility significantly predicted supervisory ratings of promotability and performance among law enforcement officers in the U.S. Despite promising findings, there has been criticism of the Lombardo and Eichinger conceptualization of learning agility. As a result, DeRue, Ashford, et al. (2012) proposed a broader framework of learning agility.

DeRue, Ashford, et al. (2012) perspective of learning agility. DeRue, Ashford, et al. (2012) argued that the construct of learning agility lacked definition and was poorly measured. They argued the need for learning agility to be examined within a broader nomological network of related constructs. DeRue, Ashford, et al. suggested three individual difference variables that they believe impacts learning agility: Openness to Experience, cognitive ability, and goal orientation (DeRue, Ashford, et al., 2012). Further, DeRue, Ashford, et al. hypothesized that learning agility predicts learning in and across situations, and positive performance changes over time. See Figure 2 for the DeRue, Ashford, et al. model of learning agility.

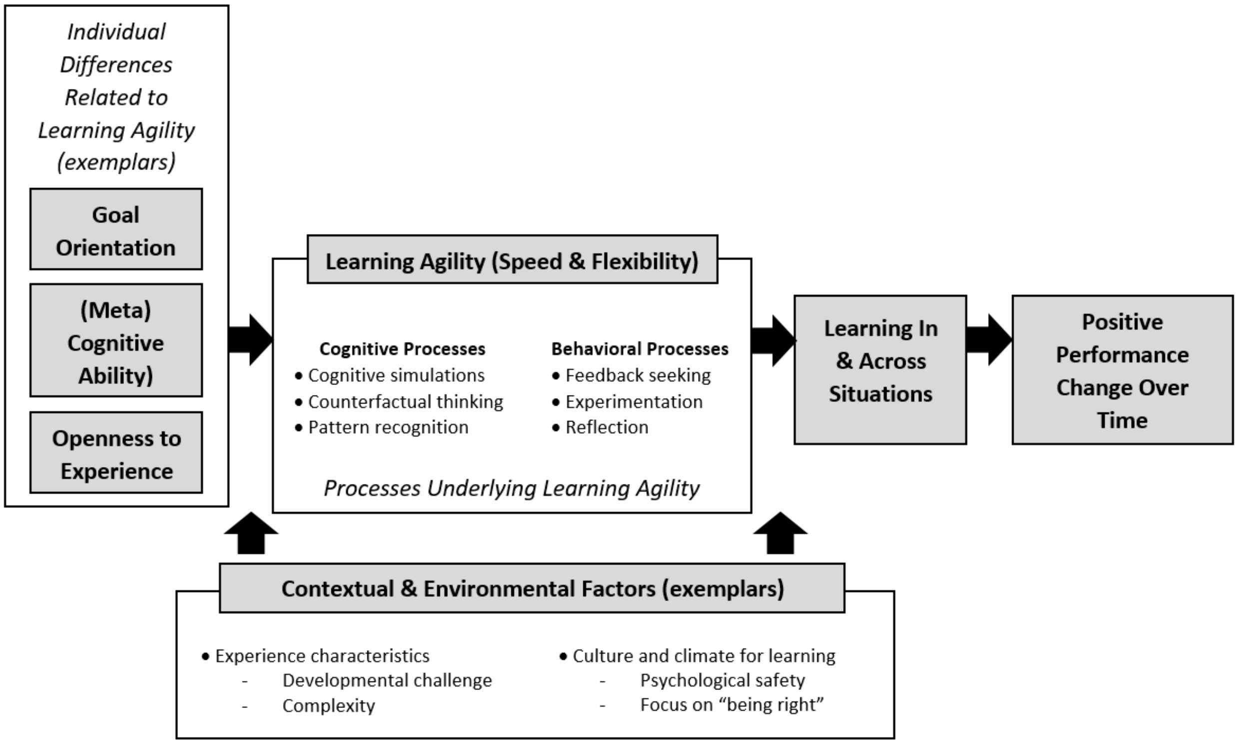

Figure 2. *DeRue, Ashford, & Myers (2012) Model of Learning Agility*

In addition to examining learning agility within a broader framework, DeRue, Ashford, et al. (2012) posited a narrower definition of learning agility focused on speed and flexibility in the experiential learning process. They defined speed as the ability to pick things up quickly, and flexibility as the ability to move among various ideas, points of view, or across situations (DeRue, Ashford, et al., 2012). As such, DeRue, Ashford, et al. concluded that learning agility should be defined and measured using cognitive (i.e., cognitive simulations, counterfactual thinking, pattern recognition) and behavioral processes (i.e., feedback seeking, experimentation, reflection) (DeRue, Ashford, et al., 2012).

Although a revised definition of learning agility was proposed by DeRue, Ashford, et al. (2012), an instrument measuring learning agility in this capacity has not yet been developed. Additionally, it has been argued that the narrower definition of learning agility proposed by DeRue, Ashford, et al. may only partially explain how individuals learn from experience (Hezlett & Kuncel, 2012). However, examining the construct within the broader framework proposed by DeRue, Ashford, et al, may provide evidence needed to form conclusions about the construct of learning agility. And although the claims illustrated by DeRue, Ashford, et al. are not shared by all academicians and practitioners, there is agreement that the construct of learning agility should be evaluated more deeply to prevent it from being a catch-all construct that loses relevance (Hezlett & Kuncel, 2012).

Although their perspective of learning agility has not been tested, a unique conceptual contribution of DeRue, Ashford, et al.'s (2012) model of learning agility is the proposition that learning agility affects outcomes *over time*. The current study will integrate the variable of time in to the proposed framework, allowing conclusions to be drawn on the long term and future implications of learning agility. The next section will provide a brief overview of the proposed framework before introducing the variables of the framework in more detail.

Overview of proposed framework. By integrating the variable of time from the DeRue, Ashford, et al. (2012) model of learning agility (long term predictions of learning agility) with the construct of learning agility as defined and measured by Lombardo and Eichinger (2000), I will examine learning agility within a broader framework that will provide further conceptual clarity around the construct and expands current understanding of the effects of learning agility over time. In doing so, the measure used to assess learning agility can be evaluated to ensure that it is measuring the construct in its entirety. For example, if performance and/or learning are truly dynamic over time, it is essential that learning agility be measured in that way.

Further, the framework proposed and tested in this study (see Figure 1) will explore the individual differences affecting learning agility—specifically focusing on the personality dimensions of Openness to Experience and Conscientiousness. DeRue, Ashford, et al. (2012) argued that examining individual difference variables is critical to the understanding of learning agility. Specifically, research on individual differences impacting learning agility can refine the construct definition by determining the boundaries of learning agility (what learning agility is and is not) (DeRue, Ashford, et al., 2012).

Additionally, there is a gap in the research on the impact of learning agility on actual learning, a critical outcome worth examining further (McCall, 2010). Therefore, the proposed framework will examine the effects of learning agility on learning and performance over time. It is evident from previous research that learning agility predicts career success such as performance, but it is not clear what these effects look like over time—are the effects of learning agility long lasting or short-lived benefits (Dai, et al., 2013)? A longitudinal study allows researchers to better understand the long-term relationship between learning agility and future career success through the examination of learning and performance over time (Dai et al., 2013; DeRue, Ashford, et al., 2012).

The next section will introduce personality as an important individual difference variable, focusing on the dimensions of Openness to Experience and Conscientiousness. Previous research on personality and learning agility will be discussed and the hypotheses imbedded in the proposed framework will be introduced.

Personality as an Individual Difference Variable

It has been theorized that learning agility is related to several individual difference variables, including personality (DeRue, Ashford, et al., 2012; LePine, Colquitt, & Erez, 2000). There has been little research on the impact that individual difference variables, specifically personality, have on learning agility, but it is possible to draw connections to other lines of research on constructs that share a nomological network with learning agility (i.e., motivation to learn, learning goal orientation, learning from experience, adaptability). The current study examines and attempts to gain clarity around the individual difference variable of personality and how it interacts with learning agility. Specifically, this paper will focus on two factors of the five-factor model (FFM) of personality—Openness to Experience and Conscientiousness.

Five-Factor Model of personality. The emergence of the FFM of personality is a result of early efforts in the 1930s to organize a taxonomy of personality (Barrick & Mount, 1991). Proceeding the original work on personality, many researchers have investigated and developed taxonomies of individual differences (e.g., Barrick & Mount, 1991; Cattell, 1948; Costa & McCrae, 1988; Digman, 1990; Fiske, 1949; Goldberg, 1993; Hogan, 1984; Hogan & Holland, 2003; John, 1990; Norman, 1963; Saucier & Goldberg, 1996; Thurstone, 1934; Tupes, 1957, Tupes & Christal, 1961). The FFM has become the most frequently used taxonomy in examining the relationship of personality and work-related outcome variables such as job performance and training proficiency (Barrick, Mount, & Judge, 2001). Although there remain reservations regarding the five-factor model regarding the number of dimensions (five, six, or seven), the definition, and characteristics of the dimensions, there is an overarching agreement that these personality dimensions are important to understanding individual differences in the workplace (Barrick & Mount, 1991; Hogan & Holland, 2003). Barrick and Mount concluded that, "the emergence of the FFM illustrates that personality consists of five relatively independent dimensions which provide a meaningful taxonomy for studying individual differences" (p. 5). These five factors, also referred to as the Big Five are: Openness to Experience, Conscientiousness, Extroversion, Agreeableness, and Neuroticism (or Emotional Stability) (Barrick & Mount, 1991, Barrick et al., 2001). In a more recent examination of previous meta-analyses, Barrick et al. (2001) concluded that the meta-analytic findings in the last 40 years have been relatively consistent, maintaining the universally agreed-upon structure of the FFM and reinforcing the importance of personality as a key individual difference variable.

