EXPLORING THE RELATIONSHIPS BETWEEN EXPERTISE AND OVERCONFIDENCE AMONG HUMAN RESOURCE MANAGEMENT (HRM) PROFESSIONALS: THE MEDIATING AND MODERATING EFFECTS OF INDIVIDUAL DIFFERENCES

A Dissertation

by

ANTHONY KARL HUNT

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Chair of Committee,	Jia Wang
Committee Members,	Khalil M. Dirani
	Robert S. Woodward, Jr.
	Deborah L. Kerr
Head of Department,	Mario Torres

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ABSTRACT

The overconfidence effect is a pervasive bias that has been shown to obstruct decisional quality and lead to harmful organizational outcomes. This widespread phenomenon has been observed across an expansive array of professional settings and has become a multidisciplinary topic of inquiry. Despite its prevalence, the overconfidence effect has not previously been extensively studied by human resource development (HRD) scholars. This study aimed to examine the overconfidence effect within an HRD lens by developing and validating a robust construct of expertise as expressed through the dimensions of domain-specific knowledge, experience, and adaptivity.

This multidimensional construct was used to explore the relationships between overconfidence and expertise, specifically within the context of human resource management (HRM) professionals. Additionally, the mediating and/or moderating effects of individual differences (i.e., personality traits, decision-making styles, and demographic characteristics) on these relationships were considered. Three theoretical resources anchored in decision-making research guided the study: the theory of bounded rationality, the biases and heuristics program (which refers to a collection of cognate research), and cognitive-experiential self-theory (CEST).

An online survey was designed and administered to gather data from the research population of interest. The sample size consisted of 414 HRM practitioners from the United States. Descriptive statistics, partial least squares structural equation modeling

(PLS-SEM), mediation analysis, and moderation analysis were the statistical techniques employed in this study. The results of these analyses validated the constructs of expertise and overconfidence. While the hypothesized relationships between (a) expertise and overconfidence and (b) expertise and individual differences were supported, the (c) relationships between individual differences and overconfidence, as well as the (d) mediating and (e) moderating effects of individual differences were not supported. The theoretical, research, and practical significance of these findings are discussed in detail, and suggestions for a future research agenda are proposed.

DEDICATION

      I dedicate this dissertation to my family, all of whom have loved and supported me throughout this endeavor. To my wife, Victoria Paige Hunt, thank you for sacrificing just as much as I have these last few years so that this accomplishment could even be within the realm of possibility. You shouldered a great deal so that I could pursue this ardent dream of mine and create the time and space needed to successfully finish my dissertation, always amid multiple competing priorities and despite our unrelentingly busy lives. To my son, Stellan James Hunt, you forever changed me the moment you entered my world on December 23, 2019 at 6:02 PM and transformed me into a first-time father. There is no joy or fulfillment quite like parenthood. You inspire me to be the best version of myself and to always strive for excellence. To my late father, Clifford Hunt, and late father-in-law, James ("Jimmy") Doman, you two are dearly and profoundly missed. I would be honored if Stellan were to grow up to be even half the generous, kind-hearted, and compassionate human beings that you both so wonderfully exemplified. And last – but certainly not least – to my mother, Debbie Hunt, who is perhaps my biggest advocate and champion. Thank you for instilling in me the assurance of unconditional love and for always being a source of encouragement, especially when I needed it most.

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*Cultivate the habit of being grateful for every good thing that comes to you,
and to give thanks continuously. And because all things have contributed to
your advancement, you should include all things in your gratitude.*

– Ralph Waldo Emerson

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This work was supervised by a dissertation committee consisting of Dr. Jia Wang, committee chair, and Dr. Khalil Dirani from the Department of Educational Administration & Human Resource Development within the College of Education & Human Development, Dr. Robert Woodward from the Department of Educational Psychology within the College of Education & Human Development, and Dr. Deborah Kerr from the Department of Public Service & Administration within the Bush School of Government & Public Service. All work conducted for the dissertation was completed by the student independently.

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CHAPTER I

INTRODUCTION

The chapter provides an introduction to the current study. This introduction includes the background of the study, the problem identified, the purpose of the study, theoretical framework that guided the study, overview of the keys concepts under study, and research questions and hypotheses. In addition, this chapter highlights the research design and justifies the significance of the study. This chapter concludes by specifying the operational definitions, delimitations, assumptions, and organization of the study.

Background of the Study

The aim of the current study was to explore the relationships between expertise and overconfidence from a human resource development (HRD) perspective, while also investigating the mediating and moderating effects of individual differences on those relationships. Additionally, the population of interest is human resource management (HRM) professionals. Therefore, my study can best be described as an overconfidence study that investigates the expertise of HRM professionals through an HRD lens. This background section presents a synopsis about the overconfidence effect, explains why this topic needs to be explored from an HRD perspective, and illustrates the importance of this study for HRM professionals.

The overconfidence effect is a cognitive bias in which individuals tend to place greater confidence in their abilities, judgments, expertise, and knowledge than what is warranted by their actual performance in those related areas (Koriat, Lichtenstein, & Fischhoff, 1980). This phenomenon occurs when there is a miscalibration between

individuals' subjective confidence with their objective performance, resulting in their confidence to exceed their actual performance (Lichtenstein, Fischhoff, & Phillips, 1982). People tend to inaccurately think they perform better than they actually do, and they have a tendency to place more faith in their decisions than what is justified by objective and outwardly observable measurements of accuracy (Tsai, Klayman, & Hastie, 2008).

The overconfidence effect manifests itself in three dimensions: (a) overestimation of one's judgment, knowledge, ability, probability of success, or performance; (b) overprecision in the level of confidence placed in the extent and frequency of one's accuracy; and (c) overplacement of one's qualities relative to the qualities of others (Moore & Swift, 2010). To what degree these three dimensions are distinctly separate constructs of overconfidence is debated (Fellner & Krügel, 2012), but the overconfidence effect does at least conceptually involve the components of overestimating one's abilities, being overly precise in one's confidence, and underestimating the relative and comparative skills of others (Kruger, 1999).

Researchers from multiple academic disciplines have extensively studied the overconfidence effect, including psychology, sociology, economics, finance, marketing, and management (Barber & Odean, 2000). The inter- and multi-disciplinarity of this topic demonstrates the ubiquitous nature of this phenomenon and the potentially widespread consequences it could have across many different contexts. There is a generalized concern in the overconfidence literature that the overconfidence effect may

result in severely erroneous, costly, and harmful decisions that negatively impact organizations (Friedman, 2007).

Despite its far-reaching applicability to numerous fields of research and practice, HRD scholars have not commonly studied this phenomenon. The potential impact that the overconfidence effect has on both individual and organizational performance makes it an important and relevant topic to study from an HRD perspective. If overconfidence can negatively impact performance, then it is crucial that HRD researchers and practitioners identify and develop interventions to help reduce the impact of this bias. Furthermore, because the overconfidence effect is often linked to performance, the nature and scope of this topic fits well within HRD's theoretical foundations (Swanson & Holton, 2009).

Expertise is the other key concept explored by the current study. It is in this area that HRD scholarship is especially invaluable and instrumental. The overconfidence literature has tended to treat expertise one-dimensionally, whereas HRD literature provides a vigorous cornerstone for more fully conceptualizing expertise. Therefore, I relied heavily on HRD scholarship by exhaustively reviewing the HRD expertise literature and proposing a multidimensional construct of expertise consisting of the three dimensions of knowledge, education, and adaptivity. The HRD literature greatly informed the current study, especially as I investigated the relationships between expertise and overconfidence.

Finally, the current study directly pertains to HRM professionals. This topic is relevant for HRM professionals because of the potential impact that overconfidence has

not only on HRM decisions but also on the aggregate decisions made by other stakeholders across the organization. One of the central roles of HRM professionals is to help organizations mitigate risk (Cascio & Boudreau, 2012). Because the overconfidence effect often creates organizational risk, it is important for HRM professionals to understand this phenomenon. Additionally, HRM decisions have also been shown to be vulnerable to overconfidence, such as selection decisions (Kausel, Culbertson, & Madrid, 2016). The overconfidence effect may also offer insight into other studies that have found that HRM practices are often based on assumptive and intuitive beliefs rather than on empirical evidence (Rynes, Colbert, & Brown, 2002).

The Problem

If there is a significant mismatch between confidence and performance, the implications of this could present a substantial and pervasive problem in the world of professional practice. Moreover, the existence of the overconfidence effect could possibly challenge the assumptions of conventional wisdom that having a high level of confidence is overall advantageous, predictive, and positively correlative of successful outcomes (Gudmundson & Lechner, 2013). Although people often regard others who have high levels of self-confidence as experts, this assessment is subjective and disposed to misapprehension or even deception (Germain & Tejeda, 2012).

Although some researchers have noted a miscalibration between confidence and performance (e.g., Brenner, Koehler, Liberman, & Tversky, 1996; Keren, 1987), a large portion of their research originated from psychology and some of them have tended to focus on observing this phenomenon as it relates to general knowledge domains

(Fischhoff, Lichenstein, & Slovic, 1977). For example, researchers have measured the miscalibration between respondents' subjective confidence and the objective accuracy of respondents' knowledge on trivia questionnaires about geography, history, and spelling (Fischhoff et al., 1977). Although these researchers detected the presence of overconfidence in general knowledge, they did not know if overconfidence in general-knowledge also translates into overconfidence in professional knowledge.

Some researchers within economics, finance, management, and other business disciplines have extended and applied the insights generated from psychology to their respective fields by examining the overconfidence effect within a business context as it relates to working professionals and real-world outcomes (Barber & Odean, 2000; Boulton & Campbell, 2016). However, these researchers have mostly focused on senior executives and measuring proximately-related appraisals of knowledge, such as the profitability of merger and acquisition activities, debt maturity, and stock performance (Ellul & Yerramilli, 2013; Huang, Tan, & Faff, 2016; Odean, 1998). Therefore, professional knowledge was not directly measured; rather, proxies for professional knowledge were created (Eichholtz & Yönder, 2015; Malmendier & Tate, 2008). Profitability, however, is an outcome indicator and should not be conflated with knowledge or expertise. Furthermore, these studies did not factor in potential differences between individuals, such as varying degrees of expertise, one's hierarchical level within the organization, personality traits, or decision-making styles.

Based on a review of the overconfidence literature, I have identified four gaps that exist in the current research related to the overconfidence effect. The first gap is

that domain-specific, professional knowledge has not typically been measured. This study aimed to bridge this gap by directly measuring the domain-specific knowledge of HRM professionals. A second gap is that expertise has been superficially constructed by overconfidence researchers and equated with either knowledge (Huang et al., 2016) or experience (Lambert, Bessière, & N'Goala, 2012). The current study addressed this deficiency by incorporating HRD scholarship regarding the multidimensionality of expertise. A third gap is whether overconfidence exists with non-managerial professionals as well as executives. Past overconfidence studies have often focused exclusively on executive overconfidence, so the current study attempted to bridge this gap by more inclusively studying HRM professionals with a diverse array of experience and level within their organizations. The fourth gap that exists is that individual differences have not consistently been studied. The overconfidence effect is often considered to be a universal bias (Johnson & Fowler, 2011), so this study attempted to bridge this gap by examining whether individual differences (i.e., personality traits, decision-making style, and demographic characteristics) impact the extent to which individuals are overconfident.

Purpose of the Study

The purpose of this quantitative study was threefold: (a) to explore the relationships among expertise, overconfidence, and individual differences related to HRM professionals; (b) to ascertain the impact that individual differences have on the relationships between expertise and overconfidence; and (c) to determine the extent to which individual differences influence the relationships between expertise and

overconfidence. Expertise is the independent variable and is represented by the dimensions of knowledge, experience, and adaptivity. Overconfidence is the dependent variable and consists of overestimation, overprecision, and overplacement. Individual differences are the mediating and/or moderating variable and are expressed through personality traits, decision-making styles, and demographic characteristics. A simplified model of the hypothesized relationships is shown in Figure 1.1.
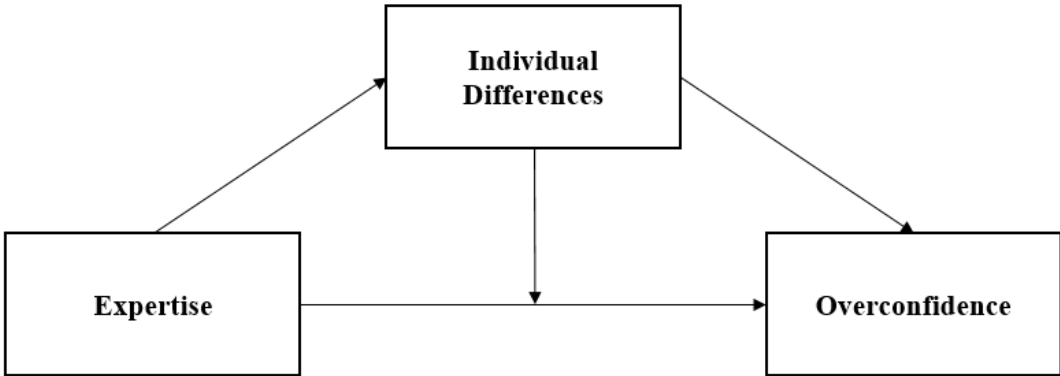
Figure 1.1. Simplified model of the hypothesized relationships

Theoretical Framework

Studies about the overconfidence effect are situated within a larger body of decision-making research (Kahneman, 2011; Koriat et al., 1980). HRD scholars have also recognized that expertise is fundamentally positioned within decision-making theory (Ceschi, Costantini, Phillips, & Sartori, 2017; Chermack, 2003a, 2003b; Korte, 2003; Swanson, 2003b). In fact, Chermack (2003a) argued that decision making is at the core of all HRD activities and that understanding decision-making theory is imperative to optimizing human expertise and advancing HRD research and practice. Accordingly, decision-making is immensely relevant and foundational to the current study. Three theoretical resources informed and guided my study: the theory of bounded rationality, the biases and heuristics program (this term refers to a collection of related research rather than to a singular theory), and cognitive-experiential self-theory (CEST). Although the theoretical framework is discussed in depth in Chapter II, an overview follows.

Bounded Rationality

The theory of bounded rationality postulates that human rationality is severely restricted by the availability of information, limited cognitive capacity, and finite properties of time, energy, and knowledge (Simon, 1955, 1986). Because human rationality is not boundless, perfect, or completely accurate, human judgment is prone to systematic error (Tversky & Khaneman, 1974). Some of these errors include inaccurate assessments, illogical conclusions, and biases that impede rational judgment (Kahneman,

2003). The central insight garnered from this theory that informs my study is that human rationality and cognitive processes are limited and prone to flaws.

Heuristics and Biases Program

The heuristics and biases program is a research paradigm that has generated a sizable body of research aimed at comprehensively studying and cataloging the many ways in which human judgment is predisposed to error. Amos Tversky and Daniel Kahneman (1974) inspired researchers from multiple disciplines to examine heuristics, which are cognitive shortcuts used in the decision-making process; and biases, which are associated with heuristics and encumber human judgment (Jacowitz & Kahneman, 1995). This paradigm is pertinent to my study because research on the overconfidence effect originated from the heuristics and biases program (Kahneman, 2011; Koriat et al., 1980).

Cognitive-Experiential Self-Theory (CEST)

Cognitive-experiential self-theory (CEST) is a dual-process theory of human cognition and posits that people tend to have a preferred or dominant thinking style (Pacini & Epstein, 1999). The analytical-rational system is characterized by a logical, reflective, and methodical approach to decision-making, while the intuitive-experiential system is characterized by an emotive, instinctual, and automatic approach to decision-making (Epstein, 2003). This theory informs my study in that it postulates that individuals differ in their styles and approaches to making decisions.

<center>**Overview of the Key Concepts**</center>

The two key concepts related to the current study are expertise and the overconfidence effect. The goal of the literature review was to identify key concepts that were extracted from the literature, propose possible relationships among those concepts, and engage in theory-building that is useful for research and practice. Even though a thorough review of the literature is conducted in Chapter II, an overview of the key concepts is provided here.

Expertise

Two important features about expertise are that it (a) is dynamic and requires continuous growth and development, and (b) is domain-specific (Swanson & Holton, 2009). This means that expertise is not immutably acquired and does not automatically transmute across other domains. Furthermore, developing a robust construct of expertise with components and dimensions that concretely, accurately, and completely measure this construct is paramount. Although there is not a universally agreed upon understanding of expertise, I have proposed that the three dimensions of expertise are knowledge, experience, and adaptivity.

Knowledge

The first dimension of expertise is knowledge. Knowledge is domain-specific, meaning that expertise in one area does not automatically transfer into every other subject matter (Herling, 2000). It is possible to be an expert in one area while being a novice in other – even adjoining – areas. For example, virtuosity as a business executive does not ineluctably equate to brilliance within public administration; business and

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public administration are two separate domains. Because knowledge is domain-specific, I have chosen to focus my study on HRM-specific knowledge, rather than general knowledge domains or proxies for knowledge (e.g., financial performance or predictive accuracy). Domain specificity, therefore, is a component of knowledge. I have identified three other components of knowledge that describe ways in which professional knowledge is conventionally thought to be acquired, certified, and validated: through education, professional credentials, and involvement with professional associations (Germain & Tejeda, 2012; McLean & Akdere, 2015).

Experience

Another dimension of expertise is experience. I have identified three ways in which work-related experience is traditionally thought to be accumulated: through the (a) length and tenure of one's experience (i.e., years), (b) level, rank, and type of experience, and (c) specific areas of professional practice to which someone has been exposed (Germain & Tejeda, 2012; Govaerts, van de Wiel, and van der Vleuten, 2013; Grenier & Kehrhan, 2008; Judge, Cable, Boudreau, & Bretz, 1995). Although experience can vary in quality and not all experience leads to the acquisition of expertise, it is generally agreed that expertise takes a considerable amount of time to develop and that it is gained through prolonged and extensive exposure to high-value and non-routine work within a particular field (Chermack, 2003b; Grenier & Kehrhan, 2008; Herling, 2000; Herling & Provo, 2000; Kuhlmann & Ardichvili, 2015; Torraco, 1999).

Adaptivity

The third dimension of expertise is adaptivity, which is a term that I proposed. It is the descriptive equivalent of adaptive expertise, which embodies problem solving, flexible expertise, and dynamic growth (Bohle Carbonell, Könings, Segers, & van Merriënboer, 2016; Bohle Carbonell, Stalmeijer, Könings, Segers, & van Merriënboer, 2014). Some scholars have called this dimension problem solving (Herling, 2000; Herling & Provo, 2000; Jeong, McLean, McLean, Yoo, & Bartlett, 2017; Swanson & Holton, 2009), while others have called it growth and flexibility (Evers, Kreiijns, Van der Heijden, & Gerrichhauzen, 2011; Frie, Potting, Sjoer, Van der Heijden, & Korzilius, 2019; Van der Heijden, 2000; Van der Heijden & Brinkman, 2001; Van der Heijden & Verhelst, 2002). Adaptivity encompasses problem solving as well as growth and flexibility, which is why it is the ideal third dimension of expertise.

Expertise is activated by adaptivity. Knowledge and experience are important components of expertise but are insufficient in producing expertise. It is this third dimension that ignites and unleashes expertise (Herling, 2000; Swanson & Holton, 2009). Adaptive experts perpetually search for information, thoroughly deliberate available options, approach new problems with originality and not just heuristically or routinely, and progressively and dynamically grow in their expertise to meet novel challenges (Bohle Carbonell et al., 2014). In fact, this is what differentiates experts from novices. Novices tend to rely on learned routines, while experts seek to solve problems by developing new and innovative solutions that are specific to the uniqueness of various situational contexts (Grenier & Kehrhan, 2008). Adaptivity is represented in the

components of domain-specific skills and innovative skills. Domain-specific skills are the competencies for an expert to dynamically continue to acquire and integrate new expertise, and innovative skills are the abilities for an expert to flexibly adapt to changing and novel contexts (Bohle Carbonell et al., 2016).

Overconfidence Effect

The second key concept of the study is the overconfidence effect. The overconfidence effect occurs when people place greater confidence in their abilities, judgments, expertise, and knowledge than what is justified by their actual performance in those arenas (Koriat et al., 1980). This concept is a well-established phenomenon that has been widely studied within psychology as well as the business disciplines, such as economics, finance, marketing, and management (Barber & Odean, 2000). Despite its relevance and practicality to applied disciplines, though, the overconfidence effect has only been modestly and superficially studied by HRD scholars.

The three conceptual components of the overconfidence effect are overestimation of the extent and scope of one's expertise, overprecision in the confidence one places in their performance, and overplacement of one's level of expertise relative to their counterparts (Moore & Swift, 2010). These components are defined in greater detail in Chapter II. Two major themes that emerged from the overconfidence literature are expert overconfidence and individual differences.

Expert Overconfidence

Expertise is covered profusely by the overconfidence literature, especially as it pertains to expert versus novice judgment. Disagreement persists, however, on whether

experts are less (Lin, Ho, & Chih, 2019), more (Glaser, Langer, & Weber, 2005), or equally (Lambert et al., 2012) prone to overconfidence compared with novices. Although expertise is widely discussed by overconfidence scholars, the construct of expertise within the literature has been rather underdeveloped and depthless. Scholars have often perfunctorily equated expertise with ether knowledge (Huang et al., 2016; Lambert et al., 2012; Lassoued, Phillips, Smyth, & Hesseln, 2019) or with years of experience (Bédard & Chi, 1993; Kirchler & Maciejovsky, 2002; Menkhoff, Schmeling, & Schmidt, 2013). The multidimensionality of expertise, therefore, has not received adequate attention from overconfidence scholars.

Individual Differences

In exploring how expertise and the overconfidence effect are related, it is important to also understand the potential role that individual differences might play in this relationship. This is especially crucial in determining if the overconfidence effect is a universal bias or if people are more situationally susceptible to it based on their differential qualities. The three individual differences most relevant to my study are personality traits, decision-making styles, and demographic characteristics. Examining these individual differences is helpful in determining how certain dispositional, attributional, and demographic factors might impact and influence the relationships between the expertise and overconfidence of HRM professionals.

Research Questions and Hypotheses

The following three questions guided my study:

1. What are the relationships among the various dimensions and components of expertise, overconfidence, and individual differences?

2. What is the impact of individual differences on the relationships between expertise and overconfidence?

3. To what extent are the relationships between expertise and overconfidence influenced by individual differences?

To explore these three overarching research questions, five hypotheses were developed and tested. The first three hypotheses relate to the first research question, the fourth hypothesis corresponds with the second research question, and the fifth hypothesis pertains to the third research question (see Figure 1.2 for a schematic representation of the hypothesized relationships):

H1: Expertise will be positively related to overconfidence.

H2: Expertise will be positively related to individual differences.

H3: Individual differences will be positively related to overconfidence.

H4: Individual differences will have a mediating effect on the relationships between expertise and overconfidence.

H5: Individual differences will have a moderating effect on the relationships between expertise and overconfidence.
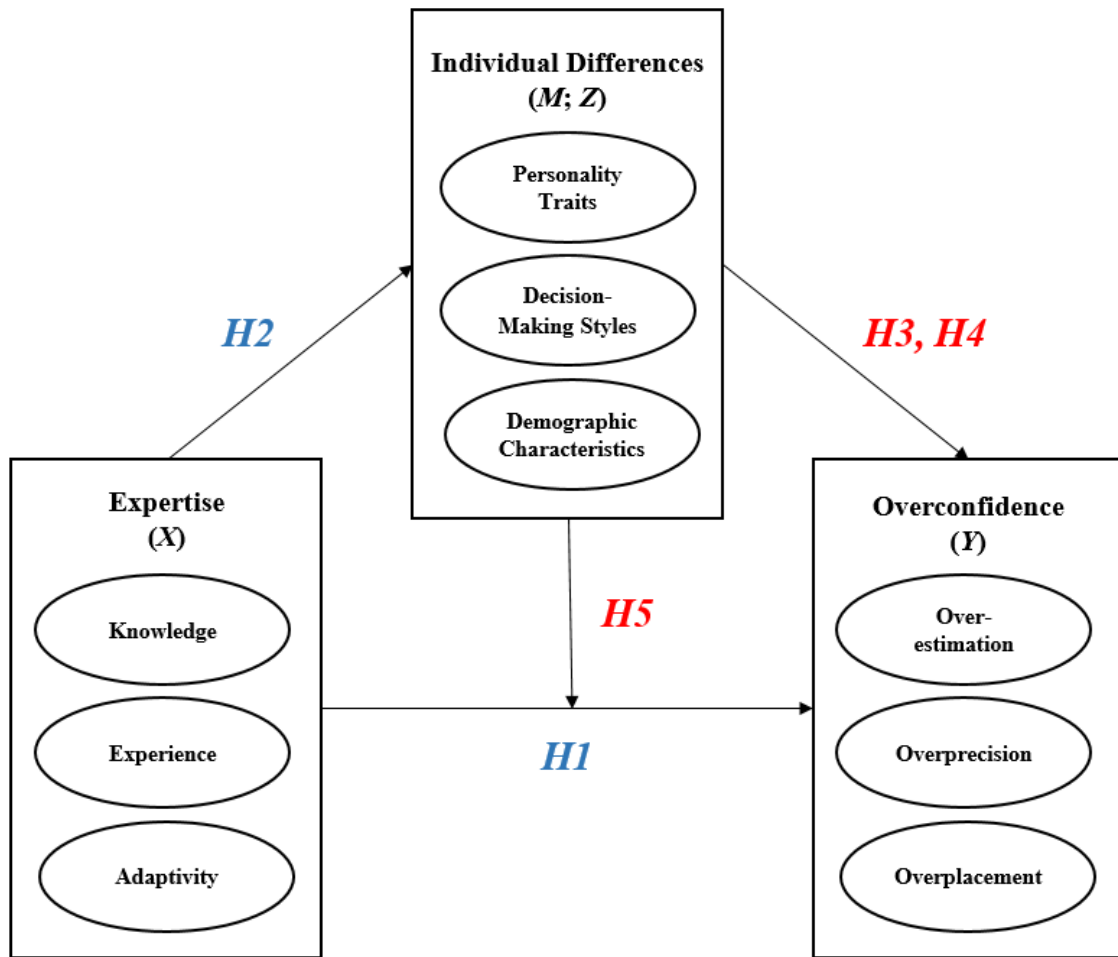
Figure 1.2. Schematic representation of the hypothesized relationships

Research Design

To answer the three research questions, I selected a non-experimental research design. This was the most appropriate design for my quantitative study because my study was observational and did not involve random assignment, experimental manipulation of an independent variable, or the introduction of a treatment or intervention. Additionally, a non-experimental research design flexibly allowed for both

exploratory and predictive modeling, which were relevant to the current study. A self-report cross-sectional survey was used to gather data from 414 HRM professionals who were affiliated with and accessible through HRM professional associations in the United States. To analyze the data and test the hypotheses, I incorporated both correlational and causal-comparative statistical techniques, including partial least squares structural equation modeling (PLS-SEM) (which combines factor and path analysis), mediation analysis, and moderation analysis. The methods and methodology that grounded the current study are discussed in Chapter III, the results of these analyses are presented in Chapter IV, and an in-depth discussion about the implications of these findings is provided in Chapter V.

Significance of the Study

This study contributes to both HRD and overconfidence scholarship. Just as HRD researchers can learn more about the impact that overconfidence has on individual and organizational performance, so can overconfidence researchers learn more about the multidimensionality of expertise. Additionally, this study is practically significant for HRM practitioners in particular.

Significance for HRD

Expertise is a complex construct and is integrally important to HRD research and practice. It is imperative that researchers continue to advance the collective understanding of the multifaceted components and domains associated with expertise. During this study, I conducted an integrative literature review of expertise from an HRD research lens. In doing so, I developed a revised construct of expertise that is manifested

through the dimensions of knowledge, experience, and adaptivity. Even though this is similar to the classical construct popularized by Swanson and Holton (2009) (who hypothesized that the three dimensions of expertise are knowledge, experience, and problem solving), my study substantially contemporized the third dimension.

There is substantial agreement among many HRD scholars that knowledge and experience are essential components of expertise. There is less consensus, however, surrounding the third dimension, and some scholars have even argued that problem solving is inadequate in encompassing the remaining dimensionality of expertise (Germain & Ruiz, 2009). Adaptivity, on the other hand, is incorporative of problem solving while also extending beyond that concept. Adaptivity is a more inclusive and robust third dimension because it more explicitly integrates the notions of growth and flexibility (Bohle Carbonell et al., 2016; Van der Heijden & Verhelst, 2002). This update to the construct of expertise is significant for HRD research because adaptivity is coalescent of competing hypothesized dimensions. Therefore, my proposed construct of expertise can be adopted as operational by other HRD scholars who are interested in researching expertise.

The current study is also significant because it is an overconfidence study done from an HRD perspective. I was unable to locate a previous HRD study where overconfidence was the primary subject of interest, so this work is unique in its undertaking. The overconfidence effect has been under-explored by HRD experts, notwithstanding how relevant and important the identified consequences of overconfidence are to individual and organizational performance. Because

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overconfidence has been shown to adversely impact performance – a key interest of HRD (Swanson, 2007) – it is necessary for HRD researchers to develop a solid understanding of its effect. I hope that my study inspires more HRD scholars to pursue this line of inquiry.

Significance for Overconfidence

Knowledge has often been examined in past overconfidence studies within the context of general knowledge (Clark & Friesen, 2009; Fischhoff et al., 1997; Moore & Healy, 2008) or proxies for knowledge (Camerer & Johnson, 1991; Ellul & Yerramilli, 2013; Haung et al., 2016). However, this approach does not allow researchers to directly observe the knowledge related to someone's domain of expertise. Because knowledge is domain-specific (Herling, 2000), I designed the current study to examine the domain-specific knowledge of HRM professionals. This is a departure from how knowledge has been assessed by previous overconfidence studies. My approach is novel and was informed by the HRD literature, thus advancing and enhancing the overconfidence literature.

Secondly, just as overconfidence has been understudied by HRD scholars, so too has expertise been underdeveloped by overconfidence scholars. The complexity of expertise has often been oversimplified by overconfidence researchers, some of whom have merely regarded it as knowledge (Huang et al., 2016; Lambert et al., 2012; Lassoued et al., 2019) or experience (Bédard & Chi, 1993; Kirchler & Maciejovsky, 2002; Menkhoff et al., 2013). Consequently, the richness of expertise has not always been fully captured or appreciated. This study fills this void by expanding expertise into

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a multidimensional construct against which expert versus novice overconfidence can be examined.

Finally, my study seeks to offer clarity amid mixed findings around whether overconfidence is universal or situational in nature. Some scholars believe the overconfidence effect is a universal bias (Johnson & Fowler 2011), while others believe it is manifested differently across various populations (Kruger & Dunning, 1999). My exploration into how individual differences mediate and moderate the relationships between expertise and overconfidence provides evidence-based, cross-disciplinary insights into this ongoing debate.

Practical Significance for HRM Professionals

Previous studies have shown that HRM professionals do not always adopt evidence-based practices and that there is a divergence between HRM practitioner beliefs with research findings (Rosseau & Barends, 2011; Rynes et al., 2002). For example, HRM professionals were found to overwhelmingly possess intuitive beliefs about selection that were counter to and not grounded in research (Tenhiälä et al., 2016). Overconfidence has even been named as a malefactor for why poor selection decisions are made within organizations (Kausel et al., 2016). The overconfidence effect offers a possible explanation for why HRM professionals frequently rely on their own judgment, do not always base their practices on evidence, and are unaware of deficiencies in their existing knowledge that should signal when they should seek out additional information (Miller & Geraci, 2014; Zacharakis & Shepherd, 2001).

The overconfidence effect does not only impact the quality of decisions made by HRM professionals, it has also been observed in many other professional contexts and settings (Koehler, Brenner, & Griffin, 2002). Because decisions are systematically vulnerable to error, this can create an exponentially harmful impact at an organizational level. Therefore, HRM professionals are encouraged to not only effectively manage the overconfidence of their own decisions, but also help improve decisional calibration and accuracy across the organization. HRM professionals are in a unique position to help organizations mitigate risk, including the inherent risks of overconfident business decisions that could result in deleterious outcomes, such as costly litigation (Moore & Healy, 2008) and labor strikes (Babcock & Olson, 1992).

Operational Definitions

The following terms were used in this study.

Adaptive Expertise Inventory

The Adaptive Expertise Inventory is a 10-item instrument that measures adaptive expertise (Bohle Carbonell et al., 2016). The two dimensions of adaptive expertise measured in this instrument are domain-specific skills, which are the competencies for an expert to dynamically continue to attain and cultivate new expertise, and innovative skills, which are the abilities for an expert to be flexible and adaptable in new environments. This instrument is used in my study to measure the expertise dimension of adaptivity.

Big Five

The Big Five comprises a five factor model (FFM) for understanding the bipolar dimensionality of five broad personality traits. The Big Five personality dimensions that are ubiquitously considered to cover an extensive range of human personality traits and related facets are extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience (Arora & Rangnekar, 2016). Personality traits is one of the individual differences that is relevant to my study.

Big Five Inventory-10 (BFI-10)

The Big Five Inventory-10 (BFI-10) is a brief 10-question measure of the Big Five personality traits and dimensions. It is an abbreviated version of the full-length Big Five Inventory (BFI), which is a 44-item scale. Short measures are appropriate to use when personality is not the primary topic of the study (Gosling, Rentfrow, & Swann, 2003; Rammstedt & John, 2007). This instrument was used in the current study to measure the individual differences in personality traits.

Cognitive Bias

A cognitive bias is a systematic error in the way individuals intuitively rather than rationally process, construct, and subsequently make decisions based on information, leading to interference in one's "ability to be impartial, unprejudiced or objective when interpreting reality" (Gudmundsson & Lechner, 2013, p. 279).

Cognitive Heuristics

Cognitive heuristics refer to mental shortcuts that enable individuals to quickly and efficiently process information and render decisions (Tversky & Kahnmann, 1974).

These shortcuts can be useful and less demanding on the brain's processing resources, but can also result in substantial decision-making errors (Kahneman, 2003).

Cognitive Reflection Test (CRT)

The Cognitive Reflection Test (CRT) is a three-question scale that assesses whether individuals responded spontaneously, quickly, and intuitively (i.e., incorrectly), or deliberatively, reflectively, and rationally (i.e., correctly). The original version uses a free-response format (Frederick, 2005). In the current study, I used the four-option multiple-choice version (CRT MCQ-4) (Sirota & Juanchich, 2018). This instrument was used in conjunction with the Decision Styles Scale (DSS) to help measure the decision-making styles dimension of individual differences.

Decision-Making Styles

Decision-making styles refers to "individuals' characteristic mode of perceiving and responding to decision-making tasks" (Scott & Bruce, 1995, p. 818). Decision-making styles are considered to be one manner in which individuals differ from other individuals. Decision-making involves gathering and interpreting information and then subsequently rendering decisions based on a cognitive process. Decision-making styles is another component of individual differences that is applicable to my study.

Decision Styles Scale (DSS)

The Decision Styles Scale (DSS) is a 10-item psychometric instrument designed to assess the approach by which individuals either rationally or intuitively make decisions (Hamilton, Shih, & Mohammed, 2016). Individuals who rationally make decisions systematically evaluate potential choices and alternatives, whereas individuals

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who intuitively make decisions rely more on feelings, hunches, and quick decision-making processes. I used this instrument in combination with the CRT MCQ-4 to examine the decision-making styles component of individual differences.

Expertise

Expertise is a component of human performance and is what differentiates experts from novices (Swanson, 1995). Although there is not a universally accepted operational definition of expertise, there are certain elements that are common in the HRD literature about expertise: (a) expertise is dynamic and requires continuous learning and ongoing information acquisition; and (b) expertise does not transfer across all areas, but instead is domain-specific (Grenier & Kehrhahn, 2008; Herling, 2000; Herling & Provo, 2000; Swanson & Holton, 2009). The three fundamental dimensions of expertise that I have proposed in the current study are knowledge, experience, and adaptivity.

Human Resource Development (HRD)

Human resource development (HRD) is characterized as "a set of systematic and planned activities designed by an organization to provide its members with the necessary skills to meet current and future job demands" (Werner & DeSimone, 2012, p. 551). It is also described as a "process of developing and unleashing expertise for the purpose of improving individual, team, work process, and organizational system performance" (Swanson & Holton, 2009, p. 4). The HRD faculty at Texas A&M University defines HRD as "the process of improving learning and performance in individual, group, and organizational contexts through domains of expertise such as lifelong learning, career

development, training and development, and organizational development" ("Doctor of Philosophy in Educational Human Resource Development," n.d.).

Human Resource Management (HRM)

Human resource management (HRM) is defined as "the policies, practices, and systems that influence employees' behavior, attitudes, and performance" (Noe, Hollenbeck, Gerhart, & Wright, 2019, p. 5). HRM is a business discipline and includes functions and responsibilities such as recruitment and selection, training and development, performance management, compensation and benefits, employee and labor relations, personnel policy administration, legal compliance, and strategy consultation.

Overconfidence Effect

The overconfidence effect refers to a cognitive bias in which a person's subjective confidence about their abilities, judgments, expertise, and knowledge exceeds what is objectively accurate and justified given their actual performance in those arenas (Koriat et al., 1980). The overconfidence effect, overconfidence, and overconfidence bias all refer to the same phenomenon and can be used interchangeably. The overconfidence effect conceptually exists in the three components of overestimation, overprecision, and overplacement (Moore & Healy, 2008).

Performance

Performance is a multidisciplinary concept and there is not just one perspective of how it should be defined (Swanson & Holton, 2009). Because of this lack of uniformity in terminology, I have chosen to define performance as how well an output operates against the standard of an intended purpose or goal. Moreover, I accept as

operational that there are four levels of performance (organizational, process, team, and individual) that are matrixed with five performance components (mission/goal, system design, capacity, motivation, and expertise) (Swanson, 2007).

Delimitations

This study has five delimitations:

1. The population of my study is HRM professionals. Therefore, the findings and implications of this study should not be extended or generalized to other disciplinary areas or fields of professional practice.

2. The BFI-10 is a shortened version of the full-length 44-item BFI (Rammstedt & John, 2007). Even though it is appropriate to use short inventories for personality when it is not the primary topic of interest, there are still some "diminished psychometric properties associated with very brief measures" (Gosling et al., 2003, p. 504). Brief measures of larger scales seek to measure the same phenomenon, but with fewer questions or items. As a result, shortened inventories are not necessarily designed to tolerate factor analyses and fit indices since the validity of the larger scales has already been established (Kline, 2000; Wood & Hampson, 2005).

3. Although I selected personality traits, decision-making styles, and demographic characteristics as the three types of individual differences relevant to my study, I realize these do not comprehensively represent all individual differences. There is an inexhaustible variety of individual differences, so accounting for the

entirety of all individual differences is impracticable. Therefore, I focused on the three main types of individual differences that I identified from the literature.

4. I selected the DSS (Hamilton et al., 2016) to measure decision-making styles and the BFI-10 (Rammstedt & John, 2007) to measure personality. There are many scales that exist, however, that measure these same constructs. For example, the Rational-Experiential Inventory-10 item scale (REI-10) (Norris, Pacini, & Epstein, 1998) and the Ten Item Personality Inventory (TIPI) (Gosling et al., 2003) were other comparable alternatives at my disposable. I ultimately chose the DSS instead of the REI-10 and the BFI-10 over the TIPI because the DSS and BFI-10 are newer and concurrently valid measures. Also, the DSS and BFI-10 both used the same 5-point Likert scale as the other sections of my survey, so the transitional fluency of these measures was also considered.

5. My main recruitment strategy for identifying HRM professionals was to ask board members at local HRM professional associations to distribute my survey to their members on my behalf. This possibly resulted in a larger sample of respondents with association involvement than what is naturally observed within this population, but this decision was judicious given the feasibility and accessibility constraints of identifying HRM professionals by any other means. When I was given permission to post on HRM group Facebook or LinkedIn pages, I did that as part of my recruitment strategy as well.

Assumptions

This study is based on five assumptions, as follows:

1. The survey instrument is valid, reliable, and accurately measures the constructs of interest.

2. The components and dimensions identified from the literature accurately represent the concepts of interest.

3. Participants understood the questions asked by the instrument and responded honestly.

4. Individual differences and variations exist between people, and personality traits, decision-making styles, and demographic characteristics are explanatory in understanding these individual differences.

5. Biases in judgment, cognition, and decision-making are widely observed. Decision-making theory provides an elucidative theoretical framework for understanding expertise and the overconfidence effect.

Organization of the Study

This dissertation consists of five chapters. Chapter I contains an introductory background about the study, the statement of the problem, purpose of the study, theoretical framework, overview of the key concepts, definition of terms, research questions and hypotheses, significance of the study, delimitations, assumptions, and organization of the study. Chapter II provides a thorough review of the relevant literature associated with the topic, identifies gaps that inspired the current study, synthesizes themes and hypothesized relationships, and examines the importance of the

study within the context of HRM professional practice. Chapter III discusses the

research methods and methodology that were used for data collection and analysis.

Chapter IV analyzes and presents the results. Finally, Chapter V provides a discussion

of findings, implications for theory, research, and practice, and recommendations for

future research.

CHAPTER II

LITERATURE REVIEW

This chapter presents the literature related to my research topic, identifies gaps in current scholarship, synthesizes themes and relationships that emerged from this review, and discusses the importance of this study as it pertains to the population of interest: human resource management (HRM) professionals. The current study aimed to explore the relationships between (a) expertise and (b) overconfidence while also examining the mediating and moderating effects of individual differences on these relationships.

The overconfidence effect is a multidisciplinary topic of inquiry, especially as it relates to experts. As such, the current study is fundamentally an overconfidence study. However, the concept of expertise has often been underdeveloped by overconfidence researchers. To rectify this deficiency, I relied heavily on human resource development (HRD) scholarship to expand expertise into a robust and multidimensional construct. This equipped me to more completely investigate the relationships between expertise and overconfidence among HRM professionals. To recapitulate, this is an overconfidence study, explored through an HRD research lens, applied to the population of HRM professionals.

In this chapter, the theoretical framework is first introduced. The overconfidence effect is securely situated within the larger framework of decision-making theory, so I reviewed the three main theoretical sources that guided the current study: the theory of bounded rationality, heuristics and biases program (this is the term given to describe a collection of allied research), and cognitive-experiential self-theory (CEST). Next, I

examined the relevant bodies of literature: expertise and the overconfidence effect. An

integrative review was conducted that exhausted the HRD expertise literature and

informed the development of a multifaceted construct of expertise. An overview of the

overconfidence effect was also provided that highlighted pivotal studies as well as

emergent themes. For example, a major theme identified from the overconfidence

literature that is pertinent to my study is individual differences (i.e., personality,

decision-making styles, and demographic characteristics). In this study, I propose that

individual differences may act as a mediator and moderator and help provide additional

context around the universality versus situational variability of overconfidence. Then I

presented a concept map of the proposed relationships identified in the literature.

Finally, I illuminated various ways the current study is important for HRM

professionals.

Theoretical Framework

Because expertise and the overconfidence effect are both firmly rooted in

decision-making theory, it is important to survey the relevant theories that provided a

foundation and framework for the current study. Decision-making theory explores the

underlying processes by which human agents evaluate and select choices among a range

of decisional options (Edwards, 1954; Peterson, 2009). Additionally, decision-making

theory is even regarded by HRD scholars as being of central and profound importance to

HRD research (Ceschi, Costantini, Phillips, & Sartori, 2017; Chermack, 2003a, 2003b;

Korte, 2003). The three major decision-making sources that shepherded my study are

the theory of bounded rationality, heuristics and biases program (this is technically not a

single theory, so this refers to a research paradigm and collective body of research), and cognitive-experiential self-theory (CEST). Together, these two theories and one paradigm offer insights that are essential to examining the overconfidence effect within the larger context of my study.

Bounded Rationality

The theory of bounded rationality was first introduced and articulated by Herbert A. Simon as a counterargument aimed at trying to revise traditional rational choice theory (RCT) (Simon, 1955). RCT emerged as a convergence of neoclassical economic theory, game theory, and utilitarianism (Zey, 1998). The fundamental postulates of RCT are that individuals: (a) are purposive, intentional, and self-interested in the decisions that they make; (b) have a structured and formalized hierarchy of choice preferences; (c) are rational actors in acquiring perfect and complete information needed to objectively weigh options and make the best choice among various alternatives; and (d) rationally and accurately select outcomes that optimally maximize personal utility and benefits while minimizing costs (Zey, 1998).

Although the theory of bounded rationality was not originally intended to replace RCT, it did result in major modifications to how human rationality was understood within the field of economics. Namely, bounded rationality introduced a behavioral component to the study of economic theory (i.e., behavioral economics), and posited that human behavior does not lead to or result from pure economic rationality (Simon, 1955, 1959, 1984). Whereas strict rationalist theory holds that humans are capable of operating with interminable rationality, the theory of bounded rationality maintains that

humans actually contravene the pivotal tenets of RCT (Simon, 1955, 1986). Therefore,

the theory of bounded rationality was developed based on five central assumptions.

First, the cognitive infrastructure of the human brain is severely limited. Second,

humans lack the time, resources, and knowledge needed to exhaustively search for all

available information. Third, illimitable information-processing and absolute decisional

precision are unattainable. Fourth, the human computational capacity to perfectly

capture and account for all compounded complexity is architecturally impossible. Fifth,

people are unable to comprehensively and accurately assimilate all of the information

required for true choice optimization (Simon, 1955, 1984, 1991).

Rationality is not boundless as previously believed, but rather it is limited and

bounded by available information, cognitive restrictions, and finite resources. As a

result, humans operate within the infrastructural and architectural confines of bounded

rationality (Conlisk, 1996). Rational choice, therefore, is significantly constrained by

these limitations. Because many decisions are too complex to calculate all potential

alternatives and unencumbered access to complete information is impracticable, human

decision-makers routinely rely on cognitive heuristics rather than on probability, logic,

pure rationality, or the stringent standards and procedures of optimization

(Katsikopoulos, 2014; Klein, 2008; Maldonato, 2007).

Cognitive heuristics are mental shortcuts that allow people to quickly and

efficiently process information and subsequently make a decision (Tversky &

Kahneman, 1974). Heuristics are utilized in order to extract and digest the essential

elements of information, simplify and reduce complexity, and render decisions with

relative promptness and ease without being overly demanding on the brain's cognitive resources (Kahneman, 2003). These mental shortcuts are useful and time-saving in many aspects and circumstances of everyday life, but they can also result in systematic errors in judgment (Tversky & Kahneman, 1974).

While RCT contends that human agents rationally and methodically consider the optimality of their choices, the theory of bounded rationality proposes that humans are conversely inclined to settle on suboptimal choices in their decisions (Simon, 1991). Because there is a propensity for the human brain to overly simplify complexity and for individuals to not engage in exhaustive searches for information, optimization is rarely achieved. Rather, people typically identify alternatives that are familiar to them, highly visible, and quickly and conveniently accessible (Kahneman, 2003; Tversky & Kahneman, 1974). Then, as options are evaluated, people tend to choose the first acceptable solution encountered. Thus, a satisfactory (suboptimal) choice is made rather than the absolute best (optimal) choice. Once someone arrives at a solution that is even cursorily or minimally acceptable, they are likely to then discontinue the search for other alternatives altogether. Committing to a decision that is good enough rather than optimal is called *satisficing* (Barros, 2010; Simon, 1955, 1997).

Even though the theory of bounded rationality acknowledges that decision-making is limited by resources, the availability of information, and cognitive processes, one might logically theorize that individuals would at least choose the best available option within this realm of constraints. However, the concept of satisficing suggests that individuals have a generalized disposition toward opting for the first available rather

than the best available option at their disposal (Kahneman, 2003; Klein, 2008; Simon, 1991). Therefore, not only do human decisions tend to suffer from suboptimality, but also from superficiality in information acquisition and choice evaluation.

The theory of bounded rationality has been around for over 60 years, making it a very mature theory to use in academic studies, especially in behavioral economics and psychology. As a result, it has been extensively studied and has generated a sizable academic literature base. Many studies have primarily demonstrated the existence of bounded rationality through economic decision-making models, cognitive algorithms, and choice simulations (Gigerenzer & Goldstein, 1996; Munier et al., 1999; Simon, 1959, 1984, 1986), but the phenomenon has been empirically observed across numerous real-world contexts as well. For example, physicians have been shown to rely on heuristics when making clinical diagnoses (Bonilauri-Ferreira et al., 2010), entrepreneurs often find it difficult to evaluate the quality of potential investment partners (Hallen & Pahnke, 2016), simplified rather than detailed information accelerates end-user adoption of complex technologies (Gounaris & Koritos, 2012), and too many healthcare choices can inversely result in consumers having lower healthcare literacy (Korobkin, 2014). Therefore, the theory of bounded rationality is strongly supported by a large body of both theoretical and empirical research.

Heuristics and Biases Program

Although the theory of bounded rationality includes the notion of heuristics, it was researchers primarily within the field of psychology who later developed this concept more thoroughly. Therefore, the theory of bounded rationality led to a

proliferation of subsequent research on how heuristics and biases influence decision-making and contribute to systematic errors in judgment (Tversky & Kahneman, 1974). Even though this area of inquiry has not produced a formalized or consolidated theory, it has successfully created a sophisticated and revolutionary research paradigm and framework known as the heuristics and biases program, which inspired the academic work of cognitive, behavioral, and social researchers from multiple fields of study (Gilovich & Griffin, 2002). Therefore, the heuristics and biases program is not represented in a single theory, but rather constitutes a collective and multidisciplinary body of research.

In their seminal work on heuristics and biases, Amos Tversky and Daniel Kahneman (1974) postulated that humans do not process information the way a computer does. Instead, humans rely on mental shortcuts and intuitive rules-of-thumb to quickly assimilate, interpret, and act on information. Heuristics can often be useful in creating efficiencies, but heuristics can also result in systematic and predictable decisional errors, which are referred to as cognitive biases. Tversky and Kahneman (1974) initially identified three main types of heuristics: representativeness, availability, and adjustment and anchoring.

Representative Heuristic

The representativeness heuristic is used when an individual intuitively makes probability judgments about the categorization of an object, event, or person based on one's own mental prototypes or stereotypes rather than on the actual probability of that object, event, or person belonging to a certain category (Tversky & Kahneman, 1974).

This is done when a decision-maker evaluates similarity or resemblance cues more heavily than mathematical probabilities. As an illustration of the representativeness heuristic, consider the following scenario: Chad is 24-years old, has a passion for life, loves the outdoors, and can be described as extremely extroverted, outgoing, adventurous, athletic, risk-taking, and thrill-seeking. In other words, Chad is an adrenaline junky who constantly pursues new and exciting experiences in life. Is Chad more likely a rock climbing instructor or an accountant?

Many people would likely choose rock climbing instructor over accountant. This is because the description about Chad more closely resembles the ostensibly representative and stereotypical characteristics people would expectedly attribute to rock climbing instructors than to accountants. However, the likelihood that Chad is an accountant is considerably greater since accountants are exceedingly more proportionally represented in the general population than rock climbing instructors ("Accountants and Auditors," n.d.; Torpey, 2016). Even when research participants are given enough information needed to accurately calculate probabilities, they still tend to rely on similarity-based and subjective evaluations than on Bayesian principles (Kahneman & Tversky, 1972; Tversky & Kahneman, 1974).

Availability Heuristic

The availability heuristic describes when an individual weighs their judgment more heavily toward recent, readily available, and vivid information (Tversky & Kahneman, 1973). People are more inclined to base judgments on information that is quickly and easily recallable, such as recent events or events that have received

extensive coverage in the media. This heuristic can lead to a systematic error in judgment when someone mistakenly overestimates the probability of an event occurring based on the ease or frequency at which that event comes to mind (Tversky & Kahneman, 1974).

Because memory strength is especially biased toward vivid and sensationalistic events, people often conclude the probability of those events as being much more likely to occur than what is supported by statistical evidence (Riddle, 2010). For example, there were 64 unprovoked shark attacks and 2 deaths attributable to those attacks worldwide in 2019 (Madden, 2020). Despite shark attacks being an extremely anomalous event, however, public fear remains visceral, widespread, and incommensurately salient given its actual level of imperilment (Nosal, Keenan, Hastings, & Gneezy, 2016). The availability heuristic helps explain why people often respond more fearfully to dramatic yet rare causes of death (e.g., shark bites, airplane crashes, terrorist attacks, and natural disasters) than to more everyday causes of death (e.g., car accidents, respiratory infections, and trip and falls), even though the latter is statistically more likely to occur than the former (Keller, Siegrist, & Gutscher, 2006).

Anchoring and Adjustment Heuristic

The anchoring and adjustment heuristic describes the tendency for someone to excessively focus on initial data (i.e., the anchor) when evaluating new evidence (i.e., adjustments). Initial information frequency provides a fixed reference point that influences how subsequent information is processed and filtered. Rather than carefully, thoroughly, and independently evaluating each piece of additional datum, individuals

merely make modest and incremental adjustments away from the original anchor (Tversky & Kahneman, 1974). Individuals are inclined to overly fixate on the first piece of information they receive, consequently failing to adequately or sufficiently adjust their judgments in light of new evidence. This heuristic can lead to biased and inaccurate decisions when the anchor overly narrows and constricts one's ability to give appropriate weight to additional information.

Once an anchor is set, it serves as a starting point upon which other judgments are based, even if the anchor is completely irrelevant. Therefore, the anchor contaminates one's ability to detachedly and broadly consider alternatives (Jacowitz & Kahneman, 1995). An example of how subsequent decisions are adjusted around the first piece of information received is the classic United Nations experiment (Tversky & Kahneman, 1974). In this demonstration, two different groups of participants were asked to estimate the percentage of African countries belonging to the United Nations. Each group was given a different arbitrary number as a starting point and asked to estimate the true percentage of member countries. The group that was given a starting number of 10 gave an average response of 25%, while the group with a starting number of 65 guessed 45% as the median estimated value (Tversky & Kahneman, 1974). This experiment showed that "different starting points yield different estimates, which are biased toward the initial values" (Tversky & Kahneman, 1974, p. 1128). The first number served as a powerful anchor for each group's estimates, even though that number was immaterial, random, and unrelated to the actual value prediction.

Other Heuristics

Tversky and Kahneman's landmark study in 1974 led to the creation of the heuristics and biases program, a prominent research paradigm that has resulted in an explosion of additional decision-making studies (Gilovich & Griffin, 2002). Even though representativeness, availability, and anchoring and adjustment are the three initial heuristics identified by Tversky and Kahneman, a plethora of other heuristics, cognitive biases, illusions, and fallacies have been extensively studied by other researchers. Some of these other heuristics and biases include the affect heuristic, which is a mental shortcut explaining one's propensity to base decisions primarily on emotional responses than on thoroughgoing research and information (Zajonc, 1980), and the hindsight bias, which is a post factum inclination for someone to think an event should have been easily predictable before it was even feasibly known (Roese & Vohs, 2012). Further research also identified the escalation of commitment fallacy, which is the phenomenon by which individuals strengthen their allegiance to a decision rather than change course, even when evidence shows the initial decision is a failure (Brockner, 1992). Moreover, the confirmation bias arose from research, which is the penchant for people to selectively seek out information that confirms preexisting beliefs while discounting disconfirmatory evidence (Lord, Ross, & Lepper, 1979).

Overconfidence Effect

The cognitive bias within the heuristics and biases program that is most relevant to my study is the overconfidence effect, which describes an individual's tendency to place greater confidence in their skills, knowledge, and abilities than what is actually and

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objectively warranted (Koriat, Lichtenstein, & Fischhoff, 1980). This bias has been widely studied by researchers within both the psychological and business disciplines. Consequently, a considerable amount of empirical evidence has been produced validating both the existence and implications of this construct. For example, studies have confirmed that individuals tend to overestimate their general knowledge in subjects such as history and geography (Fischhoff, Lichenstein, & Slovic, 1977), excessively express confidence in the accuracy of their responses (Moore & Swift, 2010), and rate their performance as superior relative to others (Svenson, 1981). Overconfidence has also been shown to have a negative impact on organizational activities. Overconfident managers tend to overly depend on debt financing (Hackbarth, 2008), embark on disastrous mergers and acquisitions without engaging in adequate due diligence (Malmendier & Tate, 2008), and fail to exercise appropriate risk mitigation strategies during volatile market situations (Ho, Huang, Lin, & Yen, 2016).

Real-World Settings

The heuristics and biases program has had a significant and pervasive impact on multiple disciplines, including behavioral economics, organizational behavior, management, marketing, political science, neuroscience, communications, law, sociology, medicine, and psychology (Fiedler & von Sydow, 2015). As a result, heuristics and biases have been expansively studied in many real-world settings and decision-making scenarios. For example, the anchoring heuristic has been shown to play a governing role in salary negotiations (Janiszewski & Uy, 2008), judicial sentencing decisions (Enough & Mussweiler, 2001), grocery store purchases (Wansink, Kent, &

Hoch, 1998), and real estate transactions (Scott & Lizieri, 2012). Therefore, the heuristics and biases program has resulted in a vigorous interdisciplinary body of empirical research that has supported the premise that various biases impact decision-making.

Cognitive-Experiential Self-Theory (CEST)

While the heuristics and biases program does not constitute a centralized or unified theory, research produced within this framework has contributed to the formation of other influential theories, including cognitive-experiential self-theory (CEST) (Epstein, 2003). CEST is a dual-process theory of human cognition that posits that people perceive and process information by using two distinct and separate systems: the analytical-rational system and the intuitive-experiential system (Epstein, Pacini, Denes-Raj, & Heier, 1996). The analytical-rational system is characterized by a deliberate, methodical, measured, and logical approach to decision-making, while the intuitive-experiential system is depicted as an automatic, unconscious, emotive, and quick manner by which decisions as made (Epstein, 2003).

The analytical-rational system involves conscious thinking and deliberation. It is slow, intentional, reasoned, and requires effort in the way it processes information. Furthermore, it is the system that enables individuals to think and act logically rather than instinctually, such as delaying gratification, considering long-term consequences to short-term actions, developing and working toward future goals, and regulating impulse and behavior (Epstein, 1991).

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In fact, it is primarily the analytical-rational system that separates humans from other animals. The analytical-rational system of cognition has uniquely endowed humankind with the ability to develop complex languages, create sophisticated societies and institutions, embark on scientific explorations, invent and advance technologies, and engage in abstract and complex thinking (Epstein, 2003). The drawback of this system, however, is that this level of cognitive effort is demanding on the brain's processing abilities. Therefore, people have limited capacity to perform exclusively or unremittingly within this mode (Epstein, 1991).