Although strong causal relationships between these personality dimensions and learning agility have not been consistently found, evidence has been found in related research that has led to continued interest in examining the personality—learning agility relationship. For example, previous research has found Conscientiousness to be negatively related to adaptability, a construct that conceptually overlaps with learning agility (LePine et al., 2000). De Meuse et al. (2012) supported the continued exploration of the personality and learning agility relationship by stating, "we envision ties between the construct of learning agility and the personality literature, especially Openness to Experience and Conscientiousness" (p. 285). In the following sections, the personality dimensions of Openness to Experience and Conscientiousness will be reviewed and research on the relationship between these personality dimensions and learning agility will be discussed. Due to limited research on the relationships between these personality dimensions and learning agility, where appropriate, constructs closely related to learning agility (those sharing a nomological network with learning agility) will be discussed and research will be shared.

Openness to Experience. Openness to Experience is one of the five dimensions of the FFM and refers to the extent to which a person desires intellectual stimulation, change, and variety (Hogan & Hogan, 2007). Persons high on Openness to Experience are described as imaginative, cultured, original, and broad-minded (Barrick & Mount, 1991; Judge, Heller, & Mount, 2002; McCrae & Sutin, 2009). Individuals having high levels of Openness to Experience are likely described as curious and broad thinking, actively seeking new experiences, more comfortable navigating change, and more willing to try something new for the sake of learning (Barrick & Mount, 1991; Judge et al., 2002; LePine et al., 2000).

Unlike some other personality dimensions, Openness to Experience has not been found to consistently and/or significantly predict job performance (Barrick & Mount, 1991). Nevertheless, in their summary of 15 prior meta-analyses of personality, Barrick et al. (2001) found that Openness to Experience significantly predicted training proficiency ($\rho = .24$). This suggests that individuals who are more open to new experiences are likely more motivated to learn and therefore may benefit from training more so than their less open colleagues.

Motivation to learn is a construct conceptually related to learning agility. Motivation to learn is defined as the willingness to engage in learning and development activities with the goal of learning from the experience (Major, Turner, & Fletcher, 2006). As mentioned previously in this paper, Lombardo and Eichinger (2000) defined learning agility as the *willingness* and ability to learn from experience and *intentionally* apply the learning to a novel situation successfully. Based on the definition of learning agility, motivation to learn will likely assist with understanding the intentionality behind the application of learning. There is both theoretical (London & Smither, 1999) and empirical evidence (Major et al., 2006) that support the relationship between Openness to Experience and motivation to learn.

In their theoretical framework on self-development, London and Smither (1999) concluded that successful self-development and continuous learning are significantly impacted by employees' motivation to learn. They describe employees' motivation to learn as taking responsibility for their learning and development, seeking out performance feedback, comparing current to future skills requirements, investigating opportunities for development, establishing goals, evaluating their progress toward goals, and adjusting their goals as progress is made (London & Smither, 1999). London and Smither theorized that individual differences impact an individual's motivation to learn. Specifically, they discuss the impact personality traits likely have on motivation to learn, including Openness to Experience. They surmised that Openness to Experience may create an interest in learning, initiate learning, and lead to persistence when learning becomes challenging (London & Smither, 1999).

Major et al. (2006) examined the empirical relationship between Openness to Experience and motivation to learn and found significant support for their relationship. They examined 183 employees in a financial services company and found, using a structural equation model, that Openness to Experience predicted motivation to learn ($\beta = .23$, $p < .05$).

In addition to motivation to learn, researchers have theorized that learning goal orientation is related to learning agility (Allen, 2016; Wong, Haselhuhn, & Kray, 2012). Learning goal orientation is described as a desire for learning opportunities (Dragoni, Tesluk, Russell, & Oh, 2009). Individuals who have a high learning goal orientation are likely described as individuals who seek to build capabilities, acquire new skill sets, and master unique, complex situations (Dweck, 1986). Wong et al. (2012) suggested that individuals who have a high learning goal orientation are more likely to reflect on their experiences as well as learn from their experiences—both characteristics of individuals who demonstrate high learning agility. Connolly

(2001) suggested that high learning goal oriented individuals are similar in nature to individuals with high learning agility in that both would be expected to remain highly motivated in new, unique, and complex situations. Openness to Experience has been theoretically and empirically linked to learning goal orientation, therefore, it is expected that Openness to Experience would also be related to learning agility.

In Dweck's (1986) theory of motivation and learning, she suggested that leaders who have a high learning orientation approach development assignments as opportunities to accelerate skill growth. Dweck suggested that high learning orientation leads to individuals being more willing to take on challenging tasks, valuing opportunities for continued growth and development (i.e., feedback), and *being open and interested in learning from experience* (cited in Dragoni et al., 2009). In conclusion, it can be inferred that being open to experiences may challenge previous ways of thinking and learning from previous experiences, and lead individuals to adapt a new strategy for applying learning (DeRue, Ashford, et al., 2012).

Little research has been conducted examining the relationship of Openness to Experience and learning agility directly. In his unpublished dissertation, Connolly (2001) found small, significant correlations between Openness to Experience and two facets of learning agility, Mental Agility ($r = .21$, $p < .05$) and Results Agility ($r = .23$, $p < .05$). However, Dries and Pepermans (2008) failed to replicate Connolly's findings.

In summary, previous research on Openness to Experience has demonstrated a positive relationship with constructs sharing a nomological network with learning agility (motivation to learn and learning goal orientation) (DeRue, Ashford, et al., 2012). Although these constructs are distinct from learning agility, they are conceptually related to one another. The findings discussed in this section provide a compelling case for further research on the relationship between Openness to Experience and learning agility. Based on the limited research demonstrating a direct relationship between Openness to Experience and learning agility, I believe it is necessary to continue to explore the relationship. It can be hypothesized that an individual's ability to be open to new ideas and experiences should be related to their learning agility. In the studies mentioned in this section, the relationship between Openness to Experience and the outcome variable was positive, therefore a positive relationship between Openness to Experience and learning agility is expected.

Hypothesis 1: Openness to Experience will be positively related to learning agility.

Conscientiousness. Conscientiousness is another dimension of the FFM of personality. Conscientiousness has been defined as the degree to which a person is willing to comply with rules, policies, norms, and standards, is dependable, planful, organized, risk averse, and achievement oriented (Barrick & Mount, 1991; Barrick et al., 2001; Hogan & Hogan, 2007). Therefore, individuals who are highly conscientious are likely described as predictable, detail oriented, hardworking, preferring to follow rules, persistent in the face of challenge, and have a strong achievement orientation (Roberts, Jackson, Fayard, Edmonds, & Meints, 2009).

Unlike Openness to Experience, Conscientiousness has not been widely examined within the learning agility literature, but researchers have made assumptions regarding the relationship that may exist between Conscientiousness and learning agility. De Meuse et al. (2012) hypothesized that Conscientiousness may be negatively related to learning agility, meaning that individuals who are less conscientious are likely to have higher learning agility. Although no published articles to-date have examined the relationship between Conscientiousness and learning agility, there is preliminary evidence to support this assertion in the literature of constructs closely related to learning agility. For example, Conscientiousness has been found to be negatively related to adaptability and experience-based development (LePine et al., 2000; DeRue, Nahrgang, et al., 2012). Before reviewing the empirical evidence in support of the negative relationship between Conscientiousness and learning agility, a practical explanation for this relationship is presented.

Conscientiousness has been widely examined regarding important outcomes related to workplace success (i.e., performance, training proficiency, intrinsic and extrinsic career success) and found to be valid predictor across occupations (Barrick & Mount, 1991; Barrick et al., 2001; Judge et al., 2002). Several meta-analyses have supported these conclusions; therefore, it is generally accepted that Conscientiousness predicts success in most jobs at least moderately well, and more so than any of the other dimensions of the FFM (Barrick et al., 2001). Due to the vast amount of research on Conscientiousness and the positive relationships it has with work-related outcomes, it may seem counterintuitive to hypothesize a negative relationship with learning agility.

Costa and MacCrae (1992) described Conscientiousness with respect to two distinct yet related facets, dutifulness and achievement striving. The facet of dutifulness (or dependability) is defined as the strict adherence to rules, and being dependable, careful, thorough, responsible, reliable, and deliberate (Barrick & Mount, 1991; Major et al., 2006). Achievement striving (or volition) is defined as working hard, having high aspirations and achievement orientation, self-discipline, and a strong sense of direction and perseverance (Barrick & Mount, 1991; LePine et al., 2000; Major et al., 2006). When considering narrower facets of Conscientiousness, it is possible to gain additional insight into the mechanisms through which Conscientiousness may relate to learning agility (LePine et al., 2000). One may assume that being highly dutiful would lead to individuals being methodical about learning from experience—assisting in the application of knowledge and skill in a careful way, utilizing a well thought out strategy. Conversely, in times of high stress or in a changing environment, it is possible that dutiful behavior may lead to a focus on maintaining order and predictability, impeding the ability to learn from experience (LePine et al., 2000). Additionally, one is likely to assume that high levels of achievement striving would be important for individuals when learning a new skill. Strong achievement striving may give individuals the perseverance and goal orientation needed to be successful at applying the learning to a unique situation or environment. Conversely, it can be argued that achievement striving may negatively impact one's ability to learn from experience in that they may be more focused on performing well on the initial task and fail to allow for cognitive exploration required for applying the learning to a unique situation/environment in the future (LePine et al., 2000). It is because of these assumptions and the empirical evidence that will be shared that the current study will examine Conscientiousness and learning agility expecting a negative relationship.