The intuitive-experiential system functions un- or pre-consciously and is characterized by its holistic, rapid, routine, and affective way of processing information (Epstein, 1994). This system requires minimal reasoning effort since decisions made within this mode are automatic and informed primarily by instinct, past experiences, habitual procedures, or emotional reactions (Epstein, 1998). Operating within this system is sufficient for processing the mundanity and tedium of most everyday tasks, which in turn allows people to allocate finite cognitive resources and attention to decisions better suited for the analytical-rational system.

The intuitive-experiential system was developed through human evolution as an adaptive mechanism of easily, quickly, and efficiently navigating complexity and uncertainty in order to conserve time and energy and ensure survival (Epstein, 1991). Even though this system served an evolutionary purpose, CEST maintains that this system still plays an integral role in modern society. For example, it is theorized that creativity, empathy, aesthetic appreciation, imagination, and interpersonal acuity emerge

from the intuitive-experiential system (Norris & Epstein, 2011). Hence, although CEST recognizes that intuitive judgments and nonanalytic thinking can lead to errors and biases, it acknowledges that intuition and emotionality can positively and constructively contribute to cognition as well (Epstein, 2003).

Both the analytical-rational system and the intuitive-experiential system are believed to function in an interactive, independent, and correspondent fashion with each other. Because these two parallel systems operate in simultaneity and sequentiality with each another, the focus of CEST is not on whether humans are either rational *or* intuitive, but rather how they are both rational *and* intuitive agents (Epstein, 2003). These two systems do not work in isolation from each other; instead, they are inextricable cognitive counterparts (Epstein, 1998).

Although individuals usually have a dominant and preferred thinking style, both decision-making modes are operable to varying degrees in everyone and there is a constant negotiation between these two systems (Pacini & Epstein, 1999). Moreover, both systems are equally important to human cognition, thus neither should be regarded as a subordinate or inferior mode (Epstein, 1998). When individuals do not appreciate both systems, one system can even bias how information is subsequently processed in the other system; either the intuitive-experiential system can prompt individuals to rationalize uncritical and unaware thoughts, or the analytical-rational system can result in the wholesale suppression or devaluation of emotionality (Epstein, 2003). Therefore, the usefulness and benefit of each system should be embraced and both systems should be mutually adjusted in relation to the other's respective strengths and shortcomings.

A theory of self is also embedded into CEST. This aspect of CEST posits that

everyone creates a unique schematic network of reality constructs (Epstein, 2003).

These schemata influence self-concept, worldviews, and attributional judgments made

about others. These ecosystems of beliefs provide perceptual lenses through which

individuals see themselves, others, and the world around them (Epstein et al., 1996).

Subsequent information is processed and assimilated through an individual's existing

mental framework, which helps explain why different people often interpret the same

information differently (Epstein, 2003). CEST conjectures that unconscious and implicit

reality constructs exist in the intuitive-experiential system, while more detailed,

conscious, and explicit theories of reality reside in the analytical-rational system.

"These two theories of reality coincide to different degrees, varying among individuals

and situations" (Epstein, 2003, p. 160).

CEST has provided the theoretical foundation for various psychometric

measures, including the Rational Experiential Inventory (REI) (Epstein et al., 1996),

Decision Styles Scale (DSS) (Hamilton, Shih, & Mohammed, 2016), and Cognitive

Reflection Test (CRT) (Frederick, 2005). In fact, both the DSS and CRT have been used

in the current study. The DSS is a self-report inventory that appraises whether

respondents' decision styles are more rational or intuitive; the CRT is a performance-

based measure that evaluates respondents' tendency to answer questions either quickly,

intuitively, and without much reflection (i.e., incorrectly), or rationally, slowly, and

deliberately (i.e., correctly). In one of the questions of the CRT, respondents are given

the following scenario: A ball and a bat cost a total of $1.10. If the bat costs $1.00 more

than the ball, how much does the ball cost? The intuitive response is $0.10, but the

correct answer is $0.05 (Frederick, 2005). Many people heuristically attempt to solve

this question by simply subtracting $1.00 from the total. By doing so, however, it

shrinks the difference in costs between the ball ($0.10) and bat ($1.00) to only $0.90,

which is violative of one of the conditions of the question. The correct response, which

requires more analytic processing, preserves the difference of $1.00 between the costs of

the ball ($0.05) and the bat ($1.05).

Empirical studies using these derived psychological tools have confirmed and

validated the dual-processing theory of CEST. For example, pharmacy students tend to

have a stronger preference for analytical thinking (McLaughlin, Cox, Williams, &

Shepherd, 2014) and conflict-handling style is related to decision-making style (Cerni,

Curtis, & Colmar, 2012). Furthermore, adherence to religious fundamentalism is

positively correlated with intuitive-experiential thinking (Razmyar & Reeve, 2013;

Watson, Morris, Hood, Miller, & Waddell, 1999) and worldview defense as a reaction to

mortality salience is intensified in the experiential mode (Simon et al., 1997). Therefore,

the existence of a rational system and an intuitive system, as well as a generalized

preference for one system over another, is well-supported by the literature.

Critique of Decision-Making Theories

Herbert Simon introduced the concept of heuristics, Tversky and Kahneman (and

associates) expanded upon this construct, and Seymour Epstein integrated heuristic

processing into a comprehensive dual-processing theory. The theory of bounded

rationality directly challenged the established premise that humans have boundless

rationality, the heuristics and biases program systematized and categorized the many

ways in which limited rationality severely restricts decision-making, and CEST provided

an incorporative model for how rationality and intuition are intricately connected.

Neither of these two theories or research paradigm perfectly encapsulates the

multifaceted complexities associated with decision-making, but together these three

provide a framework that allows for a holistic understanding of the underlying process

by which information is acquired, assimilated, processed, and acted upon.

Critique of Bounded Rationality

Even though the theory of bounded rationality significantly modified RCT, it still

upholds a predominantly rationalistic view of cognition. It maintains that human

decision-making is ultimately a rational activity, albeit in a constrained sense; humans

are still believed to be primarily rational actors, although boundedly so within the

confines of their cognitive limitations. Bounded rationality, therefore, posits that people

behave rationally within the context of simplified models constructed through cognitive

heuristics and mental shortcuts (Munier et al., 1999). A primary critique of this theory is

that it does not adequately take into account affectively-charged, emotion-laden, or

intuitive decisions (Mumby & Putnam, 1992). Consequently, although this theory helps

provide elucidation about the incomplete and imperfect nature and scope of rationality, it

is insufficient in addressing the full range of intricate components involved in decision-

making, especially the intuitive dimension of cognition.

Another weakness of the theory of bounded rationality is its insistence that

optimization is always the ideal scenario and that satisficing consistently leads to

suboptimal decisions (Simon, 1991). While satisficing may result in suboptimality,

satisficing is not always a decisional impairment or deficiency. Sometimes it is justified

to stop the search for more information once an acceptable solution has been located,

especially in real-life scenarios that require quick action or where environmental

constraints and uncertainties abound (Polič, 2009). For example, in crisis events, it

might not be feasible or even advantageous for human decision-makers to gather data for

all options, compute applicable weights, calculate an innumerable array of variables, and

assess every potential choice before finally committing to a course of action. Rather

than spending more time, money, energy, and other resources on exhaustively

researching, weighing, and evaluating all options, sometimes it is necessary to settle on

the first satisfactory solution found. In many applied settings, a quick decision is the

best option, especially in emergency situations where the rapidity of action is positively

related to lifesaving outcomes (Shan & Yang, 2016). Therefore, there can be benefits

and not just impediments to relying on cognitive heuristics.

Critique of the Heuristics and Biases Program

Whereas RCT presupposed an overly optimistic assessment of human rationality,

the heuristics and biases program perhaps advanced an overly pessimistic view,

portraying humans as nearly incapable of doing anything right (Gigerenzer, 1996).

Although Tversky and Kahneman (1974) acknowledged that heuristics can have a useful

and efficient function, most of the research informed by this paradigm has tended to

focus almost exclusively on cataloguing systematic errors, cognitive biases, illusions and

delusions, and fallacious ways of thinking (Fiedler & von Sydow, 2015; Gigerenzer,

2006). Consequently, even though the value of heuristics has been articulated, it has mostly been the adverse and negative effects of heuristics that have received the most academic attention.

Research on the fallibility and unreliability of cognition has greatly contributed to decision-making theory, but this line of research has also been criticized for its seemingly one-dimensional emphasis on reasoning defects and imperfections (Gigerenzer, 1996, 2006; Gigerenzer & Goldstein, 1996). Conversely, some researchers have sought to demonstrate conditions under which heuristic thinking outperforms optimal decision-making and produces more pragmatic decisions. For instance, although clinical judgments have been shown to suffer as a result of heuristic processes (Bonilauri-Ferreira et al., 2010; Garb, 1996), there are times when clinicians are actually more successful when employing heuristic strategies over optimization strategies, such as in emergency medicine settings (Marewski & Gigerenzer, 2012). This counterpoint emphasizes that while it is important to recognize the cognitive biases associated with heuristics, it is also important to understand when heuristic processing is efficient and useful in practice.

While the theory of bounded rationality seems to only address the rational domain of cognition, the heuristics and biases program does at least recognize that there is an intuitive dimension of decision-making. However, this paradigm only rudimentarily acknowledges the dual-processing nature of decisions and tends to negatively characterize intuitive judgments (Epstein, 1991). *System 1* refers to the fast, automatic, emotional, and unconscious mode of heuristic processing, while *System 2*

refers to the logical, deliberative, dispassionate, and conscious mode of rational processing (Kahneman, 2011).

Both systems are conjectured to work dichotomously rather than interactively, and intuition and emotionality are often equated with maladaptive, distortive, irrational, defective, and fallacious decisions (Epstein, 2003). The rational system is treated as the preferred realm of cognitive occupancy, while the emotional system is seen as harmfully invasive to rational thought (Kahneman, 2011). Although the heuristics and biases program theoretically distinguishes between two modes of thinking, it is not as conceptually developed as a dual-processing theory as CEST is. Both systems are depicted as being in opposition rather than partnership with one another, and the rational system is strongly favored over the intuitive system (Pacini & Epstein, 1999).

Despite being around for several decades and producing voluminous studies that shaped the overall interdisciplinary landscape of cognitive, behavioral, and social research, the heuristics and biases program has not led to the development of a refined or comprehensive theory (Fiedler & von Sydow, 2015). This paradigm often serves as an appendage to other theories rather than as a stand-alone or well-defined theory in its own right. Additional theory development, therefore, is needed to give the heuristics and biases program more cohesion, substance, and structure (Fiedler & von Sydow, 2015).

Critique of CEST

CEST attempts to more fully develop the dual-processing functionalities of cognition and present a balanced appraisal of intuitive judgments (Epstein, 2003). Though CEST acknowledges the potentially negative facets often associated with

heuristic processing (e.g., biases and stereotypes), it tries to demonstrate how intuitive and heuristic thinking can also be adaptive, useful, and constructive. Furthermore, this theory provides a rich contextual backdrop against which decisions are made: through individual schematic frameworks. Perceptions, emotions, experiences, values, and mental frames influence how individuals uniquely construct reality and process and interpret information (Epstein et al., 1996). The self-theory aspect of CEST is an important contribution to decision-making theory because it describes how individuals interact with and cognize the self in relation to others and the broader world.

Although CEST has a lot in common with heuristics and biases research, CEST does diverge in four important areas. First, CEST recognizes two fully functional and conceptual systems that operate in orthogonality rather than dichotomy with one another. Second, CEST presents a global theory of personality, meaning that intuition is holistically, simultaneously, and sequentially integrated with rationality. Third, CEST postulates that although individuals may have a preferred or dominant mode of thinking, both systems are employed to varying degrees by everyone. Finally, CEST views heuristics as being evolutionary as well as contemporary tools for adaptability, rather than just as quirks or deficiencies that need to be eliminated altogether (Epstein, 2003).

CEST proposes a more balanced and auspicious view of intuitive processing than the heuristics and biases program, but it is still often assumed that the intuitive-experiential system is more susceptible to judgment errors and that the analytical-rational system is unbiased and more conducive to higher decision quality (Kirkpatrick & Epstein, 1992). Accordingly, decision-makers who have a dominantly rational

thinking style are presumably less likely to engage in biased thinking than their more intuitively-minded counterparts (Pacini & Epstein, 1999). This hypothesis is based on the assumption that biases originate from and reside in the intuitive-experiential system and not in the analytic-rational system.

However, empirical findings are mixed on validating whether or not intuitive thinkers are more vulnerable to biased decisions than rational thinkers. For example, one study found that it was individuals with a preferred rational thinking style who were more likely to escalate their commitment to prior decisions (Wong, Kwong, Ng, 2008). Another study revealed no statistically significant differences between rational and intuitive thinkers and their susceptibility to the conjunction fallacy, the cognitive bias by which individuals mistakenly calculate multiple specific conditions as being more probable than just a single general condition (Lu, 2015). These conflicting results raise the question about the locality of biases within the rational and intuitive systems and seem to suggest that certain biases may possibly also occupy – or at least pervade – the analytical-rational system.

Another critique of CEST is that some elements of it are theoretically artifactual and not necessarily empirically supported. In fact, the only component of CEST that has been subjected to substantial statistical examination is the premise that individuals have a preferred mode of information-processing and decision-making (Pacini & Epstein, 1999). While the evolutionary hypothesis that heuristics were developed as a means of adaptation, the self-theory notion that people construct individual realities and filter information through their unique schemata, and the cognitive assumption that empathy

and creativity inhabit the intuitive-experimental system are theoretically descriptive and explanatory, these three constituents of CEST have not been empirically confirmed.

The lack of validation for some of CEST's tenets is not surprising given the problematic nature of evaluating certain philosophical, psychological, and evolutionary principles. Evolutionary postulates often pose appreciable testability and falsifiability challenges (Confer et al., 2010). Also, theories and concepts of self are not easily "accessible to empirical investigation" (Gecas, 1982, p. 3). Moreover, cognitive typologies and conceptualizations are frequently difficult to operationalize in quantitatively measurable ways (Haslam & McGarty, 2019). Therefore, additional methodological development is needed to translate some of CEST's fuzzy concepts into more quantifiably observable constructs and variables.

The Importance of Decision-Making Literature to the Current Study

The current study is firmly situated within a larger theoretical framework of decision-making, consisting of the theory of bounded rationality, heuristics and biases program, and cognitive-experiential self-theory. Three cumulative insights were especially gleaned from these theoretical resources. First, rationality and cognitive capacity are limited. Second, heuristics and associated biases frequently obscure human judgments (including the overconfidence effect). Third, individuals tend to have a preferred and dominant mode by which they process information and subsequently render decisions. It is this integrative understanding of human decision-making that informed this study.

Relevant Bodies of Literature

The bodies of literature that are relevant to this study are expertise and the overconfidence effect. The next two sections delve into applicable findings that were identified from these reviews. First, an integrative literature review of expertise was conducted from an HRD lens so that a multidimensional construct of expertise could be developed. Second, a multidisciplinary overview of the overconfidence effect is provided.

Integrative Synthesis of the HRD Expertise Literature

The methodology I used to research the HRD expertise literature was an integrative one, which involves reviewing, critiquing, and synthesizing the relevant and representative literature to generate new knowledge, perspectives, and frameworks about the topic (Torraco, 2005, 2016). An integrative literature review is a meticulous research method designed to reduce selection bias, enhance rigor, and increase systematicity, transparency, and reproducibility in the review process (Whittemore & Knafl, 2005). The search strategy, screening and eligibility determination process, and data management tools I employed are detailed in the following sections.

Next, I critically analyzed the themes I extracted from the HRD expertise literature. "Although some integrative literature reviews may encompass more than one body of literature, more frequently they are truly exploring the depth of a major topic within the field" (Callahan, 2010, p. 301). While expertise is a multidisciplinary topic, this integrative literature review aimed to exhaustively explore how expertise has been constructed specifically within the field of HRD. In doing so, I was able to develop a

hypothesized multidimensional construct of expertise that was informed by the literature and that guided my current study of overconfidence. This construct is presented in the final section of this integrative synthesis.

Search Strategy

Because the objective of this integrative review was to investigate how expertise has been specifically conceptualized within HRD, I comprehensively gathered data (i.e., literature) from five flagship HRD journals. Four of these journals are sponsored by the Academy of Human Resource Development (AHRD): *Advances in Developing Human Resources* (*ADHR*), *Human Resource Development International* (*HRDI*), *Human Resource Development Review* (*HRDR*), and *Human Resource Development Quarterly* (*HRDQ*). The fifth journal selected is *European Journal of Training and Development* (*EJTD*), including its predecessor journal, *Journal of European Industrial Training* (*JEIT*). These journals were selected for their centrality in advancing and publishing HRD research.

The databases I used to search for relevant literature were SAGE Complete for *ADHR* and *HRDR*, EBSCOhost Business Source Ultimate for *HRDI* and *HRDQ*, and the ABI/INFORM® Collection through ProQuest for *JEIT/EJTD*. The keyword I used was "expert" with the search modifier "*" to capture related terms like "expertise" and "experts." This Boolean expression was used without alteration to search abstracts across the three databases.

There were three initial limiters applied to my search: (a) scholarly (i.e., peer-reviewed) sources; (b) articles written in English; and (c) articles published since 1997.

I deemed peer-reviewed articles as essential to my literature review since these sources undergo a rigorous process by which submissions are reviewed by other scholars of the same discipline. These sources are often considered to have met the high-quality standards necessary for academic publication. Secondly, only articles published in English were selected because of the difficulties associated with reviewing literature written in other languages, such as having to translate those sources. Finally, January 1997 to December 2020 was the timeframe used in the search because I wanted to focus on reviewing the most current scholarship in the field. With that said, this limiter only impacted two of the five journals: *JEIT/EJTD* and *HRDQ*. The other three journals were not established until after 1997. Therefore, *ADHR*, *HRDI*, and *HRDR* were searched in the entirety of their publication.

Screening Process and Eligibility Determination

A total of 164 results were retrieved across the three databases after the initial search and one duplicate was found. Once the duplicate was removed, a total of 163 articles remained. These remaining articles were then screened for potential inclusion in the integrative literature review.

To determine which articles should be included, I conducted "a staged review (i.e., an initial review of abstracts, then an in-depth review)" (Torraco, 2005, p. 361). After I completed an initial screening of the 163 abstracts, I excluded 117 articles based on those articles not being relevant to the topic of expertise. Although "expert" or some variant of that keyword may have appeared in those excluded abstracts, it was only superficially or immaterially referenced.

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The next round of the staged review involved a full-text assessment of the remaining 46 articles. Inclusion criteria included (a) peer-reviewed articles that were (b) written in English and were (c) substantially about expertise, especially about the elements, components, dimensions, or properties of expertise. Exclusion criteria included (a) non-refereed articles (such as book reviews or editorials) that were (b) written in a language other than English and/or (c) did not substantively discuss or advance a construct of expertise. After the second round of the staged review, 16 articles were excluded and 30 articles were included.

Four additional articles were identified from the full-text assessment of the 30 included articles. These additional sources were evaluated and added to the list of included articles because of their relevance, significance, and essentiality to the topic of review. Although these four sources were published in journals outside of the five HRD journals, they were deemed germane and indispensable to my integrative literature review because of being prominently discussed by HRD researchers. In fact, two of these articles were written by HRD scholars and the other two articles closely examined the work of those HRD scholars. A total of 34 peer-reviewed articles were included in this integrative literature review about expertise from an HRD research lens (see Table 2.1 for a breakdown of the data set by source).

Table 2.1

HRD Expertise Articles by Source

	ADHR	HRDI	HRDR	HRDQ	JEIT / EJTD	Other
Initial identification	26	35	13	43	47	0
Duplicates removed	0	0	0	0	1	0
Abstracts screened	26	35	13	43	46	0
Excluded after screening	18	26	9	33	31	0
Included after screening	8	9	4	10	15	0
Full-text review	8	9	4	10	15	4
Excluded after review	1	2	0	4	9	0
Final inclusion	7	7	4	6	6	4
% of included articles	20.6%	20.6%	11.8%	17.6%	17.6%	11.8%

Data Management and Analysis

I utilized three data management tools for this integrative literature review: (a) RefWorks through ProQuest; (b) a modified flow diagram based on the PRISMA model (Moher, Liberati, Tetzlaff, & Altman, 2009); and (c) a review matrix where I entered summary information in Excel about the included articles (Garrard, 2017). These tools helped me organize, manage, and document the data used in this review process. Also, these tools facilitated a more dexterous and thorough analysis and synthesis of the data.

Once I searched the databases, I exported the results to RefWorks. From RefWorks, I was able to remove any duplicate records, complete the initial screening by reading the abstracts, and keep track of included and excluded articles by creating a "Yes" and "No" subfolder. After I read the full-text articles from the "Yes" folder, I removed any subsequently excluded articles from that stage and placed those into a

subfolder named "No-Round 2." The articles remaining in my "Yes" folder comprised

the articles included in this integrative literature review. The flow diagram I produced

graphically illustrates this multiphasic process (see Figure 2.1).
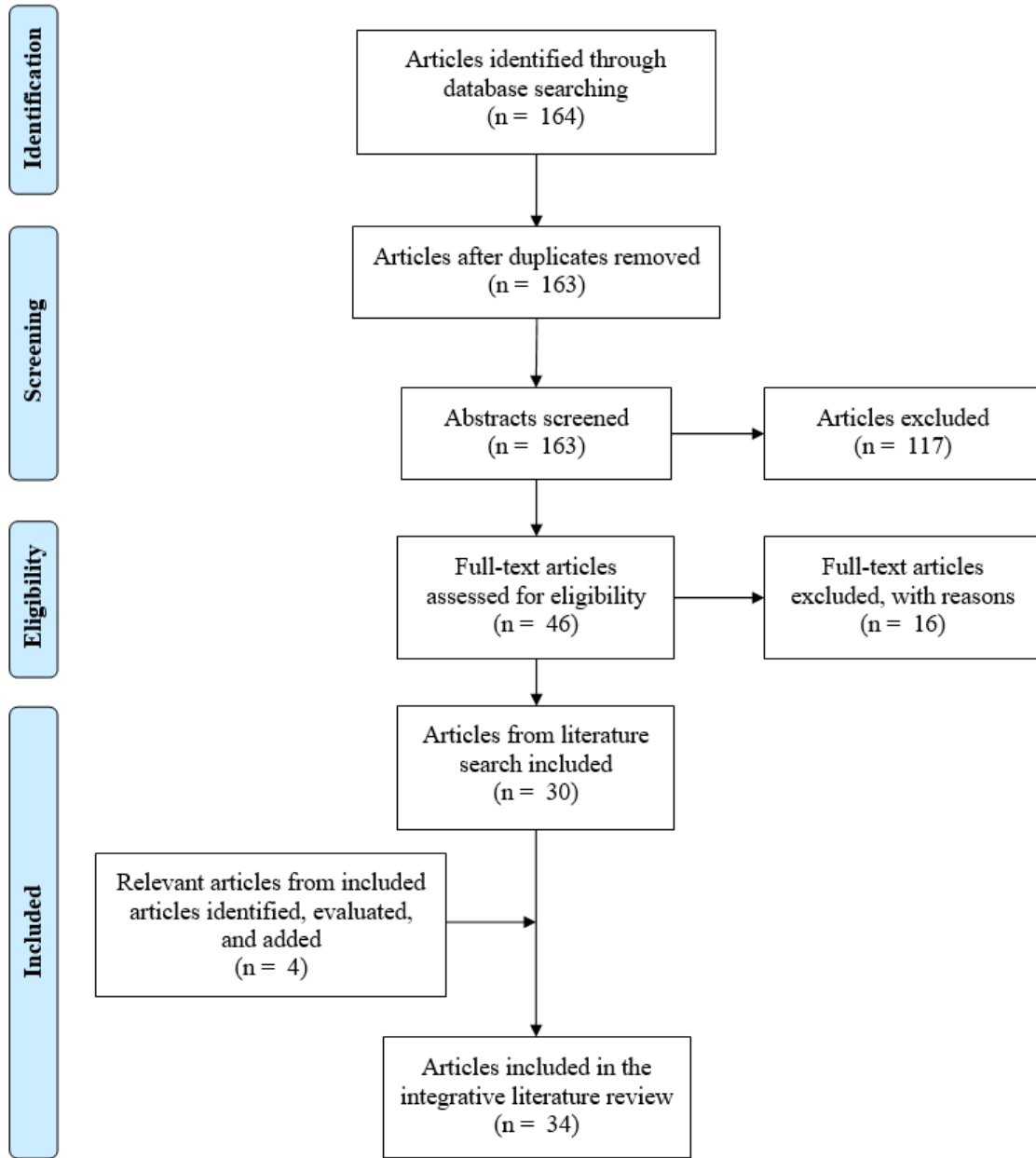
Figure 2.1. Flow diagram of the integrative review of the HRD expertise literature

Finally, the literature review matrix I created in Excel was leveraged to help me closely examine the data. As I read each article in its entirety, I extracted and transferred relevant information over to the matrix. Each row dissected and summarized one article and I used the following column headers to aid in my analysis: author(s) and publication year, title, journal, research questions and hypotheses, theoretical/conceptual frameworks, methods, context, and key findings related to expertise. This segmentation helped me identify and synthesize emergent themes from the literature. An illustrative review matrix is provided below (see Table 2.2).

Findings

Several themes materialized from this integrative literature review that were aligned with my objective to explore expertise within an HRD research lens. This section presents these major findings. The first subsection is a review and appraisal of how expertise has been constructed and conceptualized in past research. In the next subsection I closely examined each dimension of expertise that I was able to excavate from the literature. Finally, in the last subsection I proposed and adopted my own construct of expertise based on my analysis and synthesis of the literature. It is this proposed construct that has influenced the current study.

How Expertise Has Been Constructed and Conceptualized

The textbook conceptualization of expertise is that it operates within a dynamic state, is domain-specific, and contains the dimensions of knowledge, experience, and problem solving (Swanson & Holton, 2009). Although some researchers agree with these basic dimensions (Herling, 2000; Herling & Provo, 2000; Jeong, McLean,

McLean, Yoo, & Bartlett, 2017), this has not become the universally accepted construct

of expertise. Rather, there is a diversity of thought within HRD scholarship regarding

the constituents and properties of expertise (see Table 2.3).

Table 2.2

Illustrative Review Matrix of HRD Expertise Literature from 1997 to 2020

Author(s) & Year	Title	Research Questions / Hypotheses	Purpose	Theoretical/ Conceptual Framework	Methods	Context	Key Findings Related to Expertise
Gartmeier, Bauer, Gruber, & Heid (2010)	Workplace errors and negative knowledge in elder care nursing	1. What forms of workplace errors is negative knowledge related to? 2. What conclusions on error-producing conditions can be drawn from negative knowledge?	To understand what types of errors are related to negative knowledge and how negative knowledge can build expertise	Negative knowledge	Case study and prompting task technique (PTT)	Elder care nurses	Negative knowledge comes from experience and the metacognitive ability to reflect on error-producing condition. Errors provide opportunities to gain knowledge and learn insights that expand expertise.
Germain & Ruiz (2009)	Expertise: Myth or reality of a cross-national definition?	1. Are researchers' perceptions of expertise similar in Western Europe and the USA? 2. Does the construct of expertise include a self-enhancement dimension?	To offer a comparison of how human expertise is perceived by human resource development (HRD) scholars across several Western European countries and in the USA.	Expertise and employability research; work and organizational psychology	Qualitative, exploratory interviews of HRD scholars	11 different countries across Western Europe and the USA	Scholars across the world have differing definitions of expertise, but four consistent dimensions emerge: 1) knowledge, 2) skills, 3) expertise, and 4) domain specificity
Germain & Tejeda (2012)	A preliminary exploration on the measurement of expertise: An initial development of a psychometric scale	1. Can an instrument to measure expertise be developed? 2. What are the characteristics of an expert, as perceived by employees?	To develop a measure of expertise (the generalized expertise measure [GEM])	HRD expertise theory, cognitive psychology	Qualitative inquiry (panel) to generate themes; exploratory factor analysis and confirmatory factor analysis to evaluate psychometric properties of hypothesized themes	Expertise as perceived by others	The Generalized Expertise Measure (GEM) was developed, which measures expertise as perceived by another person. Objective expertise: Knows work, education, knows field, qualification, has training, does research. Subjective expertise: is ambitious, has drive, improves, charismatic, deduce, intuitive, judges, self assured, assesses, confident, outgoing, talks through
Govaerts, van de Wiel, & van der Vleuten (2013)	Quality of feedback following performance assessments: Does assessor expertise matter?	Do differences in assessor expertise affect the quality of feedback?	To investigate quality of feedback as offered by supervisor-assessors with varying levels of assessor expertise; if and how different levels of assessor expertise influence feedback characteristics	Feedback; performance development; performance assessment	Quasi-experimental design and mixed methods, qualitative content analysis	General practice supervisors in the Netherlands	Years of experience was used as a measure for expertise. Training in performance assessment and feedback may play a larger role in assessment quality than the individual characteristics of assessors.
Grenier & Kehrhahn (2008)	Toward an integrated model of expertise redevelopment and its implications for HRD	What domain or contextual factors affect expertise development and retention?	To propose a model to understand expertise development, maintenance, and adaptation in complex and ever-changing organizational contexts	Expertise redevelopment	Literature review		Presents a Model of Expertise Redevelopment (MER); expertise is renewed in three states: dependence, independence, and transcendence. These states are influenced by the territories of content, constituency, and environment.