In addition to the practical argument for the negative relationship between Conscientiousness and learning agility, previous research on constructs closely related to learning agility has found support for the negative relationship. LePine et al. (2000) examined the impact of Conscientiousness on adaptability. They defined adaptability as "learning or performance in a task that is either complex, novel, or just ill-defined" (p. 566). LePine et al. hypothesized that Conscientiousness would have a positive relationship with adaptability. They did not find support for their hypothesis, but rather, they found that individuals who were less conscientious demonstrated more adaptability in a changing environment. It is likely that the conscientious behavior led to a focus on getting the task right rather than learning from the experience, demonstrating a negative relationship between Conscientiousness and adaptability.

LePine et al. concluded that individuals who were highly conscientious were driven by the desire to be accurate, methodical, deliberate, and orderly, which inhibited their ability to adapt to the changing nature of the task context (LePine et al., 2000). A similar relationship can be inferred with regards to Conscientiousness and learning agility due to the conceptual overlap between adaptability and the construct of learning agility.

Finally, DeRue, Nahrgang, et al. (2012) examined the effects of self-reflection (after a developmental event) on experience-based development and found that Conscientiousness had a negative relationship with individual development. Based on these findings, the authors suggested that the activity of reflecting on experiences promotes experience-based development by creating intention or deliberation around learning events. Conscientiousness may get in the way of learning when the opportunity for reflection is not present (DeRue, Nahrgang, et al., 2012). The findings by DeRue, Nahrgang, et al. support the hypothesized negative relationship between Conscientiousness and learning agility in that an individual's achievement orientation may trump cognitive exploration required for learning from experience.

In summary, there are no known published articles to-date that examine the relationship between Conscientiousness and learning agility. However, hypotheses can be formed based on research conducted on constructs closely related to learning agility. The empirical evidence shared in this section demonstrate a negative relationship between Conscientiousness and adaptability and experience-based development. This empirical evidence as well as the practical argument for the negative relationship between Conscientiousness and learning agility supports the following hypothesis:

Hypothesis 2: Conscientiousness will be negatively related to learning agility.

Exploratory analyses. In addition to examining the relationship between Openness to Experience, Conscientiousness, and learning agility, I will also explore the relationship between several other personality variables and learning agility. Specifically, I examine personality variables that are believed to get in the way of career success, also referred to as derailers. These analyses are exploratory in that these relationships have not been examined previously and therefore the research questions included are based on practical assumptions. I believe that further investigation of individual difference variables that contribute to career success, as well as those that may inhibit career success are critical for understanding the construct of learning agility and the individual difference variables that predict it.

More recently, the personality literature has expanded to include research on the derailment characteristics of leaders (Hogan et al., 2010). That is, personality characteristics, that when an individual stops self-monitoring, are likely to get in the way of (or derail) performance (Hogan & Hogan, 2009). Early research on learning agility conducted by CCL examined learning from experience and leadership success vs. leadership derailment (Dai et al., 2013; De Meuse et al., 2010; Lombardo et al., 1988; McCall & Lombardo, 1983; McCall & Morrison, 1988). They found that it was the intention and persistence leaders exhibited in learning from each experience that led to success and not exhibiting those behavioral characteristics led to derailment. In conclusion, leadership derailment may be a result of having the 'wrong stuff' rather than lacking the 'right stuff' (Hogan et al., 2010).

Two personality derailers from the Hogan Development Survey (HDS)—Imaginative and Mischievous, have been shown to be highly correlated with the dimension of Openness to Experience (r = .33 and r = .35, respectively; Hogan & Hogan, 2009). The Imaginative scale predicts behaviors that range from being pragmatic, level-headed, and practical (low Imaginative) to overly imaginative, unpredictable, and having eccentric ideas (high Imaginative) (Hogan & Hogan, 2009). The Mischievous scale predicts behaviors that range from unassertive, predictable, and rule following (low Mischievous) to self-confident, impulsive, and risk taking (high Mischievous) (Hogan & Hogan, 2009). Based on what is known about personality and the relationship between the FFM dimensions and learning agility, the following questions will be examined:

Research Question 1: Are scores on Imaginative predictive of learning agility?

Research Question 2: Are scores on Mischievous predictive of learning agility?

Further, two personality derailers from the Hogan Development Survey (HDS)—Diligent and Dutiful, have been shown to be correlated with the dimension of Conscientiousness (r = .31 and r = .14, respectively; Hogan & Hogan, 2009). The Diligent scale predicts behaviors that range from being relaxed, willing to delegate, and tolerant (low Diligent) to overly conscientious, perfectionistic, and demanding (high Diligent) (Hogan & Hogan, 2009). The Dutiful scale predicts behaviors that range from independent, willing to challenge others and their ideas, and decisive (low Dutiful) to conforming, reluctant to take independent action, ingratiating, and deferential (high Dutiful) (Hogan & Hogan, 2009). Based on what is known about personality and the relationship between the FFM dimensions and learning agility, the following questions will be examined:

Research Question 3: Are scores on Diligent predictive of learning agility?

Research Question 4: Are scores on Dutiful predictive of learning agility?

The next section will introduce two important outcomes of learning agility, performance and learning. Previous research on performance and learning as it relates to learning agility will be discussed and the hypotheses imbedded in the proposed framework will be introduced.

Outcomes of Learning Agility

The present study will investigate the relationship between learning agility and two outcome variables: performance and learning. The outcome variables will be assessed longitudinally, allowing for the examination of effects of learning agility on performance and learning over time. Human capital theory suggests that the effort put in to developing knowledge, skills, and abilities leads to enhancement of an individual's career success (Ng & Feldman, 2010). Learning agility has been examined regarding multiple elements of career success, including: performance (Spreitzer et al., 1997), promotion (Eichinger & Lombardo, 2004), leadership effectiveness (Amagoh, 2009, as cited in Dries et al., 2012), leadership competence (Dai et al., 2013), leadership potential (Dries et al., 2012), and learning (Dweck, 1986; Hall, 1986; Hall, 1995). Researchers have concluded from empirical evidence that learning agility is an important factor when considering a leader's career success (Dragoni et al., 2009; Spreitzer et al., 1997). For example, Dries et al. (2012) found a significant relationship between learning agility and being selected as high potential, beyond that of job performance. From a theoretical perspective, Dweck's (1986) theory of motivation and learning postulates that leaders able to approach development assignments with the willingness and intention to learn will demonstrate accelerated skill growth (learning).

Although previous research has demonstrated significant relationships between learning agility and career success variables, no known research has examined and/or demonstrated significant and lasting effects of learning agility over time. Understanding the long-term effects of learning agility on career success has practical significance. To illustrate, organizations may find value in hiring individuals higher in learning agility, who are able to apply learning to new environments more quickly, leading to higher levels of performance over time.

Performance. Lombardo and Eichinger (2000) assessed the learning agility, performance, and potential of 55 managers using peer and supervisor ratings. They found evidence to support the relationship between overall learning agility and performance and potential (R^2 = .30). Several years later, Eichinger and Lombardo (2004) again examined the relationship between learning agility and performance. With a sample of 313 managers and individual contributors from multiple organizations, they found that learning agility was related to performance after promotion (r = .45). The authors concluded that learning agility is important in predicting performance.

The findings by Lombardo and Eichinger (2000) and Eichinger and Lombardo (2004) align with other theoretical and empirical conclusions of constructs related to learning agility (i.e., learning from experience) and performance. McCauley, Lombardo, and Usher (1989) examined the construct of learning from experience and claimed that learning from experience contained dimensions believed to be significantly related to performance. Additionally, Spreitzer et al. (1997) hypothesized that learning from experience would be related to performance and executive potential in international assignments. They surmised that expatriates are often confronted with novel situations and changing environments when on an international assignment. They found support for their hypothesis in that learning from experience differentiated high potentials and high performers from their average potential/performing counterparts. Spreitzer et al. concluded that learning agility should be taken in to consideration when assessing the potential and future performance of individuals going on an international assignment.

Additionally, using a sample of 83 sales managers at a global pharmaceutical company in the United States, Dai et al. (2013) examined the effects of learning agility on career success as measured by proximity to the CEO and total compensation. Dai et al. defined CEO proximity as the number of layers between the individual and the CEO. Both outcome measures were assessed at two points in time. Changes to an individual's proximity to the CEO was an indication of promotion. Dai et al. expected that those leaders high in learning agility would demonstrate career growth through proximity to the CEO (promotion) more so than their lower learning agility colleagues. Supporting their hypotheses, Dai et al. found learning agility was a predictor of CEO proximity (promotion) and total compensation, and concluded that leaders who are higher in learning agility are more likely to learn from their experiences, increase their contribution to the organization, and therefore be rewarded with promotions (as indicated by proximity to the CEO) and increased compensation. Although Dai et al. investigated between-person differences in learning agility predictions of career success, the outcome variables examined were not direct measures of performance, but rather CEO proximity and total compensation.

Although previous research demonstrates compelling evidence for the relationship between learning agility and performance, it does not take in to consideration how learning agility predicts performance over time. An internal research study conducted by Lominger (cited in De Meuse et al., 2012) is the only known study examining the impact of learning agility on career success *over time*.

De Meuse et al. (2012) shared research findings by Lominger that found that the predictive validity of learning agility increased over the course of two years and was significantly correlated with performance. In 2010, over 6,700 employees were assessed on learning agility using the CHOICES® *Architect* assessment; learning agility was then correlated with supervisor ratings of performance. The correlation between learning agility and performance, when assessed by a single-rater (direct supervisor only), was 0.33 and 0.34 when assessed by multiple raters (direct supervisor and peers). The following year, in 2011, a random sample of individuals who participated previously from each of the two rater groups (those who were measured using a single-rater and those were measured using a multi-raters) was selected and correlations examined again for learning agility (assessed in 2010) and current performance. The correlation for learning agility and performance, when assessed by a single-rater, was 0.40 and 0.49 for when assessed by multiple raters. Based on these findings, Lominger concluded that predictive validity of learning agility increases over time (De Meuse et al., 2012).

While findings from Lominger's research are interesting and provide initial insight for how learning agility may impact career success over time, the conclusion drawn is not entirely valid. The issue of statistical conclusion validity leads to questions regarding the generalizability of the findings. Lominger's findings could be attributed to the relationship between learning agility and performance increasing over time (as stated), or a result of both correlations being from the same population, resulting in the confidence intervals of the first measure of performance including the second measure of performance. Additionally, it is possible that that the correlations between learning agility and performance were the same over time, but there was more unreliability in the first assessment of performance than the second. To conclude that the predictive validity of learning agility increases over time, learning agility must be compared to the change in performance at (at least) two distinct and future points of time, which this study will do.

In summary, the framework proposed in this paper will examine performance as an outcome of learning agility. Further exploration of the relationship between learning agility and performance may support improved practices for the identification of high potential leaders. Current practices typically consider current performance only. If learning agility is found to predict performance over time, organizations can begin to use learning agility to identify high potential leaders and be confident that the leaders they are selecting will demonstrate improved performance over time.

Hypothesis 3: Learning agility will predict the trajectory (direction and rate of change) in performance over time, such that:

Hypothesis 3a: Leaders with higher learning agility will display higher levels of performance than those with lower learning agility; and

Hypothesis 3b: Leaders with higher learning agility will show a great growth rate than those with lower learning agility.

Learning. Despite its obvious connection to learning from the construct's name, learning agility has yet to be found to be consistently and significantly related to learning (Hezlett & Kuncel, 2012). Learning is defined as the process of enhancing skills, behaviors, and competence through acquisition of knowledge (Fiol & Lyles, 1985). McCall (2010) argued that learning is unique to the individual, dynamic in nature, and takes place over time. In their paper, *Prioritizing the Learning Agility Research Agenda*, Hezlett and Kuncel (2012) discussed the need to evaluate the relationship between learning agility and learning in more detail. They believe that clarification around this relationship is essential to understanding how learning agility leads to transferable learning from past experiences, which could then lead to interesting research on other topics. For example, they speculated that this knowledge may extend to and assist in the understanding of how deliberate practice influences expertise, performance, and future career success (Hezlett & Kuncel, 2012).

Support for the learning agility—learning relationship comes from early assumptions by Lombardo and Eichinger (2000) and two empirical studies by Spreitzer et al. (1997) and Trathen (2007). Based on early assumptions in the learning agility literature, leaders learn new skills and capabilities as a result of their experiences (McCauley, Ruderman, Ohlott, & Morrow, 1994). Today's working environment is dynamic and constantly changing, thus requiring individuals to learn from experience in one environment, then apply the newly acquired capability in a new environment. In their original work, Lombardo and Eichinger argued that change creates the need for learning, and leaders who fail to learn new ways of operating will fail in the future. They also claimed that those high in learning agility are inherently driven to learn (Lombardo & Eichinger, 2000). Spreitzer et al. agreed with the theoretical claims made by Lombardo and Eichinger and believed that the demand created by change and transition requires significant learning and that learning agility may play an important role in understanding the patterns in which individuals learn.

Spreitzer et al. (1997) assessed the relationship between the ability to learn from experience and on-the-job learning using a sample of approximately 1,100 managers from six organizations, representing 21 different countries. Spreitzer et al. measured the ability to learn from experience using a newly developed and validated tool they created for the use in their study, *Prospector*. *Prospector* measures the ability to learn from experience using 14 dimensions, including: sensitive to cultural differences, is culturally adventurous, has courage to take a stand, brings out the best in people, has integrity, is insightful, is committed to success, takes risks, uses feedback, broad business knowledge, seeks opportunities to learn, is open to criticism, seeks feedback, and is flexible. On-the-job learning was measured through supervisor ratings of job content learning and behavioral skill learning. The authors found that several dimensions of ability to learn from experience were correlated with on-the-job learning: Seeks opportunities to learn, is open to criticism, seeks feedback, is flexible (r = .58, .34 .36, .42, respectively). Additionally, the same dimensions were found to be highly correlated with behavioral skill learning: seeks opportunities to learn, is open to criticism, seeks feedback, is flexible (r = .54, .41 .50, .47, respectively). These four dimensions have previously been discussed in the learning agility literature and are considered important elements when defining and measuring the construct of learning agility. The findings by Spreitzer et al. provide empirical evidence regarding the relationship between important dimensions of learning agility and learning, but still more evidence is required to understand how learning agility effects learning over time.

Trathen (2007) examined the relationship between learning agility and learning of 47 Microsoft senior executives participating in an executive coaching program. Learning agility was measured using Lominger's assessment of learning agility (CHOICES® *Architect*) and learning was measured using gain scores on Microsoft's leadership competencies between a baseline measure of learning and after 18 months of executive coaching. Trathen found moderate correlations between learning agility and learning. The author concluded that these findings provide evidence to support the use of a measure of learning agility in the selection of executives in to a coaching program. Further, he surmised that learning agility may assist an organization in selecting those executives that would get maximum return on investment in a development experience (e.g., coaching) because executives with high learning agility are better equipped to learn from their development experiences.

The limited empirical evidence demonstrating the relationship between learning agility and learning demonstrates a need for further research. Although the empirical findings discussed in this section provide a foundation to build on, more evidence is required regarding the relationship between learning agility and learning over time. Specifically, there are questions regarding the generalizability of the findings of both studies. Spreitzer et al. (1997) measured the ability to learn from experience using their newly developed and validated measure, which likely differs from the definition of learning agility as defined in this paper. Finally, Trathen (2007) examined the relationship of learning agility and learning using between-person correlation analysis across two points in time (baseline and future learning) with a small sample of executives, whereas the current study will examine this relationship at both the between-person and within-person level of analysis over 3 points in time.

In summary, the framework proposed in this paper will examine learning as an outcome of learning agility. Exploring the learning agility—learning relationship further may lead to better understanding of how the long-term transfer and utilization of knowledge may impact future career success. This study will explore a framework of learning agility that takes into consideration learning over time, to assess enduring effects on learning.

Hypothesis 4: Learning agility will predict the trajectory (direction and rate of change) in learning over time, such that:

Hypothesis 4a: Leaders with higher learning agility will display higher levels of learning than those with lower learning agility; and

Hypothesis 4b: Leaders with higher learning agility will show a greater growth rate than those with lower learning agility.

The present study attempts to extend previous research on learning agility to gain construct clarity, demonstrate the relationship between personality and learning agility, and assess the impact of learning agility over time to determine future career success (performance and learning). The following sections will provide an overview of the methods, measures, and procedures used in this study to measure the proposed model of learning agility.

METHOD

Participants

Participants were employees at a large consulting, design, design-build, operations, and program management firm headquartered in Denver, Colorado with presence in more than 116 countries globally. A total of 78 employees served as participants in this research project. All participants were nominated by the business to take part in a 12-month leadership development program. Participants varied in age (M = 41.9, SD = 6.4) and organizational tenure (M = 8.5, SD = 5.2); most participants were male (71.4% Male, 22.1% Female, 6.5% unidentified).

Measures

Coefficient alpha reliabilities reported in this section have been extracted from the associated measures' manual.

Personality. Personality was measured using the Hogan Personality Inventory (HPI) (Hogan & Hogan, 2007). This 206-item assessment is designed to measure normal personality—qualities that describe how individuals relate to others when they are at their best. Hogan's seven primary scales of personality align to the Big Five personality dimensions as follows: Inquisitive (Openness to Experience); Learning Approach (Openness to Experience); Prudence (Conscientiousness); Sociability (Extraversion); Ambition (Extraversion); Interpersonal Sensitivity (Agreeableness); and Adjustment (Emotional Stability). For the purposes of examining Hypotheses 1 and 2, only three of the seven HPI scales were included in this study: Prudence (α = 0.71) – sample item: "I rarely do things on impulse"; Inquisitive (α = 0.80) – sample item: "I have taken things apart just to see how they work"; and Learning Approach (α = 0.78) – sample item: "As a child, school was easy for me". The HPI scales were measured using

True/False response options. The HPI scale of Prudence was used to measure Conscientiousness and the HPI scales of Inquisitive and Learning Approach were used to measure Openness to Experience.

During the development of the HPI, Hogan and Hogan (2007) discovered that the FFM dimension of Openness to Experience had two distinct, yet highly related components. One component concerns an interest in ideas and the arts and the other concerns interest in the acquisition of knowledge. When compared to other measures of normal personality (Personal Characteristics Inventory (PCI; Mount & Barrick, 2001) and Inventario de Personalidad de Cinco Factores (Salgando & Moscoso, 1999), there is empirical evidence for the relationship between Openness to Experience and the two HPI scales that make it up, Inquisitive (r = .53) and Learning Approach (r = .30; Hogan & Hogan, 2007). Based on theory and empirical evidence, a composite score was created to examine Openness to Experience, comprised of the Hogan scales of Inquisitive and Learning Approach.

The assessment of validity for the HPI has focused on construct validity of the primary HPI scales, correlations with other validated assessments, and correlations with measures of organizational performance. It was concluded, through the assessment of validity, that the HPI is a valid measure of personality and a key predictor of workplace outcomes (Hogan & Hogan, 2007).