Table 2.3

Summary of the Various Theorized Dimensions or Factors of Expertise

Author(s)	Dimensions or Factors
Herling (2000) Herling & Provo (2000) Jeong, McLean, McLean, Yoo, & Bartlett (2017) Swanson & Holton (2009)	• Knowledge • Experience • Problem solving
Germain & Ruiz (2009)	• Knowledge • Experience • Skills • Domain specificity
Evers, Van der Heijden, Kreiijns, & Gerrichhauzen (2011)	• Knowledge • Meta-cognitive knowledge • Skills • Social recognition
Evers, Kreiijns, Van der Heijden, & Gerrichhauzen (2011) Frie, Potting, Sjoer, Van der Heijden, & Korzilius (2019) Van der Heijden (2000) Van der Heijden & Brinkman (2001) Van der Heijden & Verhelst (2002)	• Knowledge • Meta-cognitive knowledge • Skills • Social recognition • Growth and flexibility

Table 2.3 (continued)

Author(s)	Dimensions or Factors
Germain & Tejeda (2012)	*Knowledge, experience, and problem solving are embedded into the following objective and subjective expertise factors:* ***Objective expertise factors:*** • Knowledge about work • Education • Knowledge about field • Qualifications • Training • Conducts research ***Subjective expertise factors:*** • Ambition • Drive • Self-improvement • Charisma • Deductive reasoning • Intuitiveness • Judgement • Self-assurance • Ability to assess work-related situations • Self-confidence • Outgoingness • Ability to talk through work-related situations

Table 2.3 (continued)

Author(s)	Dimensions or Factors
Kuhlmann & Ardichvili (2015)	*Experiential factors that activate expertise:* • High-value, non-routine work • Intelligence commensurate with the discipline • Willingness to work hard • Fascination with one's discipline • Ambiguity tolerance • Exposure to increasingly complex work issues
Bohle Carbonell, Könings, Segers, & van Merriënboer (2016)	*Dimensions of adaptive expertise:* • Domain-specific skills • Innovative skills

Cross-National Construct. A lack of consensus about how expertise should be conceptualized has led some researchers to try to create a consolidated construct of expertise. Germain and Ruiz (2009) interviewed 36 HRD scholars from the United States and across Western Europe (i.e., Denmark, England, Finland, France, Germany, Ireland, Italy, Scotland, Sweden, and The Netherlands). These scholars were asked to share their personal definition of expertise as well as the definition they believed as the most widespread in their country. Multiple definitions of expertise were offered, most of which were heavily influenced by where the participants lived. For example, the scholars from the United States commonly viewed expertise as existing within the three classical dimensions of knowledge, experience in one's domain, and problem-solving skills, while the scholars from England tended to define expertise as "a combination of skills, abilities, competence, experience, knowledge, domain specificity, and personal characteristics" (Germain & Ruiz, 2009, p. 628).

Despite lingering differences, Germain and Ruiz (2009) were able to propose a shared U.S.-European definition of expertise based on overlapping areas of agreement, which is that "expertise is the combination of knowledge, experience, and skills held by a person in a specific domain" (p. 614). The four proposed dimensions that emerged from comparing respondents' definitions of expertise were knowledge, skills, experience, and domain specificity, which are similar to the three dimensions proposed by Swanson and Holton (2009). The skills dimension especially seeks to reconcile and accommodate diverse definitions of expertise. Though some participants considered skills to be problem-solving in nature, others interpreted skills to be more accurately

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related to concepts such as judgment, intuition, deduction, critical thinking, managerial competence, or metacognition (Germain & Ruiz, 2009). While this cross-national construct does accomplish some harmony, it does not resolve every disagreement.

Multidimensional Construct and Operationalization of Expertise. Five articles from Van der Heijden and associates posited that expertise consists of five dimensions: (a) knowledge; (b) meta-cognitive knowledge; (c) skills; (d) social recognition; and (e) growth and flexibility (Evers, Kreiijns, Van der Heijden, & Gerrichhauzen, 2011; Frie, Potting, Sjoer, Van der Heijden, & Korzilius, 2019; Van der Heijden, 2000; Van der Heijden & Brinkman, 2001; Van der Heijden & Verhelst, 2002). Interestingly, the researchers opted for a four-dimensional construct in one study and did not include the fifth dimension (Evers, Van der Heijden, Kreiijns, & Gerrichhauzen, 2011). Most often, though, a five-dimensional construct of expertise has been presented. A psychometric tool based on this hypothesized construct was created that validated these five dimensions of expertise (Van der Heijden, 2000; Van der Heijden & Verhelst, 2002). Additionally, the terms *professional expertise* (Van der Heijden, 2000; Van der Heijden & Brinkman, 2001; Van der Heijden & Verhelst, 2002) and *occupational expertise* (Evers, Kreiijns, et al., 2011; Evers, Van Der Heijden, et al., 2011; Frie et al., 2019) have been used interchangeably by these researchers.

The first and second dimensions are closely related in that both refer to the different types of knowledge that experts ostensibly need to employ, which are declarative knowledge ('knowing that'), procedural knowledge ('knowing how'), conditional knowledge ('knowing when and where or under what conditions'), and

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meta-cognitive knowledge ('knowing about knowing' or 'knowing that one knows') (Van der Heijden & Verhelst, 2002). The third dimension of skills denotes the activities, responsibilities, and capabilities one needs in order to successfully perform a job (Van der Heijden, 2000). These first three dimensions are fairly similar to "earlier conceptualizations of the construct of expertise" (Van der Heijden & Brinkman, 2001, p. 180).

The fourth and fifth dimensions are what primarily set Van der Heijden's (2000) construct of expertise apart from other constructs. The fourth dimension of social recognition acknowledges that in order to be an expert, one should also possess the attributes needed to be regarded as an expert, such as social intelligence and communication dexterity (Van der Heijden, 2000). This dimension shows that there is an aspect of expertise that is not entirely self-determined but rather is established and authenticated by the perceptions of others. Finally, the dimension of growth and flexibility has to do with an expert's ability to adapt quickly to environmental changes and acquire additional expertise in adjacent or even distant areas, fields, and territories (Van der Heijden & Verhelst, 2002). This fifth dimension bears a close resemblance to the concept of adaptive expertise (Bohle Carbonell, Stalmeijer, Könings, Segers, & van Merriënboer, 2014).

Construct and Measurement of Adaptive Expertise. Adaptive expertise has been widely depicted as the configuration of both domain-specific and innovative skills, and some researchers have even conjectured that a third dimension exists as well: metacognitive skills (Bohle Carbonell, Könings, Segers, & van Merriënboer, 2016).

Domain-specific skills are the competencies for an expert to dynamically continue to acquire and integrate new expertise, innovative skills are the abilities for an expert to flexibly adapt to changing and novel contexts, and metacognitive skills are the capacities for self-awareness and self-insight (Bohle Carbonell et al., 2016). The existence of the metacognitive skills dimension of adaptive expertise is contested among scholars (Bohle Carbonell et al., 2014; Bohle Carbonell et al., 2016).

The Adaptive Expertise Inventory is an instrument that was developed based on the findings assembled from a systematic literature review of adaptive expertise (Bohle Carbonell et al., 2014). This instrument was created with the goal of measuring and validating these three hypothesized dimensions of adaptive expertise, in addition to being amendatory to Van der Heijden and Verhelst's (2002) earlier measurement. The Adaptive Expertise Inventory confirmed domain-specific skills and innovative skills as components of adaptive expertise but found no correlation between adaptive expertise and metacognitive skills (Bohle Carbonell et al., 2016). Therefore, metacognitive skills was removed as a theoretical dimension of adaptive expertise and the finalized construct includes just two dimensions: 1) domain-specific skills and 2) innovative skills.

Experiential Components of Expertise within an Applied Setting. Kuhlmann and Ardichvili's (2015) research generated new insights about the type and quality of work experience that is most conducive to the development of expertise in an applied discipline. They proposed that professionals are more likely to successfully develop expertise through years of high-value and non-routine work, especially when these professionals are intelligent proportionate to the intelligence required for their discipline,

willing to work hard, fascinated by their discipline, tolerant of ambiguity, and able to engage in increasingly more complex issues. This research does not postulate a construct of expertise, but it does suggest experiential attributes that positively contribute to the progressive growth and development of expertise. However, there are two challenges with relying on these theoretical components: (a) they have not been empirically validated; and (b) the generalizability or applicability of these findings to other settings has not yet been demonstrated.

Generalized Expertise Measure (GEM). Based on employee expertise as perceived by others, Germain and Tejeda (2012) conceptually and empirically developed a psychometric tool called the Generalized Expertise Measure (GEM). The idea of expertise as regarded by others seems to be compatible with the dimension of social recognition found in Van der Heijden's (2000) construct of expertise. The expertise dimensions of knowledge, experience, and problem-solving skills are embedded into the GEM instrument, so it does accept Swanson and Holton's (2009) construct as operational. The purpose of the GEM, therefore, is not to offer a competing construct of expertise, but rather to identify measurable factors and components of those three dimensions of expertise. One limitation of the GEM is that it is incompatible with studies designed to rely on self-report data. Nevertheless, the GEM does provide valuable insights into how the dimensions of expertise can be operationalized and translated into variables.

The GEM is composed of 18 items that are divided into two categories: objective expertise and subjective expertise. Six items measure objective expertise and 12

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measure subjective expertise. The objective expertise items include knowledge about one's work, education, knowledge about one's field, qualifications, training, and research. These objective items are considered to be formally measurable and externally verifiable, such as through certifications, diplomas, and transcripts. Subjective expertise items, on the other hand, represent the perception but not the validation of expertise and have the potential to "create the illusion of expertise without any basis or evidence" (Germain & Tejeda, 2012, p. 223). The 12 subjective expertise items include ambition, drive, self-improvement, charisma, deductive reasoning, intuitiveness, judgement, self-assurance, ability to assess work-related situations, self-confidence, outgoingness, and ability to talk through work-related situations.

Model of Expertise Redevelopment (MER). In addition to proposing constructs or measurements for expertise, HRD researchers have also advanced models in an attempt to better understand expertise. Of particular interest to the current study is the Model of Expertise Redevelopment (MER), which aims to explore how the initial development of expertise is subject to loss and must be continuously redeveloped (Grenier & Kehrhahn, 2008). The MER essentially concurs that the three foundational dimensions of expertise are knowledge, experience, and problem-solving skills. Nevertheless, it contributes the idea of redevelopment to the expertise literature, without recommending a new or replacement construct.

The MER acknowledges that expertise is not permanently attained; instead, it is dynamic and requires an unremitting "process of learning, experimenting, and reflecting in response to changes in contextual forces" (Grenier & Kehrhan, 2008, p. 202). The

MER is a bipartite model that explicates the three progressive states of expertise redevelopment (i.e., dependence, independence, and transcendence) and three contextual territories that shape the need for that redevelopment (i.e., content, environment, and constituency).

Dependence is the first state of expertise and is characterized by one's "reliance on other people or sources of information" (Grenier & Kehrhan, 2008, p. 207). Independence is the next state and occurs when someone can incorporate and supplement an existing knowledge base with new information, especially through experimentation. Finally, independence progresses into transcendence when individuals have a command for their knowledge areas and can create new knowledge and practices rather than relying on existing templates or standardized routines. Although these three states are progressive, they are not linear. Alternatively, they are cyclical and are triggered by changes to the territories of expertise (Grenier & Kehrhan, 2008).

The territories of expertise include three interrelated and overlapping contexts: content, environment, and constituency (Grenier & Kehrhan, 2008). Content refers to the knowledge and information needed for someone to successfully function in a particular role. The environmental context involves external factors such as organizational structures, legal and political landscapes, and the stability of the labor market. Finally, the context of constituency refers to groups that either influence or are influenced by someone, such as a client base or a board of directors. "When one or more of these factors are significantly altered, the result is a need for redevelopment of expertise" (Grenier & Kehrhan, 2008, p. 209). Therefore, these territories act as

galvanic currents that influence the activation of the various states of expertise and determine the conditions under which redevelopment is necessary.

Previous Integrative Literature Review. While conducting my integrative literature review about how expertise has been constructed within HRD, I came across a recent and outwardly resemblant article from *HRDR* titled "Construct of Expertise within the Context of HRD: Integrative Literature Review" (Cherrstrom & Bixby, 2018). At first glance and based on the title alone, this review appears nearly identical to my own and seems to possibly render my work duplicative and unnecessary. However, there are considerable differences between this previous integrative literature review and my own that maintain and justify the uniqueness, originality, and necessity of my review.

First, one of the inclusion criteria that Cherrstrom and Bixby (2018) used was the number of times expert(s) or expertise were referenced in each article. Articles that made five or more references were included, while articles that made four or fewer references were excluded. In developing my own inclusion criteria, I did not assign an arbitrary number of times that a particular keyword should appear in an article. Rather, I assessed the content of each article in its entirety to determine if it was significantly related to the construct of expertise, particularly if it provided insightful information about the various dimensions, properties, elements, or components of expertise. Just because an article might mention expertise a certain number of times does not mean that it necessarily makes a research contribution about the construct of expertise.

Conversely, just because an article might not reference expertise a set number of times does not mean that it fails to be informative to expertise research.

Secondly, Cherrstrom and Bixby (2018) only included the four journals that the AHRD sponsors: *ADHR*, *HRDI*, *HRDR*, and *HRDQ*. In my data search, I also selected *EJTD*/*JEIT*, which provided approximately 18% of my final data set. Although this fifth journal is not sponsored by the AHRD, it is still considered a premier publication within HRD, which is why I made the decision to include this publication in my literature search. Moreover, I added four external articles to my final data set that were identified from a full-text assessment of the included HRD articles. Although these four articles were not published in HRD journals, they were identified by HRD researchers as being notably germane to the topic of expertise; most of which are even considered to be landmark studies (viz., Bohle Carbonell et al., 2016; Van der Heijden, 2000; Van der Heijden & Verhelst, 2002).

Third, Cherrstrom and Bixby (2018) used a time period of 2006 to 2017 in their literature search, while I used a time period of 1997 to December 2020. Cumulatively, these three differences did result in some similarities, but we ultimately had divergent data sets. Cherrstrom and Bixby's (2018) review yielded an initial search of 120 publications and a final inclusion of 51 articles, while my review furnished an initial search of 164 publications and a final inclusion of 34 articles. My search strategy generated a larger initial literature base, while my more selective inclusion criterion to determine relevance based on a full-text analysis rather than the number of mentioned occurrences of expert/expertise produced a smaller final data set.

The last and most significant difference between our reviews is the overall

outcome of our research. The aims of my review were to extract dimensions of expertise

from the literature and propose a construct based on this review that could then be

translated into measurable factors for the purpose of the current study. The outcome of

Cherrstrom and Bixby's (2018) review was that they catalogued the major topics that

have recently become associated with expertise. In fact, despite what the title of their

article might suggest, their review does not actually define or recommend a construct of

expertise. Rather, their work is more exploratory in that they identified and itemized the

six emergent themes of "expertise and assessment, workforce development, professional

development, leadership development, redevelopment, and elicitation and transfer"

(Cherrstrom & Bixby, 2018, p. 440). These are broad associated topics rather than

dimensions or elements of expertise that have been incorporated into a revised definition

or proposed construct of expertise. Therefore, although their review helps survey

current and developing themes related to expertise, my review is more focused on

advancing an operational construct of expertise.

The Dimensions of Expertise

In this section, I examined each of the dimensions of expertise that surfaced from

my review of the literature. Although contemporary constructs of expertise range from

three to five dimensions, I organized them into three categories as follows: knowledge,

experience, and the elusive "it" factor of expertise. There is appreciable concurrence

among scholars about the existence of knowledge and experience as dimensions of

expertise, but there is greater incongruity about the composition of the remainder.

Therefore, I have explored the varied thoughts around what all should be encompassed within a theorized third dimension.

Knowledge. There is an overwhelming consensus that knowledge is a key dimensional component of expertise (Evers, Kreiijns, et al., 2011; Evers, Van der Heijden, et al., 2011; Germain & Ruiz, 2009; Herling, 2000; Herling & Provo, 2000; Jeong et al., 2017; Swanson & Holton, 2009; Van der Heijden, 2000; Van der Heijden & Brinkman, 2001; Van der Heijden & Verhelst, 2002). The distinctive feature of expert knowledge is its domain specificity (Herling & Provo, 2000). Although Germain and Ruiz (2009) presented domain specificity as its own dimension, it is more commonly considered to be the differentia of expert knowledge as opposed to general knowledge (Herling, 2000; Herling & Provo, 2000; Swanson & Holton, 2009). Since knowledge is domain-specific, "the demonstration of expertise in one domain is no guarantee of expertise in other areas" (Herling, 2000, p. 14). For example, being a technical expert does not automatically translate into being an expert trainer of that same technical skill. Training requires its own unique knowledge and skill set, such as instructional design, effective and engaging communication, and planning techniques (Johnson & Leach, 2001). The same principle applies to expert nurses who might be relied upon to mentor nursing students. Because nursing and nursing education are actually two separate knowledge domains, these clinical experts are often placed in situations where they are essentially novices in the area of preceptorship (Miller, Vovona, & Roth, 2017).

Another major theme of knowledge is how it is attained and developed. Even though academic education is often what first comes to mind when thinking about how

knowledge is acquired, formal learning by itself is not sufficient to develop expertise. This is because professional knowledge requires interactive skills as well as cognitive skills (Grenier, 2013). Additionally, formal education imparts general technical knowledge, however, as Melo and Beck (2005) noted, it "does not deliver the specific knowledge required in the professional workplace" (p. 159). This type of professional education frequently occurs through channels such as networking (Melo & Beck, 2015), knowledge sharing (Valkeavaara, 2000), and professional organizations and associations (McLean & Akdere, 2015).

Furthermore, the initial attainment of knowledge is transitory. The requisite content (i.e., knowledge and skills) needed to proficiently perform a job is unstable and subject to rapid and wholesale contextual changes. Therefore, knowledge must be recurrently cultivated, maintained, and even redeveloped in order to remain functional and relevant (Grenier & Kehrhan, 2008). Because domain-specific knowledge changes quickly and frequently, experts must seek out opportunities for continuous improvement. Expert knowledge can be nurtured through continuing professional education (CPE)/continuing professional development (CDP) (Hashim & Ahmad, 2013), communities of practice (Valkeavaara, 2000), and learning sponsored by organizations, professional associations, specific industries, etc. (Melo & Beck, 2015). The "process of continuous learning is characterized by the constant acquisition of knowledge [and] reorganization of information" (Herling, 2000, p. 14).

The final theme related to knowledge is how it can be validated. Knowledge is deeply rooted in the Generalized Expertise Measure (GEM) through the objective

expertise items of knowledge about one's work, education, knowledge about one's field, qualifications, training, and research (Germain & Tejeda, 2012). Some of the primary ways that knowledge can be confirmed and verified are through knowledge assessments, diplomas, transcripts, credentials, and active involvement in one's profession (Germain & Tejeda, 2012). Furthermore, certifications such as those provided by the Society for Human Resource Management (SHRM) can "show that the holder of the certificate is competent to perform in that role" (McLean & Akdere, 2015). Although these might not be perfect measures, these do at least provide some substantiable evidence about someone's acquisition of professional knowledge.

Experience. Experience does not enjoy as extensive of a consensus among HRD scholars as knowledge, but it is still widely considered to be a fundamental component of expertise (Germain & Ruiz, 2009; Germain & Tejeda, 2012; Herling, 2000; Herling & Provo, 2000; Jeong et al., 2017; Swanson & Holton, 2009). While Van der Heijden and Verhelst (2002) do not formally recognize experience as a dimension of expertise, they do at least acknowledge that the accumulation of professional experience "results in a certain degree of expertise in various domains and in different aspects" (p. 166). Notwithstanding, experience is largely regarded as a core element of expertise by the majority of HRD researchers.

Expertise requires specific decision-making mental models that can only be gradually developed over time with experience (Chermack, 2003b; Swanson, 2003b). Likewise, the development of skills necessitates prolonged exposure to opportunities for practice, these opportunities come primarily through work experiences, and these work

experiences are especially what help translate experience into expertise (Torraco, 1999). The MER also acknowledges that expertise is derived from vast amounts of experiences in a particular domain (Grenier & Kehrhan, 2008).

While it is generally agreed that a sizable amount of experience is crucial before one achieves expertise, the exact amount of experience is arguable. The "10,000-hour rule" is a well-known and often-cited benchmark for the minimum number of hours it purportedly takes for expertise to sprout from experience (Herling & Provo, 2000). This rule is based on the observation that it took chess players between 10,000 and 20,000 hours of practice before reaching a master level of chess. From this study came the hypothesis "that to become an expert, one must have the equivalent of ten years of combined studies and related work experience" (Herling, 2000, p. 15).

It should not be generalized from a chess study that expertise always takes 10,000 to 20,000 hours to develop. The findings of this one study should not be assumed to be unrestrictedly effective and binding across all domains. Domains such as chess-playing are narrow and stable in scope and have limited transfer to domains with a greater degree of multiplicity and unpredictability, such as "business and industry where employees are challenged to attend to situations that require multiperceptual demands" (Grenier & Kehrhahn, 2008, p. 204). Furthermore, even years or decades of experience in a profession do not automatically produce expertise, and "only a small percentage of individuals will become experts – the vast majority will remain experienced non-experts" (Kulhmann & Ardichvilli, 2015, p. 263). Conversely, some people might even develop expertise in fewer than 10 years, especially in nascent fields where experience

working in highly challenging and unexampled environments acts as an accelerant to the development of expertise (Frie et al., 2019).

Although years of experience does not inerrably equate to expertise, it does remain one of the best factors for researchers to measure expertise. Even after conceding that years of experience is not a flawless indicator of expertise, Frie et al. (2019) still used it as a central gauge for selecting their research participants. In another study by Govaerts, van de Wiel, and van der Vleuten (2013), expertise was the sole touchstone for participant selection and expertise was even defined "as the number of years of task-relevant experience" (p. 111) that participants had. Also, though not listed as one of the objective expertise items of the GEM, Germain and Tejeda (2012) still asserted that years of experience is "an objectively verifiable aspect of expertise" (p. 215). With that said, years of experience cannot be the sole determinant of expertise. Depth, breadth, and complexity of experience, as well as one's level of rank and responsibility, must also be considered (Germain & Tejeda, 2012). Additionally, task variety is needed to develop expertise (Bohle Carbonell et al., 2016). Therefore, expertise is heavily dependent not just on the quantity of experience, but also on the quality and type of experience (Herling, 2000).

The Elusive "It" Factor of Expertise. Knowledge and experience are critical dimensions of expertise, but they are inadequate in and of themselves and insufficient in engendering expertise (Swanson, 2003a). Expertise is "more than knowledge residing in an expert's head; it is also an outcome of the relationship between an individual and a context" (Valkeavaara, 2000, p. 255). Also, although it may take years of experience to

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develop expertise, experience itself is not the foremost or exclusive stimulant of expertise (Kuhlmann & Ardichvili, 2015). Rather, there is another dimension that is considered to be the activating agent, differentiatory ingredient, and *sine qua non* that is principally responsible for the actuation and propulsion of expertise. Although scholars define this dimension differently and disagree with what all is encompassed within, they are in covenant with one another that it is the indispensable additive that ignites and animates expertise.

Some scholars refer to this third dimension as problem solving (Herling, 2000; Herling & Provo, 2000; Jeong et al., 2017; Swanson & Holton 2009). Herling (2000) describes problem solving as "the key to expertise," "the primary component of expertise," and "the single dynamic element in the growth of expertise" (pp. 15-16). Knowledge can become obsolete and experience can be prosaic, so it is this problem solving dimension that enkindles expertise (Grenier & Kehrhahn, 2008). Problem solving involves the leveraging and deployment of existing knowledge and experience (Wolf, 1997), but it also results in the expansion of knowledge and experience (Brockman & Dirkx, 2006). Chermack (2003a) adds that problem solving can be equated with responsive decision-making, especially in contexts of crises; Swanson (2003a) refers to this as decision-making expertise and claims that it carries over into problem solving.

Furthermore, the acquisition of expertise is not forever attained and does not exist in a fixed or static state. Instead, expertise requires maintenance, cultivation, and continuous and dynamic growth and development (Grenier & Kehrhahn, 2008). It also

involves being comfortable and embracive of ambiguity and repeatedly searching for new ways to stretch one's capabilities (Kuhlmann & Ardichivili, 2015). This enhancement of expertise occurs as one develops an approach to solving novel and complex problems rather than just relying on routinized and scripted procedures (Torraco, 1999). Indeed, it is this tendency to solve progressively more challenging and situational problems that separates experts from novices (Herling, 2000). Novices tend to uniformly rely on previously learned conventions to address a wide range of issues, while experts tend to seek out additional alternatives and cognitively sort through the complexities of unique problems (Kuhlmann & Ardichivili, 2015). Whereas novices replicate habituated skills to address subsequent and ongoing challenges, experts demonstrate ingenuity and originality in how they solve increasingly more difficult problems (Herling & Provo, 2000).

Some researchers do not believe that the concept of problem solving satisfactorily captures the remaining dimensionality of expertise. When surveying HRD scholars from around the world, Germain and Ruiz (2009) found that the dimension of problem solving was largely a U.S. construct and that scholars from other countries – particularly throughout Western Europe – did not necessarily incorporate it into their definitions of expertise. In effect, the residuum of what scholars believed constituted expertise was nebulous and multivocal. In an attempt to create a consolidated cross-national construct of expertise, Germain and Ruiz (2009) proposed a dimension they labeled skills.

Problem solving is certainly included in this skills domain, but it is also meant to more comprehensively interfuse with other identified constituents of expertise as well, such as analytical skills, critical thinking, managerial proficiency, recognition by peers, and metacognition. Two of these other elements were especially found in other sources of the literature: social recognition and metacognition. Even though Germain and Ruiz (2009) collapsed these into one conjectured dimension of skills, Van der Heijden (2000) considered skills, social recognition, and meta-cognitive knowledge to be three discrete dimensions.

The idea that there is a facet of expertise that is determined by one's reputation as perceived by others is consistent with Germain and Tejeda's (2012) Generalized Expertise Measure (GEM). However, social recognition is subjective and based on perception rather than validation of expertise. As a result, it has the potential to "create the illusion of expertise without any basis or evidence" (Germain & Tejeda, 2012, p. 223). Additionally, social recognition is not assessable through self-report measures. Consequently, social recognition is incompatible with the design of the current study and is excluded as a dimension of my proposed construct of expertise.

Meta-cognitive knowledge involves self-awareness and self-insight (Van der Heijden & Brinkman, 2001). Gartmeier, Bauer, Gruber, and Heid (2010) proposed that self-reflection is also a metacognitive activity that is augmentative of expertise, especially as professionals reflect on error-producing conditions (i.e., negative knowledge) and develop new and corrective practices to avoid repeating similar mistakes. Gartmeier et al. (2010) viewed this more as a function of problem solving,

though, than as a distinct dimension of expertise. Moreover, Bohle Carbonell et al. (2014) conducted a systematic literature review and found limited evidence that metacognition was a separate domain of expertise. Subsequently, a study based on that review did not find a correlation between metacognition and expertise (Bohle Carbonell et al., 2016). Therefore, meta-cognitive knowledge is not one of the dimensions of my proposed construct of expertise.

The notion that experts must be flexible is another theme that arose from the literature. In fact, growth and flexibility is one of the dimensions in Van der Heijden and Verhelst's (2002) construct of expertise, and is related to an expert's ability to adapt and even acquire additional expertise amid comprehensive environmental changes. This aspect of expertise has also been designated as "flexpertise" and those who possess flexpertise are sometimes referred to as "flexperts" (Van der Heidjen, 2000). Flexperts possess "in-depth domain-specific knowledge and skills combined with the ability to develop and materialize new areas of expertise, that is, expertise renewal (Frie et al., 2019, p. 61). Other researchers have also found that expertise requires the professional characteristics of growth, flexibility, and agility (Beausaert, Segers, & Gijselaers, 2011; Choi, Lee, & Jacobs, 2015). This is all consistent with Grenier and Kehrhan's (2008) Model of Expertise Redevelopment (MER), which states that experts must constantly adapt their expertise "to fit new parameters, new scenarios, and new challenges" (p. 199) in response to the ever-changing contextual territories of their profession.

Problem solving as proposed by some researchers (Herling, 2000; Herling & Provo, 2000; Jeong et al., 2017; Swanson & Holton, 2009) and growth and flexibility as

propounded by other researchers (Evers, Kreiijns et al., 2011; Frie et al., 2019; Van der Heijden, 2000; Van der Heijden & Brinkman, 2001; Van der Heijden & Verhelst, 2002) are both closely aligned with the concept of adaptive expertise (Bohle Carbonell et al., 2014; Bohle Carbonell et al., 2016). As a result, I consider adaptive expertise to be a stronger catch-all for the balance of expertise than the skills dimension as articulated by Germain and Ruiz (2009). Skills is an obscure, vague, and oversaturated dimension that was intentionally defined loosely in an attempt to account for the miscellaneity of expertise (Germain & Ruiz, 2009). Adaptive expertise, on the other hand, seems to more fully and naturally encapsulate both problem solving as well as growth and flexibility while also more inclusively extending beyond those concepts. Accordingly, it is the more durable dimension and a better candidate for amalgamating other theorized dimensions of expertise.

As previously stated, adaptive expertise incorporates elements of both problem solving and growth and flexibility. Adaptive expertise is characterized by flexibility, innovation, and creativity, and has two components: domain-specific skills and innovative skills (a third theoretical component of metacognitive skills was not empirically supported and was, therefore, removed from the construct) (Bohle Carbonell et al., 2016). Furthermore, a psychometric tool based on this construct, the Adaptive Expertise Inventory, was developed and validated as an instrument that measures adaptive expertise.