In this study, exploratory analyses were conducted using dimensions of the Hogan Development Survey (HDS). The HDS is designed to measure personality characteristics that when an individual is not self-monitoring, likely will get in the way of successful performance—or in other words, likely derail a leader (Hogan & Hogan, 2009). For the purposes of examining Hypotheses 3a, 3b, 3c, 3d only four of the 11 HDS scales were included in this study:

Imaginative (α = 0.61) – sample item: "I am creative about my appearance"; Mischievous (α = 0.59) – sample item: "I have few regrets"; Diligent (α = 0.56) – sample item: "I take pride in organizing my work"; and Dutiful (α = 0.46) – sample item: "I leave the big decisions up to others" (Hogan & Hogan, 2009). The HDS scales were measured using True/False response options across 168 items.

The assessment of validity for the HDS has focused on construct validity of the primary HDS scales, scale correlations with other scales from validated assessments, and correlations with measures of organizational performance. The validity of the HDS scales was assessed by examining the relationship with scales from other validated measures. The results of the scale to scale correlations demonstrate validity for the 11 primary HDS scales. For example, when compared to measures of normal personality, the HDS scale of Mischievous was found to be highly correlated with the NEO PR-I scale of Excitement Seeking (r = 0.35) and the 16PF scale of Dominance (r = 0.36) (Hogan & Hogan, 2009). These findings are consistent with Hogan's definition of Mischievous in that they describe an individual who is likely impulsive and easily bored, socially assertive, and self-confident (Hogan & Hogan, 2009). Therefore, these correlations were anticipated based on the conceptual overlap between the HDS scales of Mischievous and the similar scales on other measures of normal personality.

Lastly, the primary scales on the HDS were examined with respect to criterion measures of organizational behavior as measured by competencies across a four-competency domain model—i.e., Intrapersonal Skills, Interpersonal Skills, Business, and Leadership. Through meta-analysis, 26 independent samples were reviewed and estimated true validities assessed. The findings align with the construct validity analyses and provide evidence for the predictive validity of the HDS primary scales on organizational outcomes (Hogan & Hogan, 2009).

Learning Agility. Learning agility was measured using Korn/Ferry International's viaEDGE™ assessment. The viaEDGE™ assessment is based on Lombardo and Eichinger's (2000) model of learning agility, adapted from the CHOICES® *Architect* assessment. viaEDGE™ is a self-assessment of learning agility is designed to measure an individual's work preferences and values, personality characteristics, life experiences, and work-related behaviors to assess and understand an individual's learning agility (De Meuse et al., 2011). The viaEDGE™ assessment provides scores on the four facets of learning agility: Mental Agility (α = 0.74), People Agility (α = 0.76), Change Agility (α = 0.77), and Results Agility (α = 0.78). In addition to the four facets of learning agility, the viaEDGE™ assessment also measures Self-Awareness (α = 0.74) another indicator of executive success.

Each of the four facets of learning agility (i.e., Mental Agility, People Agility, Change Agility, and Results Agility) were measured with eight items on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Sample items from each facet follow, respectively: "At work, I am quick to understand complex concepts;" "I always look for opportunities to work with others;" "I am always searching for better ways to do things;" and "People can count on me when things getting tough" (De Meuse et al., 2011). Additionally, Self-Awareness was also measured with eight items using the same five-point Likert scale. A sample item from the Self-Awareness facet is: "I constantly try to examine myself objectively" (De Meuse et al., 2011). In addition to the four facets of learning agility and the measure of self-awareness, an overall measure of learning agility was provided. For the analyses presented in this paper, overall learning agility was used.

In prior research, construct validity of the viaEDGE™ assessment was examined by comparing it with the scores from two other instruments measuring learning agility (*Learning* *from Experience (LFE)* interviews and CHOICES® *Architect*) and an instrument measuring a separate psychological construct (*Decision Styles*) (De Meuse et al., 2011). Correlations resulting from the comparison of learning agility with two other instruments measuring learning agility were mostly significant, supporting the construct validity of the assessment (ranging from 0.41 to .53, for *LFE* and 0.23 to 0.61 for CHOICES® *Architect*). Finally, little overlap was found between viaEDGE™ assessment and *Decision Styles*—the two measures together account for less than 3% of the shared variance (De Meuse et al., 2011). Both the convergent and discriminant validity evidence indicate strong construct validity for the viaEDGE™ assessment of learning agility.

Learning. Learning was measured using both self and supervisor ratings of competency proficiency and assessed by examining the changes in competency proficiency over time (Voorhees, 2001). Competency proficiency, measured throughout the development program, provided insight in to one's baseline capabilities (perceived or observed) as well as how the capabilities developed over the course of the development program (learning). Self-ratings of learning were measured three times and supervisor ratings were measured two times throughout the course of the 12-month program.

Responses for the firm's 26 leadership and management competencies were measured using a 5-point Likert scale (1 = Need, 2 = Underdeveloped, 3 = Skilled, 4 = Talented, and 5 = Towering Strength). The leadership and management competencies were developed and implemented within the participating organization in 2011 and integrated into the leadership development strategy and development program curriculum. Of the 26 leadership and management competencies measured, 13 were particularly important given their alignment to the curriculum of the development program. See Table 2 for a list of these 13 leadership and management competencies and their broader competency domains.

Table 2

Leadership and Management Competencies

Competency Domain	Competency
Strategic Skills	Strategic Agility
Strategic Skills	Dealing with Ambiguity
Strategic Skills	Decision Quality
Personal & Interpersonal Skills	Motivating Others
Personal & Interpersonal Skills	Composure
Personal & Interpersonal Skills	Interpersonal Savvy
Personal & Interpersonal Skills	Listening
Personal & Interpersonal Skills	Aligning Around Vision and Purpose
Operating Skills	Priority Setting
Operating Skills	Timely Decision Making
Operating Skills	Developing Direct Reports and Others
Courage	Conflict Resolution
Courage	Managerial Courage

Note: Adapted from Career Architect by Lominger (Lombardo & Eichinger, 2007)

Each participant of the program was assigned two required classroom-based training courses. The course objectives aligned to the 13 leadership and management competencies. To assess learning over time, a composite score was created for everyone based on their responses to the 13 leadership and management competencies. To justify the use of a composite score for measuring learning, a confirmatory factor analysis (CFA) was conducted. Based on the leadership and management competencies a one factor model and a four-factor model (based on the competency domains) were examined and compared. Results of the CFA are provided in the Results section. In summary, the CFA results demonstrated that there was no significant difference between the one and four factor models of learning. Based on these findings, a one factor model of learning was used in the analyses in the form of a composite score.

Since the courses focused development on competencies, it is assumed, in the current study, that conclusions regarding learning can be made from the competency proficiency ratings. Thus, positive changes in proficiency ratings can be construed to mean learning has occurred (Voohees, 2001).

There are implications for using a composite score to assess learning. Although it allows for a simpler examination of learning that can then be assessed over time, it may mask the unique effects at the competency level—meaning, there may be certain competencies that are contributing more to the main effects (Rotundo & Sackett, 2002). For the purposes of this study, a composite score will be used to provide meaningful data from which to draw conclusions regarding learning trajectories, despite the potential implications.

Finally, learning was examined using growth trajectories and determined by any pattern or trend that constitutes a significant increase over time.

Performance. Performance was measured using the supervisor-rated performance evaluation provided by the participating organization. Ratings on four work behaviors (i.e., Commitment to Health, Safety, Security and Environment, Commitment to Quality, Interpersonal Skills, and Integrity & Ethics), four foundational competencies (i.e., Business Acumen, Client Focus, Drive for Results, and Self-Development) and one overall performance rating were gathered. Responses on the work behaviors and foundational competencies were captured on a three-point Likert scale (1 = Underperforming, 2= Performing, and 3 = Outperforming). Responses for the overall performance rating were captured on a four-point Likert scale (1 = Underperforming, 2 = Performing, 3 = Performing Plus, and 4 = Outperforming). Items on the performance evaluation were created to rate employees on an annual basis against strategic performance priorities of the organization and the goals of the individual employee. Hence, the annual performance evaluation measures performance as defined by the organization and therefore demonstrates evidence of content validity. Only the overall performance rating was used in the analysis of this research project, as the overall performance rating was intended to represent general performance, taking in to consideration the work behaviors and foundational competencies.

Finally, performance will be examined using growth trajectories and determined by any pattern or trend that constitutes an increase over time—e.g., incremental growth.

Procedure

A representative from the participating organization sent an email to all employees in the 12-month development program to inform them of the opportunity to participate in the research project. A cover letter explaining the purpose of the research project was sent and consent was received when the participant replied to the email stating their intentions to participate. Their immediate supervisors were informed of the research project and their employee's decision to participate and they were also given an opportunity to consent to participate. Data were collected through a series of web-based surveys over the course of the program. Data were collected from the employees and their supervisors at various points in time from January through December 2013 (see Figure 3).

To protect the confidentiality of the participants, each participant was assigned an identification number and all survey responses were linked to this identification number. The linked list of identification numbers and names was destroyed after all survey data was received and entered. Of the 152 employees participating in the accelerated development program, 86 consented to participate in the research project, giving permission to access employment and performance metrics from Human Resource records. Of those participants that consented to participate in the research project, 78 actively participated by completing the web-based surveys. Finally, performance evaluations were obtained through Human Resource records for employees for 2012, 2013, and 2014.