Domain-specific skills refer to an expert's ability to create new knowledge and effectively solve unprecedented problems. Adaptive experts regard their body of

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knowledge as dynamic and seek opportunities to continuously acquire new knowledge

and skills, including learning from mistakes and experimentation (Bohle Carbonell et al.,

2014). Non-routine experiences elicit opportunities for problem-solving, which in turn

stimulates expertise growth. The innovative skills component denotes the cognitive

flexibility an adaptive expert has to deconstruct and reconfigure their knowledge and

skills in order to build the new mental models needed to solve novel problems (Bohle

Carbonell et al., 2014). Innovative skills is also related to one's ability to adapt and

demonstrate principled agility in the face of rapid, frequent, and unrelenting change.

Given the multiplex nature of adaptive expertise, I believe it is this dimension that best

captures the "it" factor of expertise that has so often been elusive and difficult to define

by researchers. Therefore, this is the third dimension of my proposed construct.

Proposed Construct of Expertise

Based on my review of the HRD expertise literature, I propose a three-

dimensional construct of expertise as follows: (a) knowledge, (b) experience, and (c)

adaptivity. Knowledge consists of the information and skills someone needs to be

successful in their respective profession and will be explored through the components of

domain specificity, education, professional credentials, and involvement with

professional associations (Germain & Tejeda, 2012; McLean & Akdere, 2015).

Experience refers to the realized opportunities one has had to apply knowledge and skills

and will be examined through years, level/type, and area(s) of experience (Germain &

Tejeda, 2012; Govaerts et al., 2013; Grenier & Kehrhan, 2008). I chose to express the

third dimension as adaptivitiy rather than adopting the term adaptive expertise.

Adaptivitiy is the nounal variant and is tantamount to adaptive expertise. Furthermore, it is this dimension that is singularly responsible for the galvanization and mobilization of expertise and is the embodiment of problem-solving, flexible expertise, and dynamic growth. Therefore, adaptivity is the most robust dimension of expertise and is displayed in the components of domain-specific skills and innovative skills (Bohle Carbonell et al., 2016). Figure 2.2 shows how expertise has been constructed in the current study.
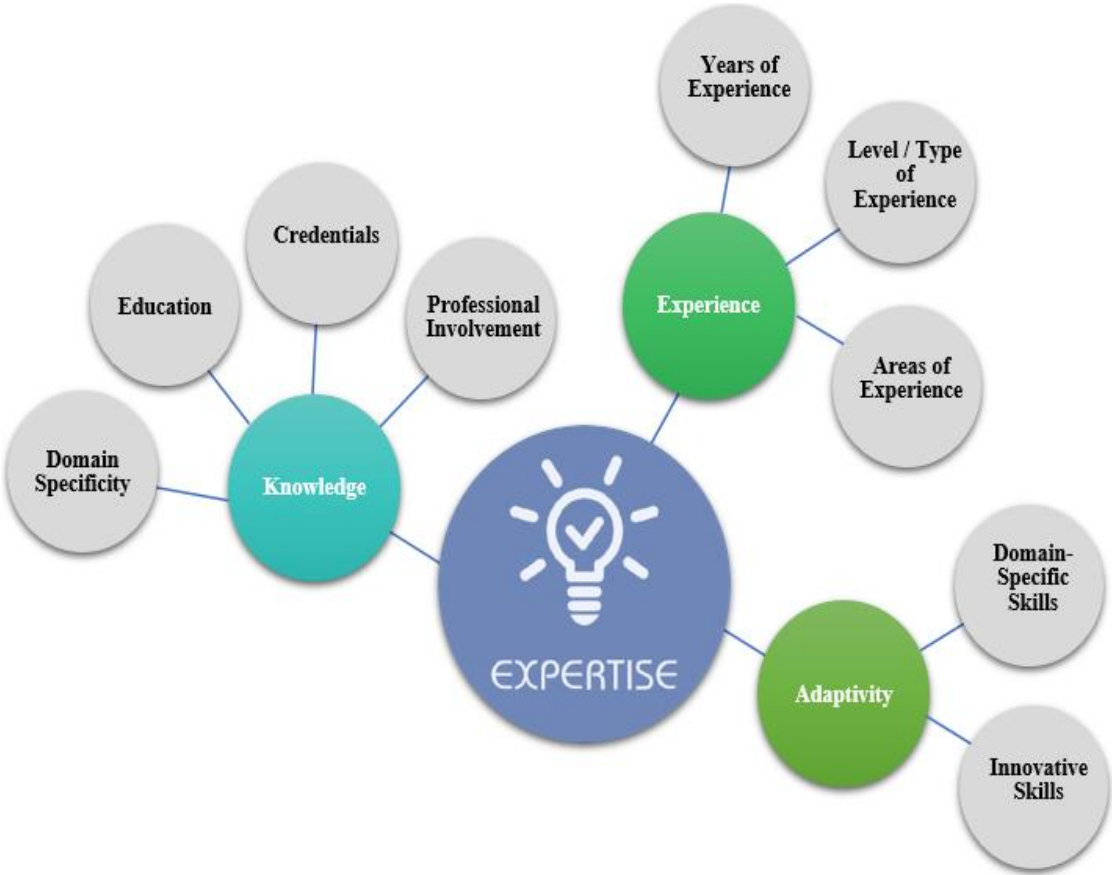
Figure 2.2. Hypothesized dimensions of the proposed construct of expertise

Overconfidence Effect

The overconfidence effect is a very well-developed concept with over 50 years of psychological research history. Over the last couple of decades, this topic has even garnered the attention of researchers within the business disciplines, such as economics, finance, marketing, and management. This trend demonstrates that the overconfidence effect is not some recondite academic topic; instead, itis immensely concordant with applied disciplines as well. Despite its promising applicability and practicality to HRD, the overconfidence effect has not been widely studied by HRD scholars.

Because the overconfidence effect is such a mature topic with a magnitudinous literature base, the objective of this section is to provide an overview of the main and seminal works, while also underscoring recent or emergent findings. In the next three subsections, I outlined how overconfidence has been studied within psychology, the business disciplines, and HRD. Afterwards, I explored how expertise has traditionally been constructed by overconfidence researchers. Following that, I examined specific individual differences that are potentially relevant to understanding the universality versus circumstantiality of the overconfidence effect. Finally, I identified and critiqued the major gaps in the overconfidence literature and proposed how my current study might bridge those gaps.

Overconfidence as a Psychological Construct

The overconfidence effect is a well-established phenomenon within psychological scholarship. It is considered to be one of the most grievous and ubiquitous decision-making biases because of how preponderantly susceptible people are

to it and the severity of error propensity associated with overconfident decisions

(Kahneman, 2011). Some psychology researchers view overconfidence as a

multifaceted construct consisting of three distinct dimensions: overestimation,

overplacement, and overprecision (Meikle, Tenney, & Moore, 2016; Moore & Swift,

2010). Although these three conceptually distinct components of overconfidence may

be theoretically compelling, empirical studies have shown mixed results regarding

whether such a distinction exists. Resultantly, some researchers question whether these

components are "merely differing operationalizations of the same underlying construct"

(Moore & Healy, 2008, p. 503). Figure 2.3 graphically displays the three traditional

components of overconfidence and provides a brief definition of each term.
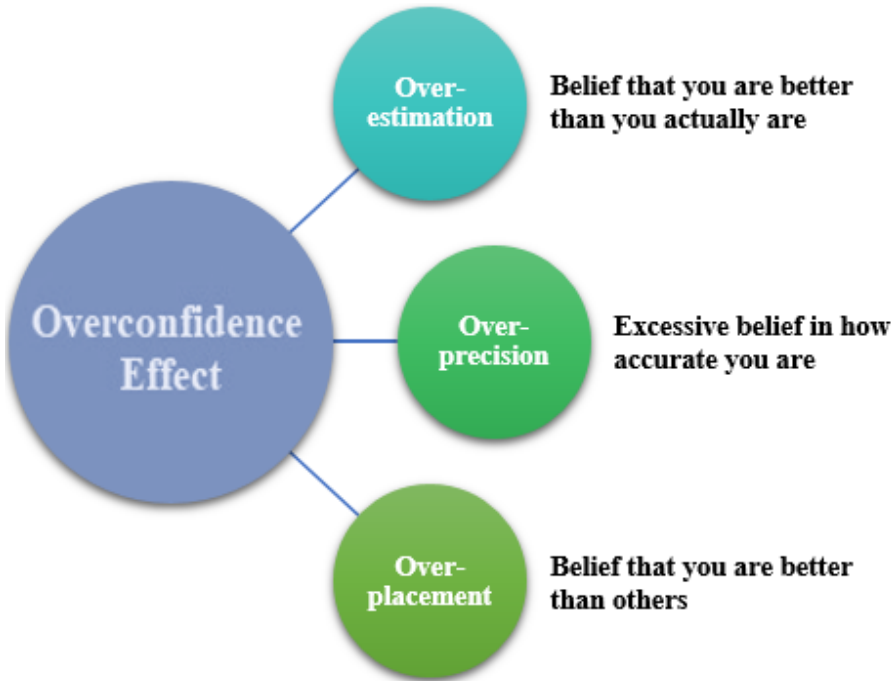
Figure 2.3. Definitions of the three theorized components of the overconfidence effect

Overestimation

The first definition of overconfidence is the overestimation of one's judgment, knowledge, performance, ability, probability of success, or level of control relative to actual achievement in those areas (Meikle et al., 2016). For example, people tend to overestimate how much they know compared to how well they actually perform on tasks that measure their knowledge and abilities (Dunning, 2005). Early overconfidence studies focused mainly on how individuals overestimated their knowledge on a wide range of general knowledge questions in subject areas such as geography, history, literature, and music (Fischhoff et al., 1977). More recent studies have explored how overestimation impacts more practical domains of life, such as students overestimating how well they will perform on exams (Clayson, 2005; Shepperd, Ouellette, & Fernandez, 1996), workers miscalculating how quickly they can accomplish work tasks (Buehler, Griffin, & MacDonald, 1997), and unemployed individuals misjudging how easily and quickly they can obtain a job (Spinnewijn, 2015).

Although some researchers have insisted that the overconfidence effect is a universal bias and that most people have a generalized tendency toward overestimation (Johnson & Fowler, 2011; Odean, 1998), *underestimation* about performance has also been observed in some circumstances, especially in easy and routine tasks performed by skilled individuals (Clark & Friesen, 2009; Kruger & Dunning, 1999; Lichtenstein & Fischhoff, 1977). This occurrence is known as the hard-easy effect and suggests that overconfidence may likely surface in difficult situations while underconfidence may appear when tasks are easy (Fischhoff et al., 1977). The presence of underestimation

suggests that overestimation may be more situational and context-driven than universal, although underestimation has been observed with mixed and conflicting results (Lichtenstein, Fischhoff, & Phillips, 1982).

Overprecision

Overprecision refers to the excessive confidence that people place in their judgments (Moore & Swift, 2010). In studies that measure overprecision, participants are typically asked to place a confidence interval around the accuracy of their responses (Lichtenstein et al., 1982). When participants are overly precise, this means that their responses do not fall within the range specified in the confidence interval, resulting in a miscalibration between perceptions of accuracy and actual accuracy. Miscalibration is a common feature of overconfidence, and occurs when the perceived accuracy of a response exceeds the actual accuracy (Fischhoff et al., 1977).

If judgments of accuracy were truly calibrated, then actual response accuracy would align with the confidence level assigned. Researchers have consistently found, though, that individuals are correct less than 50% of the time when they place a 90% confidence interval around their responses (Alpert & Raiffa, 1982; Moore & Swift, 2010). This characteristic of overconfidence highlights the tendency that people have to place too much confidence in the correctness of their responses.

One major area of interest that has emerged from studies of overprecision is whether experts are better calibrated than non-experts or novices. Juslin (1994) claimed that experts should assumedly be well calibrated and appropriately confident (i.e., not over- or underconfident) in areas related to their work. Contrariwise, other researchers

have disputed this assertion about expert calibration, and argue that experts are also susceptible to decisional miscalibration (Miller, Spengler, & Spengler, 2015). Koehler, Brenner, and Griffin (2002) conducted a meta-analysis of expert judgment among physicians, meteorologists, attorneys, economists, and sports commentators, and found that "in all domains of expert judgment surveyed, systematic miscalibration was observed" (p. 710). Probability judgments were miscalibrated among all five professional domains, but the magnitude of this miscalibration was less for experts with training in statistical models (i.e., meteorologists and economics).

Overplacement

Overplacement has also been referred to as the above-average effect, illusory superiority, and the Lake Wobegon effect, and is described as the tendency for people to overestimate their talents, strengths, and abilities relative to those as possessed and displayed by others (Alicke & Govorun, 2005; Kruger, 1999; Moore & Swift, 2010). One of the most cited examples of overplacement from the literature is Svenson's (1981) finding that 93% of U.S. drivers rated themselves as being above the median in their driving skills. Another example is that 37% of engineers at a firm rated themselves as being among the firm's top 5% of high-performers (Zenger, 1992). In a normal distribution, it is impossible for a majority of people to exceed the median or for 37% of people to be in the top 5%.

People are inclined to perceive themselves as superior to others, especially in regards to positive traits and attributes, such as intelligence, morality, honesty, generosity, popularity, and humor (Stavrova, Köneke, & Schlösser, 2016). In one study,

a majority of the participants viewed themselves as less biased or prejudiced than others and even reacted defensively at the notion that they could possibly have implicit biases (Howell & Ratliff, 2016). It has also been observed that many individuals extend the "better-than-average" assessment to their close friends and family, but not to people outside of their close relational circles (Pedregon, Farley, Davis, Wood, & Clark, 2012). Overplacement also occurs frequently in professional settings and people tend to view themselves more positively than their co-workers, colleagues, and even other professionals within the same field (Dunning, Heath, & Suls, 2004).

While some researchers have "pointed towards a universal better-than-average effect" (Benoît, Moore, & Dubra, 2015, p. 294), others have countered that inflated self-assessments are more commonly demonstrated by the unskilled since they putatively lack a metacognitive awareness of their actual skill level (Kruger & Dunning, 1999). The notion that the unskilled are more likely to display relative overconfidence and experts are more likely to exhibit underconfidence is known as the Dunning-Kruger effect (Dunning, 2011). Although some researchers contend that overplacement is not universal and suggest that lower skilled individuals engage in overplacement more often than their higher skilled counterparts, these researchers have primarily examined these conditional properties within the contexts of trivia (Moore & Healy, 2008), intelligence (Eil & Rao, 2011), word games (Clark & Friesen, 2009), math and logic puzzles (Benoît et al., 2015), and general knowledge (Merkle & Weber, 2011). More research is needed to determine if higher skilled individuals engage in overplacement less often than lower skilled individuals within professional and workplace settings as well.

Overconfidence in Business Contexts

Researchers in the business-related disciplines such as finance, economics, and management commonly have studied the overconfidence dimensions of overestimation, overprecision, and overplacement jointly rather than separately. These researchers typically consider these dimensions to exist as the consolidated quality of overconfidence rather than as three distinct operationalizations (Alba & Hutchinson, 2000). A business definition of the overconfidence effect, therefore, includes an overestimation of the precision and accuracy's of one's abilities, underestimation of risk and uncertainty, and exaggerated faith placed in the meliority of one's own judgment and decision-making prowess above others (Ancarani, Di Mauro, & D'Urso, 2016).

Additionally, business researchers have frequently focused on how the overconfidence effect applies to executive and managerial decisions related to proxies for expertise, such as financial performance (Ellul & Yerramilli, 2013; Huang, Tan, & Faff, 2016; Odean, 1998). Overconfident managers are more likely to engage in overly risky behaviors, have excessively optimistic assessments of potential market volatility, and trust that they are superiorly capable of predicting the future and producing profitable results compared with their counterparts (Ho et al., 2016). Executive overestimation of predictive ability and underestimation of risk often leads executives into aggressive risk-taking, which regularly catalyzes substantial financial loss for organizations (Ho et al., 2016). When these executives overly simplify the complexities and uncertainties associated with the market, incautiously disregard risk, and only rely on their own limited knowledge for guidance (which they erroneously regard as

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definitive and indefectible), it can expose their organizations to too much risk and result in detrimental financial outcomes (Ancarani et al., 2016).

The adverse consequences of managerial and executive overconfidence have been studied across many different business contexts, activities, and decisions. Compared to rational CEOs, overconfident executives more often embark on value-destroying mergers and acquisitions (Malmendier & Tate, 2008; Roll, 1986), disproportionately rely on debt financing (Hackbarth, 2008), expose firms to higher levels of default risk (Ho et al., 2016), experience diminished stock return performance (Ellul & Yerramilli, 2013), misstate and misreport financial earnings (Schrand & Zechman, 2012), fail to prudently manage and repot write-offs (Pierk, 2020), and reduce dividend payouts to investors (Deshmukh, Goel, & Howe, 2013). Overconfidence is a pervasive phenomenon documented in the business literature and researchers use overconfidence to help explain why companies fail (Männasoo & Mayes, 2009), financial crises occur (Ho et al., 2016), stock prices crash (Al Mamun, Balachandran, & Duong, 2020; Hutton, Marcus, & Tehranian, 2009), and corporate scandals materialize (Schrand & Zechman, 2012; Zona, Minoja, & Coda, 2013).

Whereas Kruger and Dunning (1999) posited that skilled individuals are better at properly calibrating their confidence with their actual abilities, this proposition is not consistent with other major findings from the business overconfidence literature. For example, Glaser, Langer, and Weber (2005) found that expert judgment was even more prone to overconfidence than novice judgment. In their study, finance professionals exhibited more overconfidence than finance students, indicating that the expertise level

of the professionals did not mitigate the overconfidence effect. Another study showed that overconfidence increased as participants gained more experience, suggesting that one's level of experience might not reduce the overconfidence effect (Kirchler & Maciejovsky, 2002). Similarly, Lambert, Bessière, and N'Goala (2012) found that students and experienced bankers were equally prone to overconfidence. What these three studies demonstrate is that experts are not less inclined to be overconfident as proposed by Kruger and Dunning (1999); instead, they are equally inclined if not more so compared with novices.

Overconfidence in HRD Research

Even though the overconfidence effect is a mature topic within psychology and the business disciplines, HRD scholarship on this subject has been sparse. In fact, I did not locate a single HRD article that focuses primarily on overconfidence. Instead, the articles I found made only ancillary references to overconfidence.

In my attempt to identify HRD literature on overconfidence, I searched the same five premier HRD journals I used for the integrative literature review on expertise: *ADHR*, *HRDI*, *HRDR*, *HRDQ*, and *ETJD/JEIT*. The keyword I used was "overconfiden" with the search modifier "*" to locate related terms like "overconfident" and "overconfidence." Furthermore, I did not specify a date range, so each publication was scanned in its entirety through December 2020. No articles were found when only the abstracts were searched, so I had to expand my search to include the full-text articles. This yielded a total of 17 articles where some variant of overconfidence was mentioned

(six results from *ADHR*, two from *HRDI*, two from *HRDR*, two from *HRDQ*, and five from *ETJD/JEIT*).

Overconfidence was mentioned as being a result of biased data (Korte, 2003); reason that organizations fail to embrace change (Dirkx, Gilley, & Gilley, 2004); cognitive barrier that limits the scenario development process (Bradfield, 2008); source of poor leadership decisions (Keller, 2007); consequence of academic training being misaligned with the talent needs of the market (Wang & Sun, 2018); and contributing factor of a participant's academic failure (Wang, Anne, & McLean, 2016). Overconfidence was also found to be a cognitive and motivation effect that can differ among individuals (Hadré, 2003); possible reason for why organizations overestimate how effective their line managers are at managerial coaching (Beattie, Kim, Hagen, Egan, Ellinger, & Hamlin, 2014); outcome of inflated perceptions of self-efficacy (Gedeon, 2014); and an inimical influence on organizational success, resulting in unfavorable outcomes such as risky decision-making, inflexibility, "careless thinking and blindness to alternatives" (Lee & Wang, 2017, p. 531). Also, increased experience can result in overconfident problem solving (Lukic, Margaryan, & Littlejohn, 2013), yet "new employees may be prone to be overconfident about their knowledge prior to successful socialization" (Holton, 1996, p. 245).

Senior managers were found to overconfidently assume that unstructured experiential learning would automatically result in their middle manager employees increasing their managerial capability (Johnson, Blackman, & Buick, 2018). Another study found that overconfident individuals tend to invest very little time and effort on

continuous learning and development through training since they already regard

themselves as being fully proficient (Clark, 1992). London and Sessa (2006) noted that

because individuals have a tendency to be excessively optimistic and overconfident in

self-assessments of their performance, group feedback is critical in helping to calibrate

perceptions and performance expectations. Similarly, McCarthy & Garvan (1999) found

that repeated 360-degree feedback may help individuals develop self-awareness and, as a

result, decrease the overconfidence of their decisions. Finally, Ceschi, Costantini,

Phillips, and Sartori (2017) asserted that decision-making competence could be

improved through debiasing interventions, including techniques to counteract the

overconfidence effect, such as "by encouraging individuals to contemplate a different

spectrum of solutions through deliberate consideration…of the effective odds" (p. 15).

While overconfidence has been addressed to varying degrees by HRD scholars,

none of the identified articles focused primarily on overconfidence. In fact, the majority

of these articles only made a singular reference to it, and no article made more than four

total references. With that said, I understand that the number of occurrences

overconfidence is mentioned does not necessarily equate to how significant an article is

as it pertains to overconfidence. Nevertheless, overconfidence has at least been a subject

matter of relevance and interest to HRD researchers, albeit sporadically and auxiliarily.

Expertise within the Overconfidence Literature

Expertise is expansively addressed in the overconfidence literature, especially

when it comes to the topic of expert versus novice judgment. There is disagreement,

though, regarding the impact that expertise has on overconfidence. Juslin (1994)

claimed that experts are well calibrated in areas related to their work content compared to novices. Likewise, Kruger and Dunning (1999) noticed that higher skilled individuals are less likely to be overconfident than lower skilled individuals because of the metacognitive awareness that the former group presumably possesses. More recently, Lin, Ho, and Chih (2019) found that more experienced financial analysts were less susceptible to overconfidence than lesser experienced analysts. These researchers suggest that experts are less likely to be overconfident compared to novices.

However, there is inconsistency in the literature on whether expert judgment is in fact less disposed to overconfidence. In studies that exclusively examined CEOs, overconfidence was found extensively within this highly skilled population (Huang et al., 2016; Malmendier & Tate, 2008; Odean, 1998). Although experts were not compared to novices in those specific studies, the fact that the presence of overconfidence was so widespread suggests that experts might not be reliably immune or impervious to overconfidence after all. Koehler, Brenner, and Griffin (2002) confirmed this suspicion and found that overconfidence was prevalent among experts. Lassoued, Phillips, Smyth, and Hesseln's (2019) study reinforced the belief that novices and experts were both vulnerable to overconfidence and that "expertise (i.e., being more knowledgeable) does not necessarily reduce over-confidence" (p. 46). Some researchers even found that experts were *more* susceptible to overconfidence compared with novices (Glaser et al., 2005; Russo & Shoemaker, 1992), and that novices possibly even render more accurate predictions than experts (Camerer & Johnson, 1991; Önkal, Yates, Simga-Mugan, & Öztin, 2003). In my current study, I have attempted to reconcile these

disagreements by examining the relationships between expertise and overconfidence, and if any factors might potentially influence these relationships (e.g., individual differences).

Individual Differences

Individual differences is another area that I identified from the overconfidence literature that is relevant to the current study. In exploring how expertise and the overconfidence effect are related, it is important to also examine the potential influence that individual differences might have on this relationship. Examining individual differences is especially important to determine whether the overconfidence effect is collective in scope or individually contingent. Currently, incongruity and contradictions exist in the overconfidence literature concerning whether the overconfidence effect is a universal tendency or is manifested differently according to individual differences (Moore & Healy, 2008). Based on my review of the literature, I have identified three main individual differences for the current study: personality traits, decision-making styles, and demographic characteristics.

Personality Traits

Some researchers have found significant differences in how individuals exhibit the overconfidence effect based on personality traits (Campbell, Goodie, & Foster, 2004; Kausel, Culbertson, & Madrid, 2016; Larkin & Leider, 2012; Schaefer, Williams, Goodie, & Campbell, 2004). Other researchers, on the other hand, have found little support that overconfidence varies based on personality differences (Larrick, Burson, &

Soll, 2007; Moore & Healy, 2008). Therefore, there is a lack of consistency in the literature on whether personality dimensions are correlative of overconfidence.

The Big Five personality model is a ubiquitous model for understanding the bipolar dimensionality of the personality traits of extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience (Arora & Rangnekar, 2016). The Big Five is an illustrious and widely used model that covers a broad range of human personality traits and has been validated multiple times (Gosling, Rentfrow, & Swann, 2003). In fact, the Big Five has even been used in past overconfidence studies (Kausel et al., 2016; Schaefer et al., 2004). In this current study, I have explored whether personality traits contribute to differences in overconfidence, which will hopefully contribute to the body of knowledge since there are contradictory results in the existing literature.

Decision-Making Styles

The second component of individual differences that I identified is decision-making styles. It is defined as the "individuals' characteristic mode of perceiving and responding to decision-making tasks" (Scott & Bruce, 1995, p. 818). Decision-making is a complex cognitive process in which individuals gather and interpret information in order to make judgments. Because the overconfidence effect is solidly anchored in decision-making research (Kahneman, 2011) and is a bias specifically about errors in judgment (Kukacka & Barunik, 2013; Schlösser, Dunning, Johnson, & Kruger, 2013), it is appropriate for me to explore through this study, whether decision-making styles influence the accuracy of the judgments that people ultimately make.

There are various ways in which individuals cognitively evaluate information and render judgments during the decision-making process. Individuals who engage in rational decision-making go through a systematic process of evaluating multiple choices and alternatives before making a final judgment, whereas individuals who engage in intuitive decision-making tend to rely more on spontaneity, feelings, and instincts (Hamilton et al., 2016). Two measures are used in the current study to determine respondents' decision-making styles: the Decision Styles Scale (DSS) (Hamilton et al., 2016) and the Cognitive Reflection Test (CRT) (Frederick, 2005). The reason I selected decision-making styles as an individual difference to study is that I am interested in understanding whether the style and approach by which people make judgments ultimately influence the accuracy of those judgments, and, if so, whether those judgments are either more or less susceptible to the overconfidence effect.

Demographic Characteristics

Demographic characteristics such as age, gender, and race and ethnicity are frequently used in quantitative studies to help explain the relationships among other variables (Dillman, Smyth, & Christian, 2014). So far, there has not been an agreed-upon demographic characteristic that has consistently revealed differences in overconfidence (Moore & Healy, 2008). Instead, the literature provides conflicting results regarding which demographic characteristics, if any, explain or influence overconfidence. For example, some researchers have been able to measure statistically significant differences in the overconfidence of men and women (Barber & Odean, 2001; Soll & Klayman), but other researchers have not found a significant gender-based

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difference (Kausel et al., 2016; Moore & Healy, 2008; Proeger & Meub, 2014).

Therefore, I consider demographic characteristics as relevant to the current study to help identify what, if any, characteristics might be helpful in better understanding overconfidence.

Gaps in the Overconfidence Literature

Based on my thorough review of the overconfidence literature, I have identified four research gaps. The first gap is related to how knowledge has been examined in previous studies. Overconfidence researchers in the discipline of psychology have attempted to study overconfidence within the context of general knowledge domains (Clark & Friesen, 2009; Fischhoff et al., 1977; Merkle & Weber, 2011; Moore & Healy, 2008). This approach overlooks professional and expert knowledge. While overconfidence researchers in the business disciplines have more often studied overconfidence within professional settings, they have frequently done so by creating proxies for evaluating knowledge, such as by measuring the accuracy of predictions and forecasts made surrounding one's domain of knowledge (Camerer & Johnson, 1991; Ellul & Yerramilli, 2013; Huang et al., 2016; Lambert et al., 2012; Önkal et al., 2003; Von Holstein, 1972; Yates, McDaniel, & Brown, 1991). With this approach, however, professional knowledge is not directly examined. Therefore, the current study ameliorates this gap by investigating domain-specific professional knowledge rather than reducing knowledge to either domain-general knowledge or proxies (i.e., outcomes) of knowledge.

The second gap in the literature is in regards to how expertise has been constructed by overconfidence researchers. Just as overconfidence has not been robustly explored by HRD researchers, so too have overconfidence scholars not fully developed the construct of expertise. Numerous overconfidence studies have either superficially equated expertise to knowledge (Huang et al., 2016; Lambert et al., 2012; Lassoued et al., 2019), or simply defined it as years of experience (Bédard & Chi, 1993; Kirchler & Maciejovsky, 2002; Menkhoff, Schmeling, & Schmidt, 2013). However, this does not represent an adequate or complete conceptualization of expertise. The current study redresses this gap by situating the exploration of expertise in the richness of HRD scholarship and by appropriately expanding expertise into a multidimensional construct.

A third gap in the overconfidence literature is the population that has often been studied. Overconfidence researchers in the business disciplines have almost exclusively focused on managerial and executive professionals (Malmendier & Tate, 2008; Roll, 1986). Such a narrow focus does not help generate a balanced or holistic understanding of the overconfidence effect. In the current study, professionals with a diversity of experience were included, which will hopefully help illuminate whether overconfidence is pervasive or situationally related to experiential characteristics such as hierarchical rank and one's level within an organization.