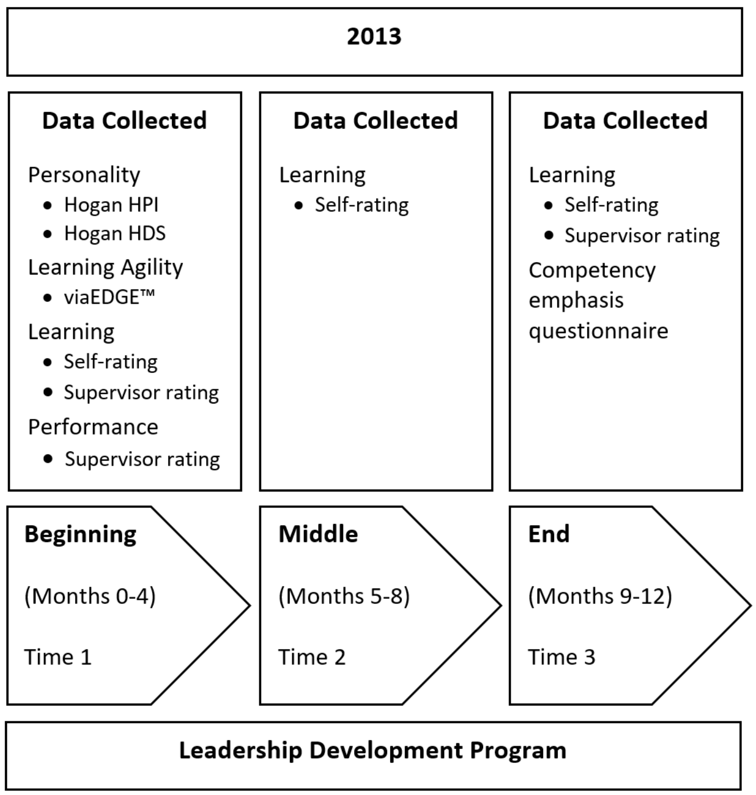

Figure 3. *Data Collection Timeline*

RESULTS

Descriptive Statistics

Means, standard deviations, and correlations among observed variables are summarized in Tables 3 and 4. The means for overall learning agility, the facets of learning agility, and the personality variables are based on percentile scores.

Table 3

Means, Standard Deviations, and Intercorrelations for Overall Learning Agility and the Facets of Learning Agility

Variable	*M*	*SD*	1	2	3	4	5
Overall Learning Agility	43.36	25.53	--				
Mental Agility	62.04	21.10	.63**	--			
People Agility	62.00	25.96	.49**	.07	--		
Change Agility	51.69	26.79	.58**	.46**	.02	--	
Results Agility	59.60	28.67	.62**	.31**	.05	.30**	--

*$p < .05$. ** $p < .01$.

The correlations among observed variables show many significant correlations with variables of personality and learning agility, demonstrating preliminary evidence of convergent validity. Additionally, the facets of learning agility all significantly positively correlated with overall learning agility and learning agility was significantly positively correlated with learning, but not performance.

Pairwise deletion was used when conducting analyses for Hypotheses 1 & 2, and for Research Questions 1, 2, 3, and 4 when all data were not available for a participant. A series of

Table 4

Means, Standard Deviations, and Intercorrelations for Learning Agility, Personality Variables, Performance, and Learning

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9
Overall Learning Agility	43.36	25.53	--								
Openness to Experience	62.04	21.10	.28*	--							
Conscientiousness	62.00	25.96	-.16	.03	--						
Imaginative	51.69	26.79	.37**	.22	-.47**	--					
Mischievous	59.60	28.67	.42**	.32**	-.51**	.51**	--				
Diligent	51.40	32.85	.01	.14	.11	-.02	-.12	--			
Dutiful	45.38	29.29	-.24*	.15	.23	-.35**	-.16	.08	--		
Performance (Time 3)	3.22	.72	.24	.00	.06	-.15	.13	.02	.07	--	
Learning (Time 3)	3.49	.55	.41**	.21	.10	.18	.29*	.03	-.21	.20	--

*$p < .05$. ** $p < .01$

independent samples *t* tests were conducted to determine the effect of missing data on the primary variables in this study. The first *t* test evaluated whether mean difference existed between cases with missing data and cases with no missing data on personality variables (i.e., Openness to Experience and Conscientiousness) and learning agility. The mean on learning agility for cases with missing data (M = 29.50, SD = 21.49) was not significantly different from the mean on learning agility for cases with no missing data (M = 44.14, SD = 24.59), t (73) = 1.16, p = .25. A second *t* test evaluated whether mean differences existed between cases with missing data and cases with no missing data on the three performance measures and learning agility. The mean on learning agility for cases with missing data (M = 42.55, SD = 24.53) was not significantly different from the mean on learning agility for cases with no missing data (M = 43.50, SD = 24.72), t (73) = .12, p = .91. A third *t* test evaluated whether mean differences existed between cases with missing data and cases with no missing data on the three learning measures and learning agility. The mean on learning agility for cases with missing data (M = 42.95, SD = 26.18) was not significantly different from the mean on learning agility for cases with no missing data (M = 43.53, SD = 24.07), t (73) = .09, p = .93. These results indicated that there were no mean differences in learning agility for cases with missing data and cases with no missing data across the primary variables.

Test of Hypotheses

Hypotheses 1 and 2. A multiple regression analysis was conducted to evaluate how well the personality variables of Openness to Experience and Conscientiousness together predicted learning agility. The linear combination of the two personality variables was significantly related to learning agility F (2, 68) = 4.03, p < .05. The sample multiple correlation coefficient was .33

(adjusted R = .08), indicating that approximately 11% of the variance of learning agility in the sample can be accounted for by the linear combination of the two personality variables.

Hypothesis 1 predicted a linear relationship between Openness to Experience and learning agility, while Hypothesis 2 predicted a relationship between Conscientiousness and learning agility. In Table 5, indices to indicate the relative strength of the individual predictors are presented.

Table 5

Regression Analysis Summary for Personality Predicting Learning Agility

Variable	*B*	*SE B*	β	*t*	*p*
Overall Learning Agility					
Openness to Experience	.32	.13	.28	2.47	.02
Conscientiousness	-.16	.11	-.17	-1.48	.15

Note. R^2 = .11 (N = 71, $p < .05$)

As shown in the table, Openness to Experience is a significant predictor of learning agility (β = .28, $p < .05$). This is consistent with the zero-order correlation between Openness to Experience and learning agility (r = .28, $p < .05$). The results provide support for Hypothesis 1, Openness to Experience predicts learning agility, demonstrating that leaders who are more open to experience will have higher learning agility.

Conscientiousness was not found to be a significant predictor of learning agility (β = -.17, $p > .05$). This is consistent with the zero-order correlation between Conscientiousness and learning agility, which was also negative and non-significant (r = -.16, p >.18). The results did not provide support for Hypothesis 2, Conscientiousness does not predict learning agility. Although the results were not significant for the relationship between Conscientiousness and learning agility, the results demonstrate the expected directionality.

Research Questions 1, 2, 3, and 4. A multiple regression analysis was conducted to evaluate how well personality variables predicted learning agility together. The personality variables were Imaginative, Mischievous, Diligent, and Dutiful. The linear combination of the four personality variables was significantly related to learning agility F (4, 67) = 4.87, $p < .01$. The sample multiple correlation coefficient was .48 (adjusted R = .18), indicating that approximately 23% of the variance of learning agility in the sample can be accounted for by the linear combination of the four personality variables.

The research questions examined the linear relationship between learning agility and Imaginative (Research Question 1), Mischievous (Research Question 2), Diligent (Research Question 3), and Dutiful (Research Question 4). Table 4 presents correlations of learning agility with each personality variable, while Table 6 presents indices to indicate the relative strength of each predictor.

As shown in Table 4, learning agility was significantly related to Imaginative (r = .37, p < 05), Mischievous (r = .34, $p < .05$), and Dutiful (r = -.24, $p < .05$), but not Diligent (r = .01, $p > .05$). Thus, the zero-order correlations provide affirmative responses to Research Questions 1, 2, and 3, but not 4. Because personality variables are intercorrelated, it is instructive to also look at the predictive relationship of each with learning agility with other variables in the equation. These findings demonstrate that leaders who are more creative, eccentric, and sometimes impractical in their ideas (Imaginative); impulsive, limit testing, and nonconforming (Mischievous); willing to take independent action and not needing/seeking the approval of others (low Dutiful) will have higher learning agility.

As shown in the Table 6, only Mischievous was found to be a significant predictor of learning agility (β = .32, $p < .05$) when other personality variables are taken into account.

Table 6

Regression Analysis Summary for HDS Personality Variables Predicting Learning Agility

Variable	*B*	*SE B*	β	*t*	*p*
Overall Learning Agility					
Imaginative	.14	.12	.16	1.18	.24
Mischievous	.28	.11	.32	2.56	.01
Diligent	.05	.08	.06	0.55	.58
Dutiful	-.12	.10	-.14	-1.24	.22

Note. R^2 = .23 (N = 72, p < .01)

Hypotheses 3 and 4. Before analyzing Hypotheses 3 and 4, several analyses were conducted to examine the outcome variables of performance and learning. A one-way within-subjects ANOVA was conducted to examine whether scores measuring performance were significantly different across three points in time. The means and standard deviations for performance are presented in Table 7.

Table 7

Means, Standard Deviations, and Intercorrelations for Performance Measured Over Time

Variable	*M*	*SD*	1	2	3
Performance Time 1	3.31	.76	--		
Performance Time 2	3.25	.74	.34**	--	
Performance Time 3	3.22	.72	.14	.50**	--

*p < .05. ** p < .01.

The results of the ANOVA indicated a non-significant time effect for performance, Wilks's Λ = .99, $F(2, 62)$ = .23, p = .80. Although not significant, the analyses indicate a decrease in mean performance across the three points in time, which is opposite of what was expected of individuals identified as high potential and participating in an accelerated development program.

A second one-way within-subjects ANOVA was conducted to examine whether scores measuring learning were significantly different across three points in time. The means and standard deviations for learning are presented in Table 8.

Table 8

Means, Standard Deviations, and Intercorrelations for Learning as Measured by Self and Supervisor Ratings Over Time

Variable	*M*	*SD*	1	2	3	4	5
Learning (Self) Time 1	3.40	.49	--				
Learning (Self) Time 2	3.47	.56	.64**	--			
Learning (Self) Time 3	3.49	.55	.70**	.86**	--		
Learning (Supervisor) Time 1	3.43	.42	-.04	.11	.14	--	
Learning (Supervisor) Time 3	3.46	.50	.22	.02	.13	.77**	--

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

The results of the ANOVA indicated a significant time effect for learning, Wilks's Λ = .88, $F(2, 51) = 3.41$, p = < .05, multivariate $\eta^2 = .12$. Follow-up polynomial contrasts indicated a significant linear effect with means increasing over time, $F(1, 52) = 5.72$, $p < .05$, partial η^2 = .10. These results suggest that individuals reported greater learning over the course of the leadership development program.

Learning was measured using both self-ratings (measured at three points in time) and supervisor ratings (measured at two points in time—at the beginning and end of the leadership development program). A paired-samples *t* test was conducted to evaluate whether mean difference existed between self-ratings and supervisor ratings of learning at Time 1 (beginning of the program). The results indicated that the mean for self-ratings (*M* = 3.37, *SD* = .45) was not significantly different from the mean for supervisor ratings of learning (*M* = 3.43, *SD* = .42), t (47) = -.73, p = .47. A second paired-samples *t* test was conducted to evaluate whether mean difference exist between self-ratings and supervisor ratings of learning at Time 3 (end of the program). The results indicated that the mean for self-ratings (*M* = 3.41, *SD* = .54) was not significantly different from the mean for supervisor ratings (*M* = 3.47, *SD* = .53), t (27) = -.43, p = .67. Based on these findings, self-ratings of learning were used to examine learning over time.

Recall that learning was measured based on ratings of competency proficiency and assessed by examining the changes in competency proficiency over time. To assess learning over time, a composite score was created for everyone based on their responses to the 13 (of the 26) leadership and management competencies in the organization at Time 1 (α = .88), Time 2 (α = .91), and Time 3 (α = .92). Since the courses within the leadership development program focused on the development of competencies, it is assumed, in the current study, that conclusions regarding learning can be made from the competency proficiency ratings. I examined the difference between the set of 13 competencies that were developed through the courses offered as part of the leadership development program and those that were part of the organization's leadership and management competency framework, but not developed through the courses throughout the program. This was done to ensure that the ratings of learning actually differed from the competencies emphasized in the program with those not emphasized in the program (Haccoun & Hamtiaux, 1994). A paired-samples *t* test was conducted to evaluate whether mean difference exist between the competencies developed through the courses offered as part of the leadership development program and the competencies not developed through the leadership development program. The results indicated that the mean for the competencies developed through the program (*M* = 3.18, *SD* = .41) was significantly greater than the mean for the competencies not developed through the program (*M* = 2.99, *SD* = .45), t (55) = -5.48, $p < .01$.

As discussed previously, to examine the appropriateness of a one factor model of learning, a confirmatory factor analysis (CFA) was conducted using R, Lavaan package. Specifically, I compared the fit of a one factor (or a global model of leadership and management competencies) to a four-factor model based on the competency domains aligned to the leadership and management competencies as identified in the Career Architect by Lominger (see Table 2; Lombardo & Eichinger, 2007). A four-factor model was found to fit the data adequately, χ^2 = 92.07, CFI = .899, TLI = .866, RMSEA = .086, SRMR = .074. Additionally, a one factor model fit the data adequately, χ^2 = 98.90, CFI = .896, TLI = .875, RMSEA = .083, SRMR = .073. Because both models adequately fit the data, modification indices were not considered. Most importantly, the four-factor model did not fit the data significantly more than the one factor model (χ^2_{Dif} = 6.83, df_{Dif} = 6, p = .34). Therefore, the more parsimonious one factor model was used to assess learning. Means and standard deviations for all observed variables are provided in Table 9.

To investigate changes in performance (Hypothesis 3) and learning (Hypothesis 4) over time, a latent growth curve model was tested using R, Lavaan package (Byrne, 2006; Ullman, 2007). The latent variable labeled intercept in the models reflects the initial score on performance or learning (at Time 1) and the latent variable labeled slope reflects the rate of linear change in the outcome across the three points of time (e.g., the rate of change in performance or learning). Using latent growth curve modeling, the association between intercept and slope as well as the individual variability in intercept and slope can be examined.

Table 9

Means and Standard Deviations for Leadership and Management Competencies Over Time

Leadership & Management Competency	Time 1		Time 2		Time 3	
	M	*SD*	*M*	*SD*	*M*	*SD*
Strategic Agility	3.45	.68	3.24	.81	3.37	.63
Dealing with Ambiguity	3.51	.82	3.58	.80	3.48	.70
Decision Quality	3.69	.57	3.56	.65	3.59	.52
Motivating Others	3.39	.65	3.62	.51	3.45	.52
Composure	3.65	.79	3.61	.79	3.50	.71
Interpersonal Savvy	3.72	.81	3.74	.76	3.71	.63
Listening	3.65	.70	3.48	.75	3.61	.66
Aligning Around Vision and Purpose	3.38	.74	3.25	.72	3.28	.60
Priority Setting	3.57	.69	3.47	.71	3.43	.58
Timely Decision Making	3.63	.65	3.55	.73	3.51	.60
Developing Direct Reports and Others	3.24	.51	3.26	.67	3.32	.58
Conflict Resolution	3.35	.70	3.36	.75	3.27	.61
Managerial Courage	3.54	.85	3.52	.75	3.50	.65

To assess the model fit, two standard fit indices were used. The first fit index is the comparative fit index (CFI), which compares the baseline with the tested model where all variances are free parameters and covariances are zero (Bentler & Bonett, 1980). Fit levels above .90 as indicated by the CFI value are considered an acceptable fit (Hu & Bentler, 1995). The second fit index, root mean square error of approximation (RMSEA), was also used and serves as an absolute fit index measuring discrepancy per degrees of freedom (Steiger, 1990). RMSEA levels below .10 are considered an acceptable fit.

Because latent growth curve modeling requires complete longitudinal data, data were analyzed only for those participants who had outcomes measures at all three points in time. Fourteen participants were excluded from the analysis for Hypothesis 3, due to missing (non-complete) performance data, resulting in N = 64. The results of Hypothesis 3 indicated that the linear model fit the data fairly well, χ^2 (df = 64, 2) = 3.57, p = .17, CFI = .95, RMSEA = .11. The average baseline score on performance was 2.88 and performance, on average, improved by .02 each year, but this increase was not significant. Learning agility was found to significantly predict the intercept of performance (β_0 = .01, p < .01), but not the slope of performance (β_1 = -0.00, p = .55).

Based on the analyses, partial support was found for Hypothesis 3. Results indicate that leaders with higher learning agility do in fact display higher levels of performance than those with lower learning agility (3a), but do not necessarily show greater growth rates in performance over time (3b).

To test Hypothesis 4, twenty-five participants were excluded from the analysis due to missing (non-complete) learning data, resulting in a N = 53. The results of Hypothesis 4 indicated that the linear model fit the data well, χ^2 (df = 53, 2) = .84, p = .66, CFI = 1.0, RMSEA = 0.0. The average baseline score on learning was 3.01 and learning, on average, improved by .03 each year, but this increase was not significant. Learning agility was found to significantly predict the intercept of learning (β_0 = .01, p < .01), but not the slope of learning (β_1 = .00, p = .45).

Based on the analyses, partial support was found for Hypothesis 4. Results indicate that leaders with higher learning agility do in fact display higher levels of learning than those with lower learning agility (4a), but do not necessarily show greater growth rates in learning over time (4b).

To examine discriminant validity, hierarchical multiple regression was conducted to investigate whether learning agility predicted performance after controlling for personality dimensions (Openness to Experience and Conscientiousness). Due to the non-significant findings for Hypothesis 3b (a flat slope for performance over time), performance at Time 3 was used in the hierarchical multiple regression analysis. Correlations among the predictor variables were examined and are presented in Table 5. All correlations were weak to moderate, ranging between $r = .00$ and .28, indicating that multicollinearity is unlikely to be a problem. In the first step of hierarchical multiple regression, the two personality dimensions (Openness to Experience and Conscientiousness) were entered. This model was not significant F (2, 60) = .09, $p = .91$, with neither of the personality dimensions making a significant contribution to the model. After entering learning agility in to the model at step 2, the overall model remained non-significant F (3, 59) = 1.5, $p = .22$, but learning agility did make a significant and unique contribution to the model ($\beta = .28$, $p < .05$).

A second hierarchical multiple regression was conducted to investigate the effects of learning agility on learning, after controlling for Openness to Experience and Conscientiousness. Due to the non-significant findings for Hypothesis 4b (a flat slope for learning over time), learning at Time 3 was used in the hierarchical multiple regression analysis. Correlations among the predictor variables were examined and are presented in Table 5. All correlations again were weak to moderate, ranging between $r = .03$ and .41, again indicating low levels of multicollinearity. In the first step of hierarchical multiple regression, the two personality dimensions (Openness to Experience and Conscientiousness) were entered. This model was not significant F (2, 50) = 1.38, $p = .26$, with neither of the personality dimensions making a significant contribution to the model. After entering learning agility into the model at step 2, the total variance explained by the total model was 20% and the model was significant (F (3, 49) = 4.18, $p < .01$). The introduction of learning agility explained an additional 15% of variance in learning, after controlling for the personality dimensions (Openness to Experience and Conscientiousness) ($\Delta R^2 = .15$; F (1, 49) = 9.3, $p < .01$). In the final adjusted model only learning agility significantly contributed to the model ($\beta = .41$, $p < .01$).