The fourth gap is the inconsistency that exists in the literature. There have been mixed results regarding the circumstances under which overconfidence is manifested. Some researchers contend that the overconfidence effect is a universal bias (Johnson & Fowler, 2011), yet underconfidence has also been observed (Kruger & Dunning, 1999;

Lin et al., 2019), albeit with conflicting results (Lichtenstein et al., 1982). If there is a

range of confidence that individuals exhibit, this calls into question the ubiquity of

overconfidence. Furthermore, I am interested in understanding the situations under

which overconfidence and underconfidence occur, and factors that might contribute to

this variability (e.g., individual differences along the experience spectrum). Through

this study, I hope to contribute to the ongoing debate by examining if overconfidence is

an insidious inclination or if individual factors produce differences in the level of

overconfidence among HRM professionals.

Concept Map of the Proposed Relationships

Figure 2.4 maps out the relationships proposed for this study. The three main

concepts are expertise (X: independent variable), overconfidence (Y: dependent

variable), and individual differences (M: mediating variable; Z: moderating variable).

These concepts emerged from an integrative review of the literature. Furthermore,

dimensions or components of each of these main concepts are also included. For

example, knowledge is presented as a dimension of expertise. The purpose of this

concept map is to provide conceptual clarity around the proposed relationships of the

current study.
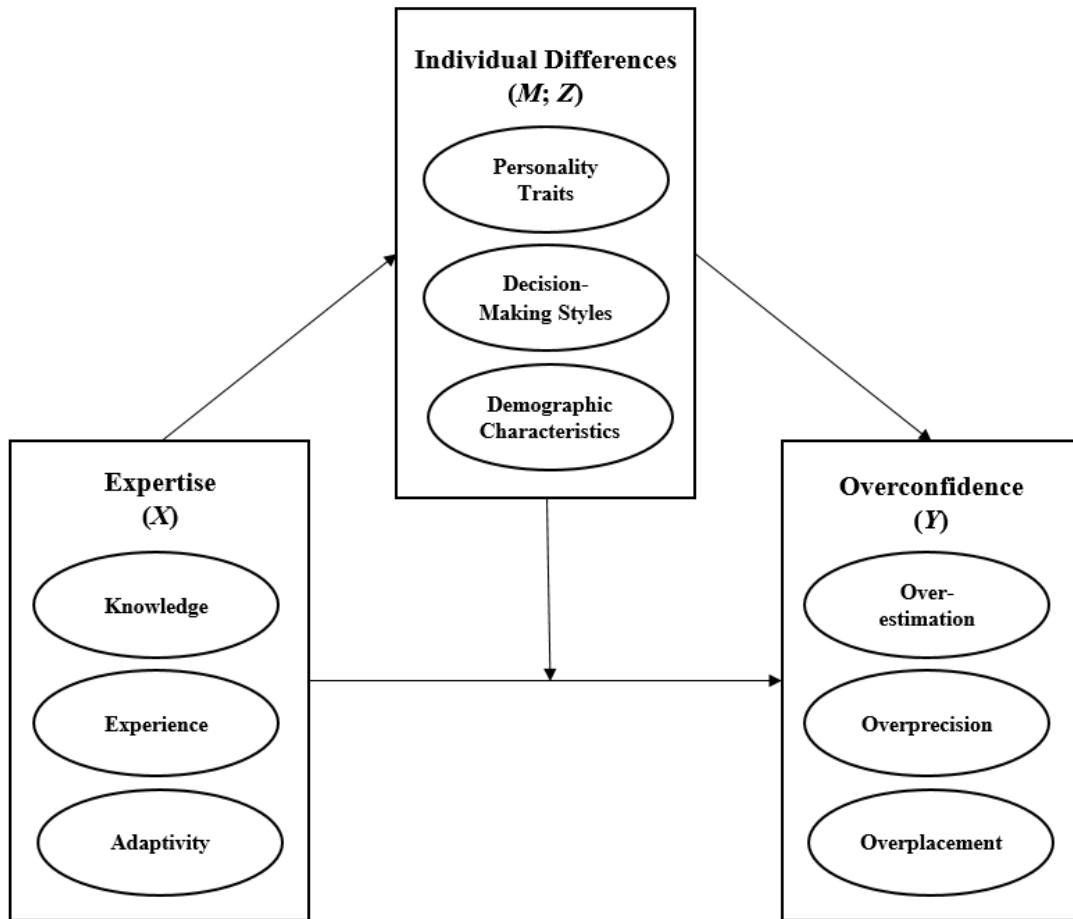
Figure 2.4. Concept map of the proposed relationships

Relevance of the Current Study to HRM Professionals

This section seeks to explore how the current study is relevant to HRM

professionals, the population of interest. Because the overconfidence effect is a bias of

miscalibration (Koriat et al., 1980), I have considered how miscalibration exists across

various contexts that impact HRM practitioners. The discrepancies I have identified are

between confidence and HRM expertise, research and practice, and the grander issue of

HRM professionals' perceived contribution with their actual level of influence on

organizational success. Although the overconfidence literature does not necessarily

offer a solution for every issue raised, it does at least provide helpful insights into these gaps.

The Gap Between Confidence and HRM Expertise

Even though the literature presents mixed information on whether expert knowledge is less (Lin et al., 2019), more (Glaser et al., 2005), or equally (Lambert et al., 2012) susceptible to overconfidence relative to novice judgment, I do expect to find some degree of overconfidence applied to HRM professionals within the realm of their domain-specific knowledge. If HRM experts are prone to the overconfidence effect, this will have significant implications for the world of professional practice. First, it challenges the conventional wisdom that having an abundance of confidence is overall advantageous or positively correlative with top performance and successful work outcomes (Gudmundson & Lechner, 2013). Confidence is often portrayed as a greatly valued trait in employees and predictive of their achievement. In fact, individuals who exude high levels of self-confidence are often perceived by others as being experts, even though self-confidence is not an objectively verifiable characteristic of expertise and could potentially even lead to illusions of expertise (Germain & Tejeda, 2012). Also, although confidence is an important component of self-efficacy and self-efficacy can promote individual performance, high levels of self-efficacy can actually lead to inaccurate self-assessments (i.e., overconfidence) and debilitating performance results (Moores & Chang, 2009; Schönfeld, Preusser, & Margraf, 2017). Therefore, the existence of the overconfidence effect confronts the notion that confidence is a reliable indicator of expertise or is an unconditionally positive contributor to individual performance.

Secondly, the overconfidence of experts could potentially cast serious doubts on the purported ways in which experts are differentiated from novices. Education and professional qualifications (i.e., credentials and certifications) are considered two ways in which expertise is measured (Germain & Tejeda, 2012). It is often presumed that higher levels of education and professional training validate and certify expertise and produce better performance (Babcock, 2016; Blackwell, 2015; Daniels, 2011; Germain & Tejeda, 2012; McLean & Akdere, 2015). However, if experts are just as – or possibly even more – susceptible to the overconfidence effect as novices, then this raises the question about how efficacious education and professional designations truly are for mitigating overconfidence and creating better calibration between confidence and actual knowledge.

The third implication of the overconfidence of expert knowledge is that it poses significant challenges for organizational performance. Organizations depend on the expertise of their people as the primary medium for executing objectives, advancing initiatives, and delivering results (Ogedegbe, 2014). Because the overconfidence effect is measured as the difference between what people think they know and what they actually know, expert miscalibration could be detrimental for organizations. This is because organizations particularly rely on the knowledge of experts to help shape and implement organizational initiatives (Eubanks, Read, & Grushka-Cockayne, 2015). Furthermore, expert decisions are counted on to be accurate, unbiased, and systematic. If experts' decisions are miscalibrated, it could result in costly, harmful, and inaccurate decisions that severely and negatively impact the organization, such as lawsuits (Moore

& Healy, 2008), labor strikes (Babcock & Olson, 1992), misinvestments (Heaton, 2002), and failed mergers and acquisitions (Malmendier & Tate, 2008). In this sense, organizational performance is inextricably linked to the effectual decisions of people.

Because HRM practitioners play a leading role in helping organizations navigate complex legal and compliance issues, calibrated knowledge in these areas of practice is paramount. Otherwise, organizations may face expensive and unnecessary litigation issues (Moore & Healy, 2008). Since HRM professionals often shoulder the responsibility of organizational risk mitigation and management, performing this function successfully requires specialized knowledge that must be accurate. At the very least, it requires HRM practitioners to be able to honestly evaluate their knowledge and assess any potential gaps. When there is a gap, it might be necessary to defer to the expertise of someone else (e.g., an attorney). Overconfident professionals, however, do not tend to perceive their own knowledge gaps and might therefore make overly risky decisions, place misguided faith in those decisions, and gratuitously expose organizations to liability (Moore & Swift, 2010). This is very relevant to HRM professionals as they are expected to help minimize organizational risk, not contribute to it (Cascio & Boudreau, 2012).

Moreover, HRM professionals are not just tasked with compliance-related activities but are also increasingly expanding their role in designing and implementing organizational change management initiatives (Lewin, 2008). HRM professionals' knowledge about the human behavioral dimension of organizations offers an insightful perspective through which to help organizations understand, frame, and guide change

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initiatives (Robbins & Judge, 2018). Nonetheless, change initiatives often fail. A frequently cited figure is that change initiatives fail approximately 70% of the time (Burnes & Jackson, 2011), but this statistic has been heavily criticized as being exaggerated and lacking empirical evidence (Hughes, 2011). Regardless, when change initiatives turned out to be unsuccessful, the overconfidence effect was often named as a possible culprit for that failure (Pasmore, 2015). Additionally, experiencing failure does not seem to be a calibrant or diminution of overconfidence, and may actually even escalate overconfidence and risk-taking behaviors (Ucbasaran, Westhead, & Wright, 2006).

Change initiatives are materialized by the conglomerative decisions made by a multitude of individuals. If these decisions are systematically prone to error, it becomes apparent how accumulatively and exponentially damaging overconfidence can be at an organizational level. Consequently, HRM professionals are urged to be mindful of the overconfidence effect and other human biases that threaten to disrupt and sabotage the success of change initiatives; not only biases within their own ranks but throughout the organization as well. HRM professionals can leverage research to manage the overconfidence effect and more effectively contribute to organizational success and performance.

The Gap Between Research and Practice

Studies have consistently shown that there is a considerable gap between research and practice and that HRM professionals regularly employ practices that are not well supported by evidence (Rosseau & Barends, 2011). This results in a significant

discrepancy between HRM practitioner beliefs and the prevailing findings of research (Rynes, Colbert, & Brown, 2002). In fact, the HRM knowledge instrument used in the current study is based on the work of Rynes, Colbert, and Brown (2002). By not implementing evidence-based practices, the potential for HRM to add value to the organization is severely restricted and undermined (Buyens & Verbrigghe, 2015). Furthermore, not adopting evidence-based practices frequently leads to the widespread acceptance of ineffective HRM practices that are incapable of adequately addressing complex organizational issues (Rosseau & Barends, 2011).

The leading concerns facing organizations today are the recruitment, retention, and development of top talent (Allen, Bryant, & Vardaman, 2010). Unsurprisingly, it is especially within these areas that HRM practices have been criticized for lacking strong evidence-based support (Allen et al, 2010; Lawler, 2007; Rynes et al., 2002) and for relying on an aggregate mythology of misconceptions, antiquated assumptions, intuitive beliefs, and unsubstantiated conventionalities in decision making and strategy formulation (Rynes, Giluk, & Brown, 2007).

An example of the divergence between research findings and practitioner beliefs is in the area of selection. Although researchers have demonstrated that consistently-applied structured interviews are the most valid type of interview for candidate selection, most HRM professionals incorrectly believed that interviews should be flexibly tailored around a candidate's individual strengths and background (Tenhiälä et al., 2016). In fact, one study even found that overconfidence led to poor hiring decisions (Kausel et al., 2016). Another example is that a majority of HRM professionals considered

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extraversion to be the most predictive trait for leadership success, yet research has

shown that intelligence is more highly correlated with leadership effectiveness (Rynes et

al., 2002). A third example of HRM practitioner beliefs not being informed by or

aligned with research is in the area of training. Most HRM practitioners believed that

leadership training was overall ineffective because of their underlying assumption that

leadership is dispositional and innate (Rynes et al., 2002), even though research has

shown that employees' leadership behaviors can be learned and cultivated through

leadership training (Barling, Weber, & Kelloway, 1996).

Sometimes ineffective practices emerge not from a reliance on outmoded beliefs,

but from an uncritical adoption of new practices that have not been empirically

investigated or thoroughly vetted. HRM professionals sometimes base their practices on

popular yet uninformed management trends that impersonate evidence-based best

practices (Rosseau & Barends, 2011). For example, many companies joined the open

office movement in a sincere effort to promote collaboration; however, research has

shown that this workspace configuration can decrease employee satisfaction,

participation, and productivity (Brennan, Chugh, & Kline, 2002; Haynes, 2008).

Another example of a recent topic that has propagated almost unbridled intrigue

and acceptance is generational differences in the workplace. There has been a

proliferation of popularized theories that Millennials have unique work attitudes towards

motivation, supervision, organizational commitment, and work-life balance that are

fundamentally different from their other-generational colleagues (Glass, 2007). As a

result, many HRM professionals have been quick to embrace differentiated recruitment,

engagement, retention, and performance management strategies aimed at catering to these perceived generational differences (Thompson & Gregory, 2012). However, there is a lack of consensus among academicians on whether generational differences even exist or if differences are actually better explained by other factors such as age, career stage, or life stage (Arnett, 2010; Becton, Walker, & Jones-Farmer, 2014).

Theorized differences associated with generational typologies have not consistently withstood empirical examination (Wong, Gardiner, Lang, & Coulon, 2008). For instance, a meta-analytic study revealed no statistically significant differences among generational cohorts in terms of job satisfaction, turnover intention, or organizational commitment (Costanza, Badger, Fraser, Severt, & Gade, 2012). In addition, focusing on generational differences may create damaging and demotivating employment strategies, and perpetuate stereotypes that ignore the differences within and similarities among generations (Kriegel, 2016; Sanner-Stiehr & Vandermause, 2017). Although the topic of generational differences is debated and unsettled among scholars, many HRM professionals unreservedly accepted this idea by heedlessly redesigning practices to manage generational cohorts differently. Therefore, HRM professionals must not only critically reflect on traditional and established beliefs in light of new evidence, but must also exercise prudence when endorsing new and potentially faddish theories.

The overconfidence effect might help explain why HRM professionals do not always base their practices on research, but instead rely on their own beliefs. Overconfident individuals may not even realize there is a disparity between their

confidence and knowledge (Miller & Geraci, 2014) and may tend to think they know more than they actually do. If individuals are not aware of the deficits in their existing knowledge, then they are not likely to be motivated to acquire the additional information necessary to fill in their knowledge gap (Zacharakis & Shepherd, 2001). HRM professionals might be more likely to adopt evidence-based practices if they were more cognizant that gaps exist with their current level of knowledge and that their practices do not always yield positive outcomes.

The Gap Between Perceptions and Reality

There have been considerable efforts made by HRM professionals to expand their role and image from merely being a transactional player to becoming a more strategic business partner (Cascio & Boudreau, 2012). Although there has been some noticeable progress made toward achieving this goal, the HRM profession is at large, still perceived by other business practitioners as being an administrative function in achieving organizational success (Noe, Hollenbeck, Gerhart, & Wright, 2019). While some HRM professionals may view the evolution of their field as largely fulfilled and claim that HRM has now firmly secured a seat at the strategic planning table, a more veracious assessment reveals that a sizable gap between this perception and reality still exists (Mundy, 2012). In other words, there is a discrepancy between how HRM often views itself with how HRM is viewed by others.

The criticality and indispensability for strategic HRM is not in dispute, but the degree to which this ambitious objective has already been accomplished is still contested (Cappelli, 2015). On a positive note, a compelling case for why strategic HRM is

needed has already been established. The challenge remains, however, in the

programmatic creation and execution of an agenda that is both aligned with and

contributive to organizational strategy and performance (Brenner, 2016). Therefore,

HRM professionals do not need to focus on creating a business case for why there is a

necessity for HRM, but rather on demonstrating and delivering HRM's strategic value to

the organization. In order for HRM to more fully realize its aspirational goals, its

practices must be oriented toward meeting the priorities and challenges of organizations,

especially by helping organizations build and maintain a competitive advantage (Ulrich,

Allen, Brockbank, Younger, & Nyman, 2009).

In order for HRM to be perceived more positively by its business partners, HRM

practitioners must exhibit competencies that add value to the organization. Interestingly,

the ability to effectively manage change is identified by peers as the most valued

competency for HRM professionals to possess, followed by HRM knowledge in second

place, and general business knowledge in third place (Ulrich, Brockbank, Yeung, &

Lake, 1995). This sentiment is also echoed by senior executives, many of whom

recognize effective change management as one of the most crucial challenges facing

organizations today (Anderson & Ackerman-Anderson, 2010; Hayes, 2014).

Although HRM is not the sole proprietor of change since successful change

initiatives require effective leadership and partnership across the organization, many

executives do look to the HRM to serve as a chief architect, agent, partner, facilitator,

and thought leader for change (Long, Wan Ismail, & Amin, 2013; Noe et al., 2019;

Selmer & Chiu, 2004). This increased expectation for HRM to substantively contribute

to organizational success brings about both opportunities and challenges for HRM professionals. If HRM's reputation within the organization is to be elevated, then the scope and depth of HRM competencies must correspondingly increase.

In order for HRM professionals to more adeptly become strategic business partners, they must be able to contribute to the organization's business priorities. This means that not only must HRM practitioners deliver exceptional service in the traditional areas related to HRM (e.g., compensation, benefits administration, and compliance), but they must also provide expertise in areas that are more directly and significantly linked to organizational success (e.g., change management, strategic planning, and talent management). Unfortunately, HRM professionals do not always receive adequate training in these broader areas of management, resulting in a skills mismatch or deficiency that prevents them from achieving optimal outcomes in these more strategic areas (Rynes et al., 2002). Therefore, even though there is still a gap between aspiration and reality, HRM professionals have an important and larger role to play in organizations.

Bridging the Gaps

Although the overconfidence literature does not exclusively provide every answer regarding how to bridge the gaps between confidence and professional expertise, research and practice, and HRM's perception of itself versus its actual level of strategic contribution, I have found some helpful insights from the literature. HRM practitioners can use research to help organizations confront challenges associated with overconfidence. Furthermore, it is my hope that my study will contribute to the body of

knowledge and impart actionable steps HRM professionals can take to help themselves

and their organizations alleviate some of the consequences of overconfidence.

To help bridge the gap between confidence and HRM professional expertise,

HRM professionals must first understand the various impacts of the overconfidence

effect and strive to reduce miscalibration, not only with their own decisions but with the

overall organizational decisions as well. One way to do so is to employ debiasing

strategies and interventions that aim to address the issue of overconfidence.

Furthermore, additional research is needed in this area since some biases are found to be

more resistant to debiasing efforts and some techniques have been shown to be more

effective than others (Koellinger & Treffers, 2015). With that said, one strategy that has

been shown to reduce overconfidence is to unpack time series predictions. That is, when

individuals make forecasts about the future (e.g., strategic planning), they tend to be

better calibrated when they force themselves to think about the future in smaller

increments of successive time (Ceschi et al., 2017; Jain, Murkherjee, Bearden, & Gaba,

2013). For example, if someone were making forecasts five years into the future, instead

of going straight into envisioning what realities might exist five years from now, it is

better to make predictions a year into the future, and then two years, and so forth.

Another debiasing strategy that organizations can use is to elicit diverse opinions

from multiple experts rather than just relying on one expert's opinion. Research has

shown that heterogeneous expert groups produce more accurate decisions than

homogenous expert groups (Hong & Page, 2004). Furthermore, taking the average of

estimates is likely to reduce overconfidence and produce better accuracy in judgments

(Soll & Larrick, 2009). This means that individuals might find it more beneficial to average their estimates with the estimates of others, rather than relying solely on their own assessment. HRM professionals might also need to consider when it is appropriate to rely on their own expertise versus when it is more advantageous to defer to the expertise of others (e.g., consultants or legal counsel). By employing some of these strategies, HRM professionals are better prepared to counter the overconfidence effect and produce better-calibrated decisions.

To bridge the gap between research and practice, HRM professionals need to more intentionally incorporate the findings of research into their practices. Rather than relying on their own expertise, conventional wisdom, widespread misconceptions, unverified traditions, experiential anecdotes, or popular management trends, HRM professionals need to ground their practice in evidence (Colbert, Rynes, & Brown, 2005). This requires HRM professionals to be aware of the deficiencies in their knowledge. It also requires agency on the part of the HRM professionals to actively pursue additional information to close their knowledge gap. While scholars can help bridge the divide between research and practice by making their research findings more accessible, relevant, digestible, and practical for practitioners (Friedman & Rogers, 2009; Rynes et al., 2002; Van de Ven, 1989), HRM practitioners must also take initiative in searching for evidence-based practices that have been shown to lead to positive organizational outcomes (Rynes & Bartunek, 2017). Without basing their practices on research, HRM professionals are in a disadvantageous position to address the pressing organizational issues expected of them.

Bridging the gaps between confidence and HRM expertise and research and practice will likely help HRM practitioners also bridge the gap between self-assessed relevance and their actual status within the organization. In other words, by reducing overconfidence and designing practices that are more effective and grounded in research, HRM practitioners' reputation throughout the organization is likely to improve. Furthermore, their ability to contribute to organizational strategy, success, and performance is also likely to increase. Therefore, if HRM professionals aspire to be strategic business partners, they must find means to improve their own performance (including combating the overconfidence effect) and adopt evidence-based practices.

In summary, the miscalibrations between confidence and knowledge, research and practice, and the larger contextual gap between self-assessed and actual HRM effectiveness have been explored. My hope is that the current study will contribute to a better understanding of these grander issues and assist in addressing these discrepancies. The overconfidence literature provides some possible explanations for why (a) expert decisions often incapacitate and obstruct organizational performance, such as change initiatives; (b) popular practices are frequently not informed by research and are, subsequently, unsuccessful at advancing organizational strategy; and (c) there is a noticeable disconnect between the aspirations (i.e., inflated self-assessments) of strategic HRM with the actual level of delivered services. Through this study, I hope to provide insights based in evidence that will enable HRM professionals to achieve their goal of being more strategically influential, oriented, and aligned.

Summary

In Chapter II, I reviewed and critiqued the relevant literature, identified the gaps that informed my current study, and presented major themes and relationships that emerged from the literature. The theory of bounded rationality, the heuristics and biases program, and cognitive-experiential self-theory together formed a theoretical foundation for my study. The two main bodies of literature I reviewed are expertise and the overconfidence effect. Although expertise is cursorily addressed within the overconfidence literature, I relied on HRD expertise literature to augment and further develop a sturdy and multidimensional construct of expertise. From the literature, I developed conceptual relationships among expertise, overconfidence, and individual differences. Finally, I articulated the importance of this study for HRM professionals.

CHAPTER III

RESEARCH METHODS AND METHODOLOGY

This chapter begins with a restatement of the purpose of the study and the research questions and hypotheses. Following, an overview is provided of the research design, population and sampling, instruments used for data collection, data collection procedures, and the methods utilized for data screening and subsequent data analysis.

Purpose of the Study

The purpose of this quantitative study was threefold: (a) to explore the relationships among expertise, overconfidence, and individual differences related to HRM professionals; (b) to ascertain the impact that individual differences have on the relationships between expertise and overconfidence; and (c) to determine the extent to which individual differences influence the relationships between expertise and overconfidence. Expertise is the independent variable and is represented by the dimensions of knowledge, experience, and adaptivity. Overconfidence is the dependent variable and consists of overestimation, overprecision, and overplacement. Individual differences are the mediating and/or moderating variables and are expressed through personality traits, decision-making styles, and demographic characteristics. Figure 3.1 presents the conceptual model of these hypothesized relationships.

Research Questions and Hypotheses

The following three questions guided my study:

4. What are the relationships among the various dimensions and components of expertise, overconfidence, and individual differences?
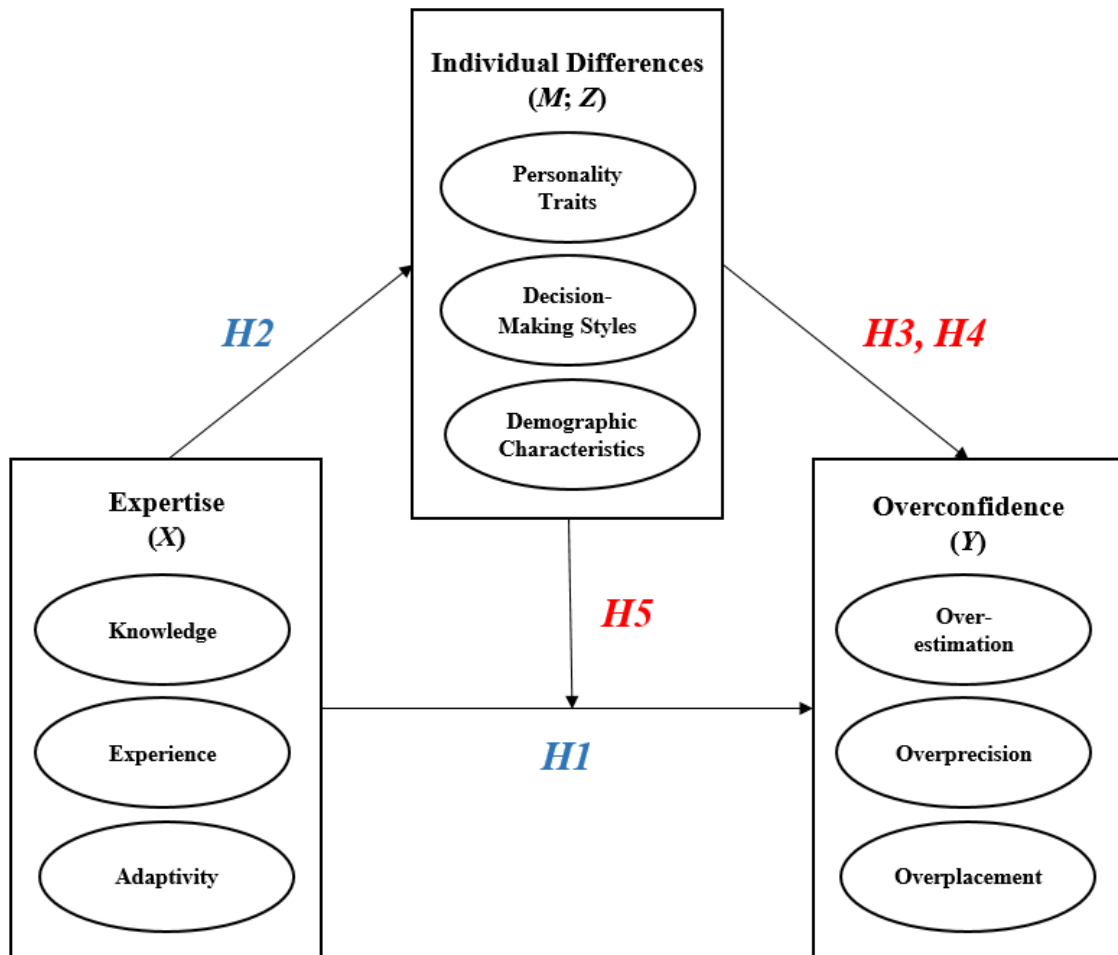
Figure 3.1. Conceptual model of the hypothesized relationships

5. What is the impact of individual differences on the relationships between expertise and overconfidence?

6. To what extent are the relationships between expertise and overconfidence influenced by individual differences?

To explore these three overarching research questions, five hypotheses were developed and tested. The first three hypotheses relate to the first research question, the fourth

hypothesis corresponds with the second research question, and the fifth hypothesis

pertains to the third research question:

H1: Expertise will be positively related to overconfidence.

H2: Expertise will be positively related to individual differences.

H3: Individual differences will be positively related to overconfidence.

H4: Individual differences will have a mediating effect on the relationships between expertise and overconfidence.

H5: Individual differences will have a moderating effect on the relationships between expertise and overconfidence.

Research Design

To answer the three research questions above, I selected a non-experimental

research design. This was the most appropriate design for my quantitative study because

my study was observational and did not involve random assignment, experimental

manipulation of an independent variable, or the introduction of a treatment or

intervention. Additionally, a non-experimental research design can incorporate both

correlational and casual-comparative features, which allowed me to (a) investigate the

degree and direction of naturally occurring associations and relationships among

multiple variables, (b) compare differences among various groups, and (c) identify

which variables predictively affect and influence outcomes (Creswell & Guetterman,

2019). The design of the self-report survey used for data collection was cross-sectional

rather than longitudinal or panel, meaning that the survey was only administered once

and not repeatedly over time (Lavrakas 2008). Non-experimental research design also

flexibly allows for both exploratory and predictive modeling, which were especially relevant to the current study (Mertens, 2019).

Correlational research refers broadly to studies that investigate relationships among variables and can range widely from simple techniques (e.g., scatterplots and linear regression) to intricate and sophisticated techniques (e.g., multiple regression, factor analyses, and path analyses) (Fraenkel, Wallen, & Hyun, 2019). Causal-comparative research refers to studies that focus on differences of variables among groups and can likewise range in the complexity of techniques employed (e.g., paired *t*-tests, chi-square tests, analyses of variance and covariance, and structural equation modeling) (Dimitrov, 2006; Salkind, 2010). Correlational and causal-comparative research can often overlap and some statistical tests even fit into both categories. The current study utilized correlational as well as causal-comparative techniques.

Population and Sampling

The target population for my study is all HRM professionals in the United States. Collecting information on this population, however, is not practicable since there is not a centralized database attainable by me that easily or comprehensively aggregates every HRM professional in the United States. There are practical limitations associated with reaching this entire theoretical population. Consequently, feasibility constraints dictated that I needed to narrow my focus and strategize on how to reach a study population instead (Banerjee & Chaudhury, 2010).

The study population is all HRM professionals in the United States who are accessible through professional channels. The study population is the available subset of

the target population. Findings from the study population may provide inferential

insights into the larger target population (Ruel, Wagner, & Gillespie, 2016). Even

though the study population is more achievable than the target population, feasibility

constraints of time and other resources still existed that prevented me from being able to

reach every member of this population. Therefore, I relied on recruiting a representative

sample of the study population who would participate in my study.

The sampling strategy I used was purposive sampling (Ruel et al., 2016) and the

criteria for the sample population were (a) HRM professionals (b) in the United States

(c) who can be easily contacted through professional channels. The United States rather

than a global HRM population was selected because of my access to and familiarity with

U.S. HRM. The primary professional channel I identified was association with a local

professional HRM chapter, especially those affiliated with the Society for Human

Resources Management (SHRM). SHRM is the largest professional HRM organization

in the United States ("SHRM 2019 Annual Report: Building Better Workplaces,

Boldly," n.d.), so my selection of this organization was based on convenience as well as

its representativeness of the target population. Other HRM groups with a sizable

number of followers were identified as additional channels. These groups were also

selected because of the large volume of HRM professionals that were recruitable through

those channels.

In total, I reached out to 87 local SHRM chapters and 17 other HRM professional

groups. Out of the 104 organizations I contacted, 16 agreed to support my study, seven

of which distributed my survey to their members on my behalf and nine of which

permitted me to post information about my study on their group Facebook and/or

LinkedIn pages. Figure 3.2 graphically displays the target, study, and sample

populations for my study.

Target Population
HRM professionals in
the United States

Study Population
HRM professionals in the
United States who are
accessible through
professional channels

Sample Population
HRM professionals in the
United States who are
accessible through
professional channels
and who participated in
the survey
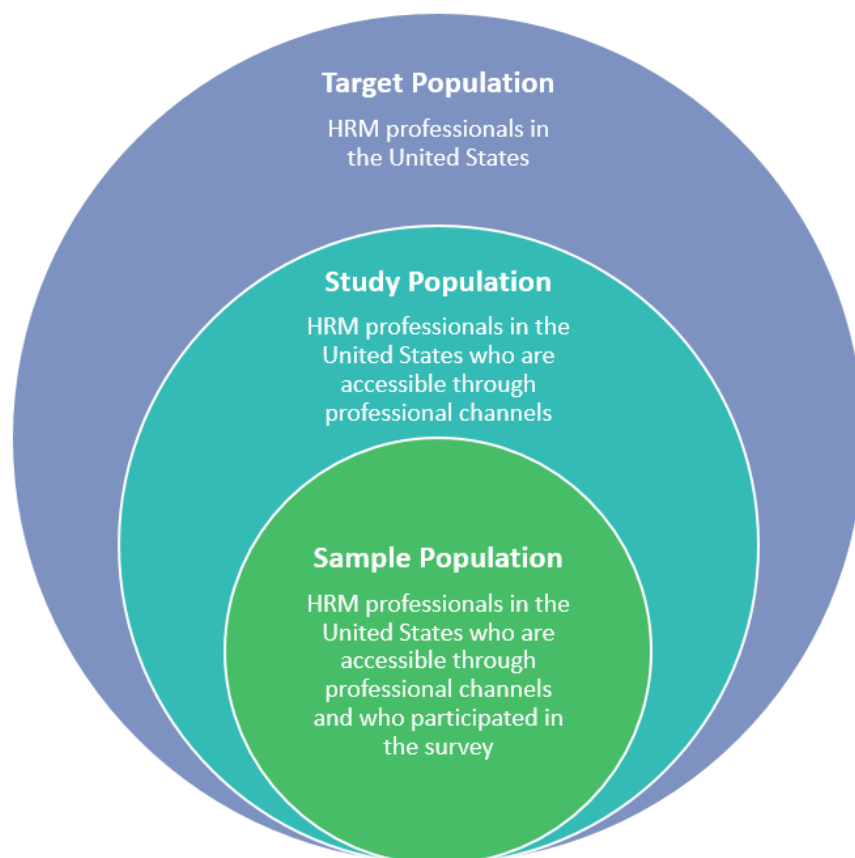
Figure 3.2. Stacked Venn diagram of population and sampling

Instrumentation

Instruments are the devices that researchers use to measure variables of interest (Cohen, Manion, & Morrison, 2017). For an instrument to be considered valid, it must accurately measure what it is supposed to measure. Construct validity refers to how well the construct is defined and operationalized, criterion validity is how well a measure relates to a particular outcome, and content validity denotes the extent to which all components of a construct are comprehensively and representatively measured by an instrument (Fraenkel et al., 2019).

For an instrument to be considered reliable, it must consistently measure what it is intended to measure. Internal reliability refers to how consistent a measure is with itself and external reliability is how consistent a measure is over time. A common assessment of external reliability is test-retest reliability and a popular measure of internal reliability is Cronbach's alpha (Fraenkel et al., 2019). Although determining a reliability score cutoff is arbitrary, a common rule-of-thumb is that reliability scores of .70 and above are generally acceptable, although lower scores (e.g., .60 to .70) are also considered satisfactory for shorter measures with few items (Streiner, 2003; Tavakol & Dennick, 2011; Ursachi, Horondnic, & Zait, 2015).

According to Creswell and Guetterman (2019), researchers have three options at their disposal for using an instrument for data collection: (a) developing a new instrument; (b) modifying an existing instrument to meet their research needs; and (c) adopting an existing instrument in its entirety. For my study, I adopted existing instruments to measure HRM domain-specific knowledge, personality traits, adaptive

expertise, and two measures for decision-making styles. I developed my own

instruments to measure experience, the other components of knowledge (i.e., education,

credentials, and professional involvement), overconfidence, and demographic

characteristics. These five adopted and four developed instruments are discussed in the

three categories of expertise, overconfidence, and individual differences.

Table 3.1 presents the number of items and reliability scores for each adopted

instrument and Table 3.2 exhibits the number of items and components of each

developed instrument. A total of 114 items were used for measurement in my survey

(two screening questions, three attention checks, and two optional questions for a prize

drawing were also asked). The full survey can be found in Appendix A. I obtained

proper permission and authorization to use the adopted instruments that were not already

available for open access use (see Appendix B for the copyright permission requests).

Expertise Instruments

The three dimensions of expertise identified for this study are knowledge,

experience, and adaptivity. I utilized a total of four instruments to measure this

multidimensional construct. I adopted two instruments and developed two other

instruments to measure expertise.

Knowledge

Commercial knowledge certification exams such as those offered by SHRM and

the HR Certification Institute (HRCI) are proprietary and designed for the exclusive use

of those certifying bodies. As a result, I did not have access to a professional exam for

the purpose of my study. Therefore, I relied on an academic HRM domain-specific

knowledge instrument designed by Rynes, Cobert, and Brown (2002), which includes 35 knowledge questions in the areas of management practices, general employment practices, training and employee development, staffing, and compensation and benefits.

In the knowledge instrument, "items were constructed to be either true or false, based on previous research results. Respondents were asked to indicate whether they agreed, disagreed, or were uncertain about each item" (Rynes et al., 2002, p. 151). Responses were converted to a binary coded dummy variable (1 for correct responses and 0 for incorrect or uncertain responses). The reliability of the questionnaire was found to be .70, which is satisfactory. I developed six questions to assess the other knowledge components of education, credentials, and professional involvement. These six questions are as follows:

1. Do you hold any professional certifications, credentials, or licenses?

2. If yes, which professional certifications, credentials, or licenses do you hold?

3. Are you a member of any national professional associations?

4. If yes, of which national professional associations are you a member?

5. Are you a member of any local professional associations?

6. What is the highest level of education you have completed?

Table 3.1

Number of Items and Reliability Scores of Adopted Instruments

Instrument	# of Items	Reliability Score	Source
Adaptive Expertise Inventory	10 (5 for each subscale)	.79 Domain Skills .78 Innovative Skills .85 Overall Adaptive Expertise	Bohle Carbonell et al. (2016)
BFI-10*	10 (2 for each personality trait)	.83 Extraversion .68 Agreeableness .77 Conscientiousness .74 Neuroticism .72 Openness	Rammstedt & John (2007)
CRT MCQ-4	3	.73 Reflectiveness .67 Intuitiveness	Sirota & Juanchich (2018)
DSS	10 (5 for each decision-making style)	.78 Rational Decision Style .73 Intuitive Decision Style	Hamilton et al. (2016)
HRM Domain-Specific Knowledge*	35	.70	Rynes et al. (2002)

Note. * Indicates that test-retest reliability was used rather than Cronbach's alpha (α).

Table 3.2

Number of Items and Components of Developed Instruments

Instrument	# of Items	Components
Demographic Characteristics	17	Age, gender, race and ethnicity, salary, referral source, information sources
Experience	5	Years, level/type, and areas of experience
Other Knowledge Components	6	Education, credentials, professional involvement
Overconfidence	18	Overestimation, overprecision, overplacement

Experience

I developed five questions to assess respondents' experience. The components of experience are years of experience, level and type of experience, and areas of experience. Therefore, I was concerned with not just the quantity of experience, but also with the quality of that experience. The five questions pertaining to experience are as follows:

1. How many years of experience do you have in your current or most recent role?
2. How many total years of professional experience do you have in HRM?
3. How many years of professional experience do you have in total (both inside and outside of HRM)?
4. Which of the following best describes your current employment status?
5. Which best describes your current or most recent position?

Adaptivity

To measure the adaptivity dimension of expertise, I adopted the Adaptive Expertise Inventory (Bohle Carbonell, Könings, Segers, & van Merriënboer, 2016). This is an existing inventory that consists of 10 questions, five of which measure the domain skills subscale and the other five measure the innovative skills subscale. A 5-point Likert scale was used for each item, ranging from "Strongly Disagree" to "Strongly Agree." Additionally, this has been validated as a reliable instrument. The reliability scores are .85 for overall adaptive expertise, .79 for the domain skills subscale, and .78 for the innovative skills subscale (Bohle Carbonell et al., 2016).

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Overconfidence Instrument

The three dimensions of the overconfidence effect were measured in my study. I developed three questions that consisted of 18 items. Participants were asked to (a) provide a self-assessment of their knowledge (overestimation) in the areas of management practices, general employment practices, training and employee development, staffing, compensation and benefits, and overall HRM knowledge; (b) determine a confidence percentage around their self-assessment (overprecision) in those areas; and (c) rate how knowledgeable they are in those domains relative to others (overplacement). Overestimation and overprecision were calculated by subtracting respondents' actual scores on the knowledge questions from their subjective self-rated confidence scores. Overconfidence will be detected if the subjective confidence scores are greater than the actual scores. Calculating the overconfidence effect in this manner is consistent with previous studies since overconfidence is defined as the miscalibration between perceived and objective performance (Ehrlinger, Mitchum, & Dweck, 2016). Overplacement was measured on a 5-point scale for each item, ranging from "Extremely less knowledgeable" to "Extremely more knowledgeable." The three questions I developed are as follows:

1. Please use the slider scale from 1 to 100 to indicate what percentile you rate yourself in each area. The higher the number means the more highly you rate yourself.

2. Please use the slider scale from 1 to 100 to answer how confident/certain you are in each area. The higher the number means the more confidence/certainty you have.

3. Compared with other HRM professionals, how knowledgeable are you in each area?

Individual Differences Instruments

The three types of individual differences most relevant to my study are personality traits, decision-making styles, and demographic characteristics. Three instruments were adopted to measure personality traits and decision-making styles and I developed questions to record respondents' demographic characteristics. The six questions I developed for individual differences are as follows:

1. What is your age (in years)?

2. From which HRM group did you access this survey?

3. Please indicate your current annual salary in U.S. dollars.

4. How often do you leverage the following resources to stay current in the HRM field?

5. With which gender do you most identify?

6. What is your race/ethnicity?

Personality Traits

To measure personality traits, I relied on the Big Five Inventory-10 (BFI-10), which consists of two items per personality trait for a total of 10 items (Rammstedt & John, 2007). A 5-point Likert scale was used for each item, ranging from "Disagree

Strongly" to "Agree Strongly." Five of the items were reverse-scored, one for each

personality trait. The reliability scores are .83 for Extraversion, .68 for Agreeableness,

.77 for Conscientiousness, .74 for Neuroticism, and .72 for Openness (Rammstedt &

John, 2007). The BFI-10 is an abbreviated version of the full length 44-item Big Five

Inventory (BFI) and shows good convergent, concurrent, and discriminant validity with

the BFI (Carciofo, Yang, Song, Du, & Zhang, 2016). Short measures are appropriate to

use when personality is not the primary topic of study and when researchers can endure

the reduced psychometric properties related to using shorter inventories (Gosling,

Rentfrow, & Swann, 2003; Rammstedt & John, 2007). Although somewhat diminished

compared with the BFI, the results of the BFI-10 still "indicate sufficient psychometric

properties" and "the findings corroborate the construct and criterion validity of the

instrument" (Rammstedt, Kemper, Klein, Beierlein, & Kovaleva, 2013, p. 233).

Decision-Making Styles

I adopted two instruments to measure decision-making styles: the Decision

Styles Scale (DSS) (Hamilton, Shih, & Mohammed, 2016) and the four-option multiple-

choice version of the Cognitive Reflection Test (CRT MCQ-4) (Sirota & Juanchich,

2018). The DSS was theoretically inspired by cognitive-experiential self-theory (CEST)

and measures whether individuals process information rationally or intuitively. It is a

10-item psychometric instrument that measures whether individuals make decisions

rationally, thoroughly, and systematically or intuitively, spontaneously, and quickly. A

5-point Likert scale was used for each item, ranging from "Strongly Disagree" to

"Strongly Agree." The reliability scores of this instrument are .78 for the Rational Decision Style and .73 for Intuitive Decision Style (Hamilton et al., 2016).

I used the DSS in combination with the CRT MCQ-4 to observe decision-making styles. The original CRT is a three-item questionnaire where questions are open-ended (Frederick, 2005). Reflective responses refer to the correct responses while intuitive responses refer to instinctive although incorrect responses. The version of the CRT I used is the four-option multiple-choice version (CRT MCQ-4) where four multiple-choice options to each question are presented in random order. The CRT MCQ-4 has been validated as an acceptable alternative to the CRT and the reliability scores are .73 for Reflectiveness and .67 for Intuitiveness, which are satisfactory given the brevity of the instrument (Sirota & Juanchich, 2018). To avoid potential redundancy between the measures, I used only the DSS for path modeling (although I did analyze both instruments through descriptive statistics and the mediation analysis).

Demographic Characteristics

I followed guidelines provided by Dillman, Smyth, and Christian (2014) to construct six questions consisting of 17 items to measure the relevant demographic characteristics of the population of interest for my study. Demographic variables provide researchers with descriptive information about the attributes and characteristics of a sample and are useful in explaining potential relationships with dependent variables (Creswell & Guetterman, 2019). The relevant demographic characteristics for the current study included age, gender, race and ethnicity, salary, the referral source (i.e., the channel by which respondents accessed the survey), and the information sources that

HRM professionals most often leverage to stay current in their field. The last question asked respondents the frequency in which they utilize 12 various information sources on a 5-point scale, ranging from "Never" to "Always." This question was prompted by a study that revealed considerable gaps between HRM practitioner beliefs with the findings of research, and that information sources may play a contributing role in this discrepancy (Rynes et al., 2002).

Data Collection Procedures

There is no such thing as a perfect data collection method; each method has its share of tradeoffs and errors that are inherent to that particular method (Bickman & Rog, 2009). Therefore, a researcher should conduct a cost-benefit analysis by taking into account the unique priorities of the researcher, the availability of resources, constraints that bound resources, and what errors the researcher can tolerate (Lavrakas, 2009). In reviewing various options for data collection, I decided to carry out a web-based survey, which was the most appropriate, attractive, and cost-effective method for my study for four reasons.

First, online data collection allows for the quick and simultaneous dissemination of a survey to a large number of people. This permits data collection in real-time, rather than having to schedule time with respondents to administer a survey face-to-face, telephonically, or wait for respondents to mail back questionnaires. In addition, online data collection is less expensive compared to traditional survey methods, such as having to pay for postage (Ruel et al., 2016). Furthermore, respondents are able to participate on their time and terms rather than having to coordinate with someone else's availability.

The second reason I selected the online method of data collection is accuracy with data entry. Data entered by respondents online is more likely to be accurate than data entered primarily by a researcher (Ruel et al., 2016). The self-reported nature of the online method removes the need for me to act as the sole or primary point of data entry. In other words, respondents enter their own responses online, rather than relying on me to enter all of the responses myself. If I acted as the exclusive source of data entry, the natural human error and fatigue associated with repetitive acts would likely result in increased data entry errors (Ruel et al., 2016).

Thirdly, the online data collection method is convenient and nonintrusive for respondents compared to mailed, face-to-face, or telephonic surveys (Ruel et al., 2016). The Internet is a widely available resource for many people and an attractive data collection channel for researchers because information can be requested from many people all at once. Mailed surveys are sometimes inconvenient for respondents because of their need to hand-write their responses and take the extra steps to return their surveys. Telephone or face-to-face solicitations may seem invasive and intrusive for respondents, which could result in potential respondents screening and ignoring phone calls, or having initial resistance to participating in the study (Ruel et al., 2016).

Finally, the degree of researcher involvement and interaction connected with online data collection is very negligible, which helps minimize researcher effects and biases (Ruel et al., 2016). Respondents have a high degree of privacy when completing a survey online, and are able to quickly and anonymously submit their responses in a way where their individual responses cannot be linked to them individually (Ruel et al.,

2016). All of these reasons made online data collection the most convenient, appealing, and cost-effective method for my study.

Once I decided to pursue this data collection method, I developed the survey for the current study by utilizing the online tool Qualtrics. Qualtrics was free for me to use since I had access to a student account through the College of Education & Human Development at Texas A&M University. After my study was approved by the Institutional Review Board (IRB) at Texas A&M University (see Appendix C), I attempted to recruit support from 87 local SHRM chapters and 17 other HRM professional groups (see Appendix D). Sixteen organizations either distributed my survey to their members on my behalf or granted me permission and access to post a link to my online survey on their social media platforms (i.e., Facebook and/or LinkedIn).

The functionality of Qualtrics allowed me to embed the informed consent document (see Appendix E) into the survey. So as not to sensitize respondents to the dependent variable of interest (i.e., overconfidence), I modified the publicized title of the study to *Exploring the Expertise of Human Resource Management (HRM) Professionals*, thereby removing any reference to overconfidence. Respondents were able to read the informed consent form online and decide whether they wanted to participate. Therefore, participation was voluntary. To participate in the survey, respondents had to click that they agreed to participate in the study and also respond affirmatively that they were at least 18 years of age. Once these two screening questions were answered, respondents were able to progress through the rest of the survey.

To attract and incentivize participation, I informed participants that I would be giving away four $50 Amazon gift cards in a drawing for those who completed the survey and provided an email address. Qualtrics permitted me to create a separate optional email capture form for those who wanted to be entered into the drawing. This helped preserve data privacy, protect participant anonymity, and store email addresses unconnectedly from survey responses. See Figure 3.3 for a timeline of the data collection phase of the current study.

AUGUST 2019	SEPTEMBER 2019	JULY 2020	AUGUST 2020
Obtained IRB approval	Launched Qualtrics survey	Closed Qualtrics survey	Prize drawing and notification

Figure 3.3. Timeline of data collection

Data Screening

At the completion of the data collection phase, the Qualtrics survey was closed and the data were downloaded into an Excel spreadsheet. The survey data were then imported into the data editor of IBM® SPSS® Statistics 25.0 (hereafter, SPSS) software so that I could conduct pre-analysis screening. The data were screened for quality, missing data, outliers, multicollinearity and common method bias, and normality. A total of 425 eligible responses were initially recorded. After eliminating 11 low-quality responses (i.e., incomplete and/or inattentive responses), a total of 414 responses were included in the sample for analysis. This represents a satisfactory sample size given the statistical techniques employed (Hair, Hult, Ringle, & Sarstedt, 2017).

Data Quality

To help preserve data quality, I designed the Qualtrics survey so that it could only be taken once, respondents were incentivized by the prospect of winning a prize, and only complete responses were recorded (i.e., partial and non-submitted responses were automatically deleted after 30 days of inactivity from the respondent). Despite anticipatory and preventive measures such as these, there is still the risk that data can become contaminated by low-quality responses, especially from careless and inattentive respondents who although may complete a survey do not exert adequate effort to read, understand, and appropriately respond to the questions (Oppenheimer, Meyvis, & Davidenko, 2009). Careless responses can decrease the validity of data and distort the findings and conclusions derived from that data (Bowling et al., 2016; Hauser & Schwarz, 2016; Huang, Bowling, Liu, & Li, 2015; Huang, Liu, & Bowling, 2015). As a

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result, some researchers suggest including attention checks in surveys so that inattentive responses can be identified, screened out, and ultimately removed prior to data analysis (Berinsky, Margolis, & Sances, 2014; Berinsky, Margolis, & Sances, 2016; Bowling et al., 2016; Huang, Bowling et al., 2015; Huang, Liu et al., 2015; Maniaci & Rogge, 2014).

Other researchers have cautioned that attention checks may also harm data quality, such as by negatively impacting scale validity, altering participants' behavior in the way they respond to subsequent questions, and introducing demographic, psychographic, and other response biases (Curran, 2016; Curran & Hauser, 2015; Hauser & Schwartz, 2015; Vannette, 2017). Objections to attention checks, however, might be overstated and based on theoretical disputations; when these objections have been subjected to empirical examination, the evidence has not supported the claim that attention checks actually threaten data quality (Kung, Kwok, & Brown, 2018). Therefore, researchers may defensibly use attention checks without compromising the integrity and validity of their data (Kung et al., 2018).

Based on my assessment of the arguments both for and against the inclusion of attention checks, I decided to incorporate three attention checks throughout my survey as a quality control measure. In my decision to leverage attention checks, I was mindful to only use fair and explicitly instructive questions (e.g., "Please select 'Disagree' for quality control") rather than unfair questions (e.g., trick questions or items that rely on memory recall). Furthermore, I established a justifiable cutoff for reliably detecting and rejecting low-quality responses by eliminating submissions from respondents who failed

more than one attention check. This is consistent with survey design guidance provided

by Prolific, the world's largest crowdsourcing community of scientific researchers

("Using Attention Checks as a Measure of Data Quality," 2020). In total, 11 out of 425

responses (2.59%) were determined to be low-quality submissions and were accordingly

eliminated from analysis.

Missing Data

In total, there were 148 missing values (0.22%) in the data collected. Handling

missing data through imputation rather than deletion methods is preferred in the context

of partial least squares structural equation modeling (PLS-SEM), regardless of how

random the missingness may be; imputation performs best in yielding the least biased

mean path coefficient estimates and mean loading estimates (Kock, 2018). Imputation is

also frequently regarded as the standard method for handling missing data for other

statistical techniques as well (Baraldi & Enders, 2010; Graham, 2009). The specific

imputation procedure I selected was multiple imputation, where missing values are

replaced with predictive values from the posterior distribution of the data (Sterne et al.,

2009; Takahashi, 2017). SPSS uses a Markov chain Monte Carlo (MCMC) algorithm

where linear regression is used for continuous variables and logistic regression is used

for categorical variables.

Outliers

Univariate outliers are extreme scores that occur on a single variable. Box plots

were used to visibly detect univariate outliers. The center line of a box plot represents

the 50th percentile (i.e., median), the top border denotes the 75th percentile, and the

bottom border signifies the 25th percentile. The two lines extending from the borders are referred to as whiskers and display the variability beyond the upper and lower quartiles. Values that fall outside of these whiskers are considered outliers (Fraenkel et al., 2019). A total of 15 univariate outliers were identified, which indicates a maximum of 3.6% of the total cases (15/414). Because the total number of univariate outliers was negligible and its potential impact was insignificant, no values were removed.

A test was also conducted to identify multivariate outliers (i.e., participants who provided multiple extreme or abnormal responses) using the Mahalanobis D^2 statistic. A total of 24 cases (5.8%) of statistically significant ($p < .001$) multivariate outliers were identified. The outliers were not excluded from analysis because outliers are expected in a large sample and the exclusion of outliers prior to statistical analysis is considered by many researchers to be a controversial and methodologically unsound practice (Cousineau & Chartier, 2010). Hair, Babin, Anderson, and Black (2018) argued that excluding outliers from a sample is a threat to external validity because it is not possible to make generalizations about the population from which the sample was drawn if a selected subset of the data has been deliberately excluded. Therefore, multivariate outliers were included in the data that were analyzed.

Multicollinearity and Common Method Bias

Multicollinearity is the condition in which independent variables are highly intercorrelated with each other. One of the most common diagnostic tools to detect multicollinearity is the variance inflation factor (VIF) (Field, 2018). VIF values greater than 10 are an indicator that there is a high degree of multicollinearity (Kline, 2015).

Additionally, VIF calculations are used within the specific context of PLS-SEM to test for common method bias, which occurs when variance is spuriously attributable to an instrument rather than to the constructs (Kock, 2015). VIF values lower than 3.3 are an indication that the model is free from common method bias (Kock & Lynn, 2012). In my study, all VIF values were less than 3.3, indicating that the model was unburdened by either multicollinearity or common method bias.

Normality

Tests for normality were conducted on the continuous/interval level variables used to measured expertise (i.e., knowledge, experience, and adaptivity), overconfidence (i.e., overestimation, overprecision, and overplacement), and individual differences (i.e., age, personality traits, and decision styles). The results of normality and skewness tests are provided in Appendix F and show that 32 out of the 38 continuous variables deviated strongly from normality (indicated by $p < .001$ for the Shapiro-Wilk test).

The skewness statistics reflected the asymmetry of the distribution of each variable (i.e., the extent to which the shape of the distribution deviated from a normal symmetrical bell-curve). Skewness $= 0$ represented a perfect bell-curve. The positive skewness statistics for 10 of the variables indicated that the distributions were right-skewed. This means that the modes (i.e., highest frequencies) were on the left side, implying that the respondents tended to respond to the questionnaire items with lower scores. Negative skewness statistics for 28 of the variables indicated that the distributions were left-skewed (i.e., the modes were on the right side, implying that the respondents tended to respond to the questionnaire items with higher scores). With

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respect to the testing of the hypotheses, the implications of the deviation from normality and skewness of the variables were minimal. This is because PLS-SEM is a non-parametric method that performs exceptionally well with non-normal data and is remarkably robust against deviations from normality (Hair et al., 2017; Kock, 2016).

Data Analysis

Following the data screening process, several statistical techniques were employed to analyze the data: descriptive analysis, PLS-SEM, mediation analysis, and moderation analysis. SPSS and SmartPLS 3.3.2 (hereafter, SmartPLS) were the software packages used to conduct these analyses.

Descriptive Statistics

Descriptive statistics are used to describe information about the participants of the current study. These include the variables used as indicators for expertise, overconfidence, as well as individual differences. The results of the descriptive analysis are presented in Chapter IV.

Structural Equation Modeling

The five hypotheses were tested by structural equation modeling (SEM). I had to consider which type of SEM should be implemented: either the covariance-based approach (CB-SEM) or the variance-based partial least squares approach (PLS-SEM). Both PLS-SEM and CB-SEM operate by modeling the statistical relationships among multiple latent variables. A latent variable is a construct or concept that cannot be directly measured but must instead be inferred using a combination of empirical measurements or indicators, particularly responses to items from survey instruments

(Ong & Puteh, 2017). Because PLS-SEM and CB-SEM are modeling tools that have ambiguities and misconceptions associated with them (Bagozzi, 2010; Tarka, 2018) and PLS-SEM is a separate technique from CB-SEM (Rigdon, Sarstedt, & Ringle, 2017; Ringle, 2016; Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016), it is imperative that a researcher explain the reasons that PLS-SEM were given priority over CB-SEM. My reasons for selecting PLS-SEM are below.

First, PLS-SEM is commonly used in the development of a new theory or extension of an existing theory or in the development of a model that has not previously been defined or established (Hair et al., 2017; Lowry & Gaskin, 2014; Willaby, Costa, Burns, MacCann & Roberts, 2015). Alternatively, CB-SEM is generally selected by researchers who wish to confirm and/or explain an existing theory and build a well-developed and previously defined model that reproduces the empirical covariance matrix (Ong & Puteh, 2017). Therefore, the application of PLS-SEM is largely exploratory and predictive instead of confirmatory and explanatory (Karima & Meyer, 2014; Riou, Guyon, & Falissard, 2016). In contexts where there is limited prior information about the potential directions and strengths of model pathways, exploratory and predictive models have been shown to be more useful than confirmatory and explanatory models (Hair et al., 2017). Moreover, PLS-SEM is a powerful and complex multivariate statistical technique that allows researchers to conduct multiple advanced analyses, including causal predictive analysis (similar to multiple regression), factor analysis, path analysis, as well as mediation and moderation analyses (Hussain, Fangwei, Siddiqi, Ali, & Shabbir, 2018; Matthews, Hair, & Matthews, 2018).