DISCUSSION

Summary of Findings

The purpose of this study was to examine the construct of learning agility to provide further evidence of its construct validity and therefore applicability in assessing leadership potential. To do so, learning agility was examined within a broader nomological network of related constructs, a framework developed by DeRue, Ashford, et al. (2012). It was hypothesized in this study that personality variables would predict learning agility and that learning agility would predict both performance and learning *over time*. All prior research has been cross sectional and therefore lacking the ability to make inferences about the effects on the outcome variables over time.

Findings demonstrated significant, positive relationships between three personality variables (i.e., Openness to Experience, Imaginative, Mischievous) and learning agility, and a significant, negative relationship between Dutiful and learning agility. Further, learning agility was found to predict performance and learning, but not the rate at which these factors changed over time. In other words, individuals with higher levels of learning agility displayed higher levels of performance and learning, but the trajectories of these changes did not significantly increase over time. Finally, learning agility was found to provide incremental validity, above and beyond that of personality, in predicting learning, but not performance. Thus, the results partially supported the tested framework demonstrating significant relationships between personality variables, learning agility, and performance and learning.

This study makes a significant contribution to the learning agility literature, as it provides support for the relationship between personality variables and learning agility and continues previous research connecting learning agility to critical workplace outcomes (i.e., performance and learning) (De Meuse et al., 2012; Eichinger & Lombardo, 2004; Lombardo & Eichinger, 2000; McCauley et al., 1989; Spreitzer et al. 1997; Trathen, 2007). Additionally, the results provide initial evidence of the impact of learning agility on outcome variables over time, which has not been previously examined in the learning agility literature.

In addition to the theoretical contributions, this study makes a significant contribution to the practical application of learning agility. Within a highly complex, constantly evolving business environment, it is critical for leaders to be able and willing to adapt to unfamiliar environments. The results of this study provide evidence to support the continued use of learning agility as an indicator of potential. The use of an objective measure of learning agility will likely increase an organization's confidence in identifying individuals who will demonstrate improved performance, apply their learning in future experiences and jobs, as well as the transfer and utilization of knowledge taught in development initiatives.

Study Strengths and Limitations

A key strength of this study is the generalizability of the findings. The sample was comprised of working adults from a global organization, whom varied in age, gender, location, and tenure within the organization, and represented a wide variety of jobs. Although study participants worked within one organization, they worked across different offices, locations, and positions (e.g., jobs) within the engineering and program management industry. Further, assessing participants from a single organization provides a control for extraneous factors that may impact the results.

Another strength of this study is the quality of measurement. This study used established measures with strong validity evidence. Personality was measured using the Hogan Personality

Inventory (HPI) and Hogan Development Survey (HDS) and learning agility was measured using Korn/Ferry International's viaEDGE™ assessment, all of which have existing validity evidence. Also, collecting criterion data at multiple points in time allows for the exploration of hypotheses that could not be addressed using a cross sectional research design. This study collected performance and learning at three points in time over the course of multiple years.

A limitation of this study was the small sample. This study was limited to a small sample of 78 global leaders participating in a 12-month leadership development program. Due to the small sample, it is possible that there may have been insufficient power for the latent growth curve modeling chi-square test and tests of variance. With smaller samples, there is also greater likelihood that sampling error could exert undue influence on both point estimates and relationships between variables. As a general rule, a minimum sample size of 200 at each point in time is required to detect person-level effects (Byrne, 2006; Curran, Obeidat, & Losardo, 2010).

In addition to the small sample size, this study relied on criterion data across three points in time, which is the minimum number of criterion data points required for latent growth curve analysis (Byrne, 2006). Having data at only three points in time limits the data patterns that can be modeled (linear versus quadradic). More research is needed with a larger sample, across more points in time, to test additional empirical relationships and determine the generalizability of the findings.

Although this study found meaningful results related to indicators of career success (i.e., performance and learning), more research needs to be conducted, with a larger sample, to determine the impact of learning agility on these indicators of career success over time. Significant longitudinal results, if found, would allow for stronger conclusions to be made regarding learning agility. For example, if organizations are able to identify who have higher learning agility, they may be quicker to adapt to new jobs, reach higher levels of performance early on, and accelerate learning and performance over time.

More specifically, additional research should be conducted with a larger sample to assess the impact on learning. Learning is defined as the process of enhancing skills, behaviors, and competence through acquisition of knowledge (Fiol & Lyles, 1985). Additionally, McCall (2010) argued that learning is unique to the individual, dynamic in nature, and takes place over time. Therefore, acquisition of knowledge over time may be a more important indicator of learning than one's baseline capabilities captured at the beginning of the development program. In this study, results indicated that leaders with higher learning agility display higher levels of learning (at Time 1) than those with lower learning agility (intercept), but the rate of change over time, was small and not significant (slope). The small sample may have contributed to the lack of findings regarding learning over time and therefore it should be considered a limitation and assessed further in the future.

Another potential limitation of this study is the use of self-report measures to assess changes in learning over time. Specifically, there may be changes in participants over time that were not detected by my measures. The concept of alpha, beta, gamma change has highlighted measurement concerns with the use of self-report measures to document change (Golembiewski, Billingsley, & Yeager, 1976; Schmitt, Pulaks, Lieblein, 1984). Alpha change is described as actual or true change over time (Schmitt et al., 1984). In this study, alpha change would be the actual change in learning over time as measured by a constantly calibrated instrument/measurement. Beta change is when apparent change is due to an instrument that has been recalibrated by the leader between the times assessed (Schmitt et al., 1984). In this study, the beta change would be if the leader's actual learning stayed the same, but the perceptions of their learning or the scale in which they are assessing their learning has changed between the times assessed. For example, individuals participating in the leadership development program may have rated their learning higher on those competencies that were emphasized in the program based on being told that the leadership development program was intended on developing specific competencies. Finally, gamma change is described as a reconceptualization by the leader of the construct being measured between times assessed (Schmitt et al., 1984). In this study, the gamma change would be if the leader has redefined what learning means between the times assessed. Because the leaders participating in the leadership development program are likely to assume that the program is aimed to increase their capability and/or learning across the target leadership and management competencies, beta and/or gamma change may have impacted how they rated their learning at times 2 and 3.

Finally, the use of a general measure of performance may have prevented the study from capturing meaningful results related to performance within a specific development context. In this study, a general measure of performance was collected as part of the annual performance management cycle of the organization. The general measure of performance did not capture performance ratings related to the competencies taught in the development program. Having specific performance metrics related to the competencies taught in the development program may provide evidence for how learning agility predicts performance within a specific development context.

Despite these limitations, this study provides initial evidence of the theoretical and practical implications and applications of learning agility. Based on these initial findings, suggestions for future research are discussed below.

Conclusions and Future Research Directions

This research contributes to the understanding of learning agility as a construct by examining it within a broader nomological network of related constructs. By understanding the individuals difference variables that contribute to a construct and how the construct relates to and predicts outcomes over time, conclusions can be made about the boundaries of the construct and the value/contribution it adds to the literature (DeRue, Ashford, et al., 2012). Additional research should further investigate learning agility by measuring it within the broader framework and as defined by DeRue, Ashford, et al.

In their review of learning agility, DeRue, Ashford, et al. (2012) posited a narrower definition of the construct focused on speed (i.e., how quickly information can be obtained) and flexibility (i.e., ability to navigate across different ideas). As such, DeRue, Ashford, et al. concluded that learning agility should be defined and measured in this way. However, at the time of my study, there was no instrument that measured learning agility based on this perspective. However, a new instrument was published recently that measures learning agility based on DeRue, Ashford, et al.'s definition—The Burke Learning Agility Inventory™ (Burke, 2017). Therefore, future research should examine learning agility, using The Burke Learning Agility Inventory™ within the broader framework developed by DeRue, Ashford, et al.

Additionally, in their theoretical model of learning agility, DeRue, Ashford, et al. (2012) suggested a relationship between goal orientation and learning agility. Goal orientation refers to an individual's inclination to pursue goals related to learning or performance and has been shown to impact one's ability to be adaptable and learn from experience (Dweck, 1986). Past research demonstrates that different goals foster different patterns of learning (Dweck, 1986). It is hypothesized that learning goal orientation would be significantly related to learning agility in that if one is motivated to learn (learning goal orientation), the learner will be less concerned with performing well (performance goal orientation) and more focused on the application of knowledge being acquired (DeRue, Ashford, et al., 2012). Previous research has examined the relationship between learning goal orientation and learning agility, but the results did not demonstrate a significant relationship between the two constructs (De Meuse et al., 2010). DeRue, Ashford, et al. suggested that the lack of findings may have been due to the use of the CHOICES® *Architect* assessment in measuring learning agility. With the introduction of The Burke Learning Agility Inventory™ it is now possible to measure learning agility, and its factors of speed and flexibility, and examine the relationship it has with learning goal orientation.

In addition to its use as a way to identify high potential leaders, organizations have started using learning agility as a development tool in succession planning. Research should be conducted to examine the long-term effectiveness of learning agility in a developmental context. Specifically, is learning agility trainable? When training and development is provided for learning agility, will leaders be able to perform better and/or learn faster? Does this vary based on a leader’s baseline learning agility? And are these effects long lasting and/or sustained over time?

In conclusion, the findings of this study reinforce the practical applications of learning agility. Specifically, learning agility can and should be used as a key indicator for selecting and hiring individuals in to critical leadership roles, selecting transformational leaders, and selecting and promoting high potential leaders. Current and previous research has demonstrated that leaders with high learning agility have higher performance and learn more from experience (Dai et al., 2013; Eichinger & Lombardo, 2004; Lombardo & Eichinger, 2000; Spreitzer et al., 1997; Trathen, 2007).

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