Second, PLS-SEM is a non-parametric method that operates using variables measured at the interval, ordinal, and nominal levels (Hair et al., 2017; Ong & Puteh, 2017). As such, it does not require that stringent assumptions (e.g., normality) be met, which is especially ideal in applied settings where such assumptions are not always tenable, at least not in full (Trinchera, Russolillo, & Lauro, 2008; Vinzi, Trinchera, & Amato, 2010). In contrast, CB-SEM is a parametric method and assumes normally distributed variables at the interval level (Hair et al., 2017). PLS-SEM was the more suitable method over CB-SEM to test the hypotheses of the current study because the hypothesized model included variables that violated the parametric assumptions of CB-SEM. PLS-SEM was justified because it is a utile alternative when the assumptions of CB-SEM are not upheld (Hair et al., 2017; Henseler et al., 2014). However, CB-SEM is also presumed to be remarkably robust against non-normality (Hair et al., 2017; Jannoo, Yap, Auchoybur, & Lazim, 2014). Therefore, deviation from normality was not the primary reason that I opted for PLS-SEM over CB-SEM.

Third, the hypothesized model included some constructs that were formative and others that were reflective. PLS-SEM is able to pliably operate with formative as well as reflective constructs (Hair et al., 2017), whereas CB-SEM operates mainly with reflective constructs and may actually become cumbersome to maneuver when formative constructs are introduced (Roy, Tarafdar, Ragu-Nathan, & Marsillac, 2012; Sarstedt et al., 2016). With CB-SEM, if a researcher incorrectly specifies a construct as reflective when it should actually be formative (or vice versa), then the integrity of the entire model could become comprised (Diamantopoulos & Siguaw, 2006).

Reflective constructs are presumed to be causal factors, consisting of multiple indicators (at least three empirical measurements) that reflect the multidimensional effects of a construct. In the current study, the reflective constructs were expertise and overconfidence. The internal consistency reliability of the indicators in a reflective construct must be good because the indicators are assumed to be the intercorrelated and interchangeable effects of a unifying construct (Hair et al., 2017).

A formative construct, on the other hand, is typically presumed to be the overall effect that consists of one or more nominal, ordinal, or interval level indicators, which are not necessarily interchangeable or related to each other but that are still assumed to be the joint causes of the construct (Cadogan, Lee, & Chamberlain, 2013). An example of a common formative construct used in research is socioeconomic status (SES), which consists of a combination of salary, educational level, and employment status (Hair et al., 2017). In this study, the formative constructs were individual differences. The internal consistency reliability of the indicators of a formative construct is not an important criterion because the indicators are not necessarily correlated with each other.

Fourth, CB-SEM uses goodness-of-fit (GOF) indices to determine whether the hypothesized model reproduces the covariance matrix, while PLS-SEM does not use these types of indices. Although a crude GOF index has been defined for PLS-SEM based on the geometric mean of the average communality and the average R^2 value, this index is not widely used (Hair et al., 2017). Moreover, goodness-of-fit does not guarantee that a model is necessarily practical or useful. Nonetheless, SEM researchers often "focus too heavily on global tests of model fit (Bollen & Pearl, 2013, p. 324). A

model constructed using CB-SEM may have little predictive ability and/or practical applications, even if it is a good fit to the covariance matrix (Tarka, 2018). Conversely, a model constructed using PLS-SEM may still be useful and have a practical application even though it is not a good fit to the covariance matrix (Maydeu-Olivares & Garcia-Ferero, 2010). Additionally, the current study leverages several shortened inventories, which are not designed to be subjected to fit indices (Kline, 2000; Wood & Hampson, 2005).

PLS-SEM was chosen for this study for four main reasons. First, the theory underpinning the hypothesized models has not previously been well-developed. Second, the hypothesized model has not previously been specified or introduced. Third, the distribution of most of the variables deviated strongly from normality. Finally, the hypothesized model included reflective constructs (i.e. expertise and overconfidence, measured with multiple questionnaire item scores) and formative constructs (i.e., individual differences, measured using age, gender, salary, race/ethnicity, salary, personality traits, information sources, and decision-making styles). The results of the PLS-SEM are presented in Chapter IV.

Mediation Analysis

Mediation means that a direct relationship between an independent variable (IV) and a dependent variable (DV) does not exist in isolation, but is partially or completely explained by indirect relationships with a mediating variable or mediator (Baron & Kenny, 1986; MacKinnon, Coxe, & Baraldi, 2012). Figure 3.4 is a path diagram using a

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triangular format to illustrate the hypothesized mediating effect of individual differences on the relationship between expertise and overconfidence (H4).

In terms of cause and effect, a mediator is the underlying cause of the correlation between an IV and a DV. Mediation is the extent to which the mediator explains that correlation and mediation effects are exemplified by the question "How did it work?" (MacKinnon et al., 2012). When a mediator is added to a model to examine the indirect relationship between an IV and a DV, the possible outcomes are: (a) no mediation, when the correlation between the IV and the DV does not change; (b) complete mediation, when the correlation between the IV and DV is reduced to zero; or (c) partial mediation, when the correlation between the IV and the DV is reduced in magnitude but is still significantly different from zero (Baron & Kenny, 1986). Mediating variables are usually measured using continuous or interval level scales. In this study, the hypothesized mediators were personality traits, age, decision-making styles, cognitive reflection, and information sources. The results of the mediation analysis are presented in Chapter IV.
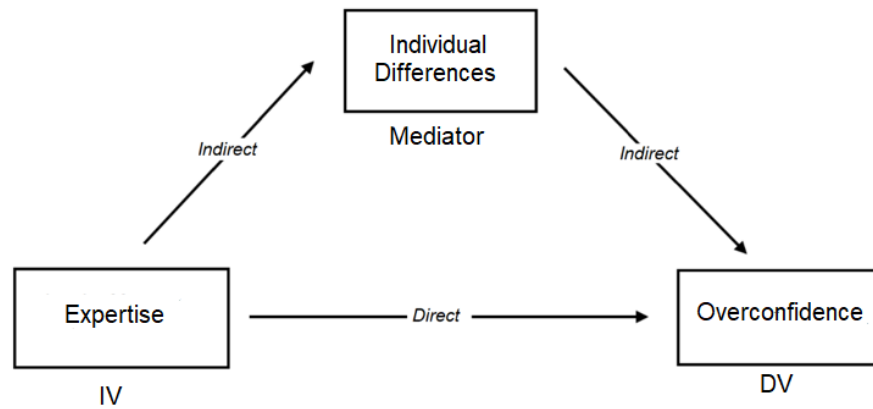
Figure 3.4. Mediator model

Moderation Analysis

A moderator is a third variable that controls the strength and/or direction of the relationship between an IV and a DV. Moderation effects are generally exemplified by the question "Who did it work for?" (MacKinnon et al., 2012). Consequently, moderators are usually categorical variables such as gender and ethnicity/race. A moderating effect is generally identified as a statistically significant correlation between an interaction term (i.e., the product of an IV and a moderator) and a DV (Fairchild & MacKinnon, 2009; Wong, 2016). The path diagram in Figure 3.5 illustrates the hypothesized moderating effect of individual differences on the relationship between expertise and overconfidence (H5). The results of the moderation analysis are presented in Chapter IV.
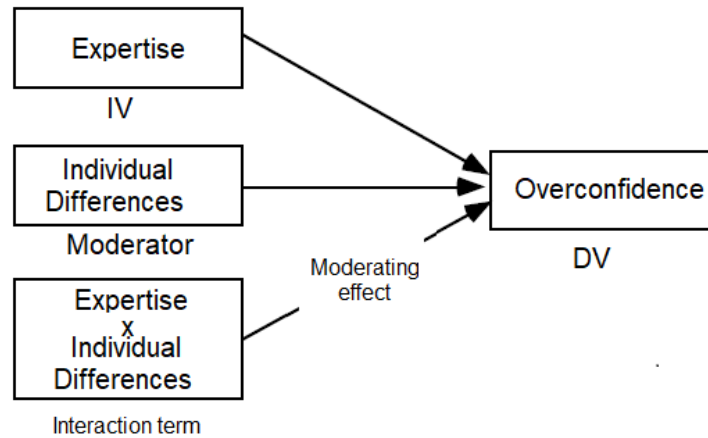
Figure 3.5. Moderator model

Stepwise Description of Statistical Methods

The following steps were taken to test the hypotheses by using the aforementioned statistical techniques:

Step 1: Following the preliminary screening of the data, the demographic and contextual characteristics of the respondents were analyzed in SPSS. Categorical variables (gender, race/ethnicity, educational level, employment status, and certifications and associations) were summarized by frequency distributions.

Step 2: The survey data were imported from the SPSS data file into SmartPLS as a CSV (comma-delimited) file. All variables were automatically transformed by SmartPLS into Z-scores and converted into a common and standardized measurement scale, with a mean of 0.0 and a variance of 1.0.

Step 3: PLS-SEM path diagrams of the previously discussed hypothesized relationships were constructed using the graphic user interface of SmartPLS. Figure 3.6

displays the PLS-SEM path diagram drawn to test H1. Figure 3.7 displays the PLS-SEM path diagram drawn to test H2, H3, and H4. Figure 3.8 displays the PLS-SEM path diagram drawn to test H5.

The oval symbols in the path diagrams represent the latent variables or constructs and the rectangular symbols denote the multiple indicators used to operationalize the latent variables. The six reflective latent variables are symbolized by a fan of arrows directed out toward the indicators (i.e., the three dimensions of knowledge, experience, and adaptivity which are composited to measure expertise, and the three dimensions of overestimation, overprecision, and overplacement which are composited to measure overconfidence). The formative construct (i.e., individual differences) has a fan of arrows directed inward from the indicators toward the latent variable. The path coefficients used to test the hypotheses were represented by the unidirectional arrows connecting pairs of latent variables, labeled H1, H2, H3, H4, and H5.

Step 4: The structural model was evaluated to test the hypotheses by interpreting the standardized path coefficients. Each standardized path coefficient had a potential range from −1 to +1. The signs and magnitudes of the path coefficients represented the strength and direction of the partial correlations among the various constructs, similar to how partial regression coefficients are used with multiple regression. Each path coefficient measured the effect of one latent variable on a connected latent variable, assuming that all of the other latent variables in the model were held constant.
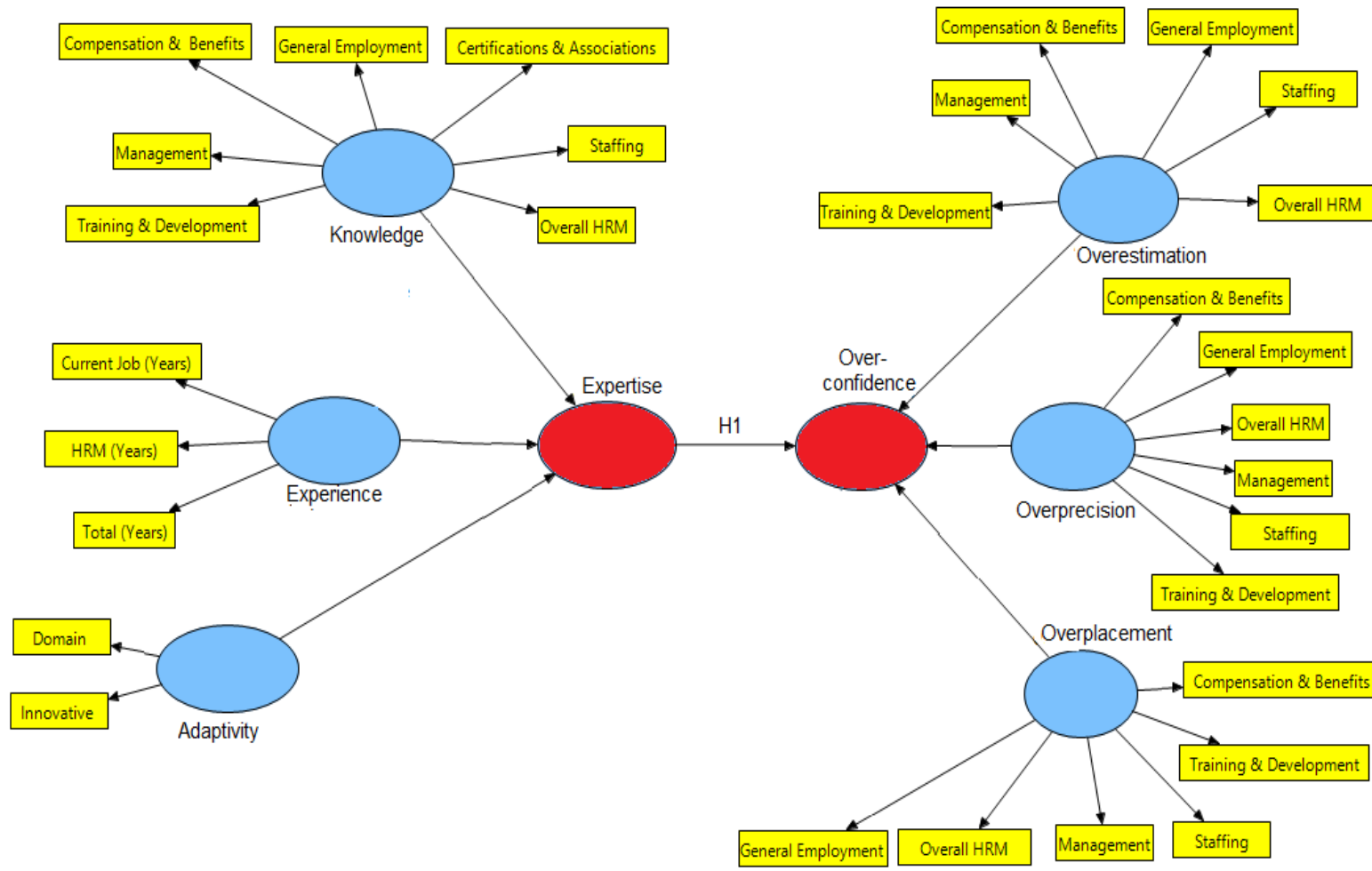
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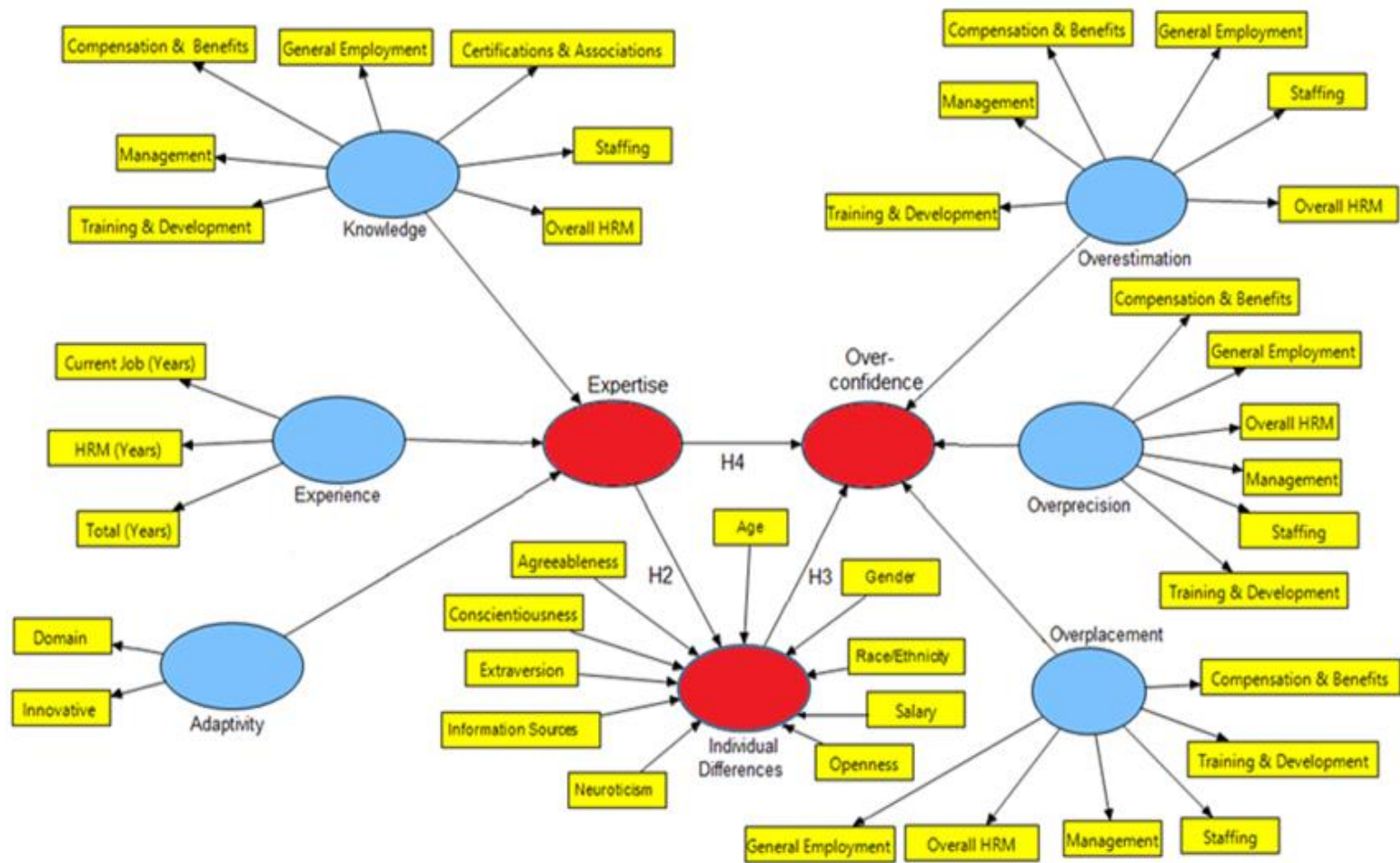*Figure 3.6.* PLS-SEM path diagram to test H1

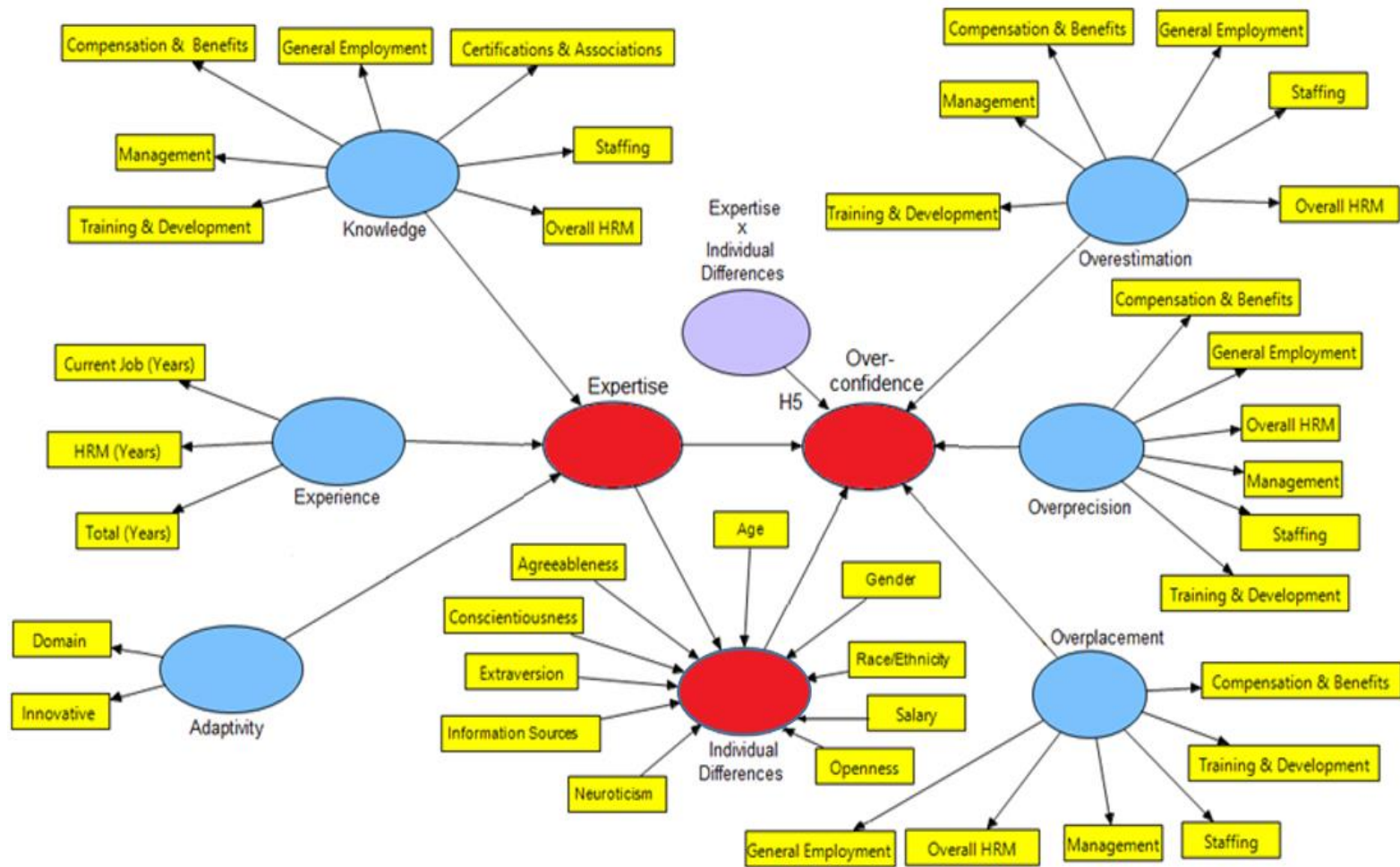*Figure 3.7*. PLS-SEM path diagram to test H2, H3, and H4

Figure 3.8. PLS-SEM path diagram to test H5

Note. The moderating effect is the path coefficient between overconfidence and the product of expertise x individual differences.

Step 5: The statistical significance of each path coefficient was evaluated by the bootstrapping procedure described by Hair et al. (2017), where 5000 random subsamples were extracted from the population of the survey data. The Monte-Carlo algorithm was applied to shuffle the population of data like a deck of cards in a casino, and a different subset of data representing 300 cases was analyzed in each random subsample. The means and standard errors (SE) of each path coefficient were estimated using the data collected in the bootstrapped subsamples. Two-tailed t-tests were then conducted (where $t = \beta/SE$) to determine if the mean value of each path coefficient was significantly different from zero at the conventional $p < .05$ level of statistical significance. Parametric statistics were applicable using the bootstrapped data because the central limit theory states that if a large number of random subsamples are drawn from a population, then the means and standard errors of the subsamples will be normally distributed, even if the underlying data distribution in the population deviates from normality (Glen, 2020).

Step 6: Mediation analysis was conducted to test H4 using the methods available in SmartPLS described by Wong (2016). The mediators were individual differences measured at the interval level, including personality traits and decision-making styles. The independent variable (IV) was expertise and the dependent variable (DV) was overconfidence. Figure 3.9 shows how the effects of mediation were estimated by the Z statistic computed using the Sobel test (Preacher & Hayes, 2004, 2010). Mediation was assumed to be statistically significant if $p < .05$ for the Z statistic.

a, b, and c' are path coefficients. Values in parentheses are standard errors of those path coefficients.

a = coefficient for the association between IV and mediator.
s_a = standard error of a.
b = coefficient for the association between the mediator and the DV
s_b = standard error of b.

$$z\text{-value} = a*b/\mathrm{SQRT}(b^2*s_a{}^2 + a^2*s_b{}^2)$$
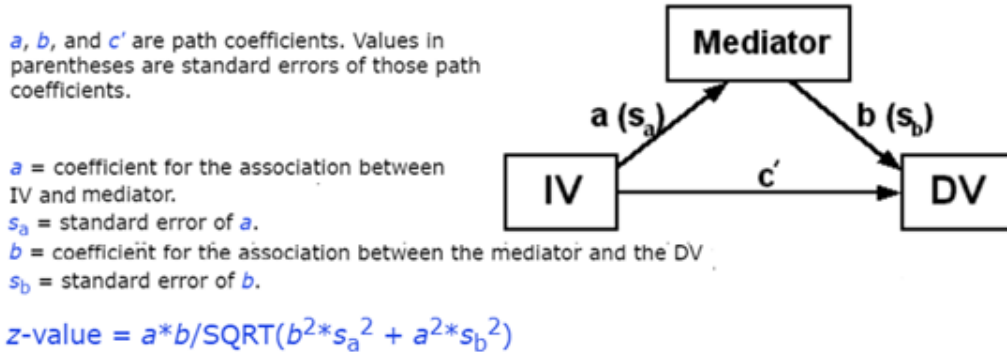
Figure 3.9. Sobel test

Step 7: Moderation analysis was conducted to test H5 using the methods available in SmartPLS described by Wong (2016). The moderators were categorical individual differences, including demographic factors (indicated by age, gender, race/ethnicity, and salary). The independent variable (IV) was expertise and the dependent variable (DV) was overconfidence. The moderating effect was identified as a statistically significant path coefficient between an interaction term (i.e., the product of expertise x individual differences) versus overconfidence. Figure 3.10 graphically displays the components of a moderation analysis.
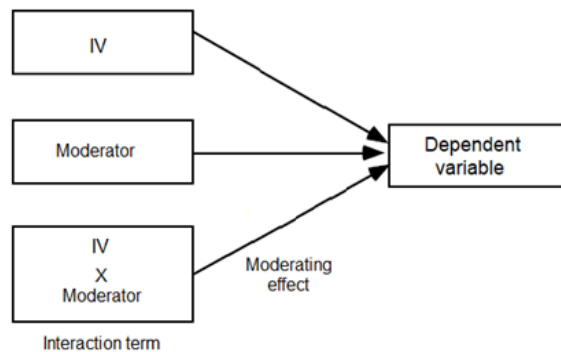
Figure 3.10. Moderation analysis

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Step 8: Coefficients of determination (R^2), which signify the proportion of the variance explained in the dependent variable (Hair et al., 2017), were the primary criteria used to evaluate the model. The R^2 values were interpreted as effect sizes and reflected the practical significance of the proposed models (i.e., their meaningfulness within the research context). The criteria defined by Ferguson (2009) were used to interpret the effect sizes. $R^2 \leq 4\%$ reflected an effect size with negligible practical significance; $R^2 = 25\%$ reflected a moderate effect size with adequate practical significance, and $R^2 = 64\%$ reflected a strong effect size with substantial practical significance.

Validity and Reliability of the Study

The measurement model (i.e., the relationships between the latent variables and the indicators) was validated by composite factor analysis using the quality criteria as defined by Hair et al. (2017). Construct validity was confirmed if the factor loading coefficients (i.e., the correlations between each indicator and their corresponding reflective latent variables) were consistently > 0.5. Discriminant validity was good if the factor loading coefficients for the indicators linked to each reflective latent variable were consistently greater than the factor loading coefficients linked to alternative latent variables. Convergent validity was good if the average variance explained (AVE) by the indicators of each latent variable was $> 50\%$, meaning that more than half of the variance in the latent variable was explained by the indicators while less than half of the variance was due only to random error. The internal consistency reliabilities of the reflective constructs were estimated with Composite Reliability coefficients rather than Cronbach's alpha. Composite Reliability is the preferred measure of reliability and

provides better estimates than Cronbach's alpha when constructs are reflective and the assumption of tau-equivalence is not operable (such as when the factor loading coefficients of all of the indicators of a construct are not equal) (Trizano-Hermosill & Alvarado, 2016). Composite Reliability coefficients > 0.8 indicated good internal consistency reliability (Hair et al, 2017). The results of the measurement model validation are presented in Chapter IV.

Summary

In this chapter, I provided a restatement of the purpose, research questions, and hypotheses of the current study. Additionally, I described the research methods and methodology I employed in carrying out this study, including the population and sampling techniques, instrumentation, data collection procedures, approaches to pre-screening the data, and techniques used to analyze the data. Finally, I discussed how I ensured the validity and reliability of the study.

CHAPTER IV

RESULTS

This chapter reports the results of this study of 414 HRM professionals, including the descriptive statistics, validation of the measurement model (i.e., factor analysis), and evaluation of the structural model (i.e., path analysis, mediation analysis, and moderation analysis). The demographic and contextual characteristics of the sample are described, and the results of PLS-SEM to test the following hypotheses are presented:

H1: Expertise will be positively related to overconfidence.

H2: Expertise will be positively related to individual differences.

H3: Individual differences will be positively related to overconfidence.

H4: Individual differences will have a mediating effect on the relationships between expertise and overconfidence.

H5: Individual differences will have a moderating effect on the relationships between expertise and overconfidence.

Descriptive Statistics

Table 4.1 summarizes the coded categorical demographic characteristics of the respondents (N = 414) that were included in PLS-SEM to represent individual differences. Salary was an ordinal variable ranked from one to 10 in order of magnitude. Even though respondents could select among seven different options for gender, only two categories of male and female were reported. Therefore, gender was transformed into a binary dummy variable (coded by 1 = Male; 0 = Female). This coding complied with the rules for using variables in PLS-SEM (Hair, Hult, Ringle, & Sarstedt, 2017). The nine options for race/ethnicity and eight options for referral source are also reported.

Table 4.1

Coded Categorical Variables Used as Indicators of Individual Differences

Indicator	Code	Category	n	%
Gender	0	Female	358	86.5
	1	Male	56	13.5
Race/Ethnicity	1	African American or Black	46	11.1
	2	American Indian or Alaska Native	2	0.5
	3	Asian American or Asian	13	3.1
	4	Hispanic or Latin American	47	11.4
	5	Middle Eastern	1	0.2
	6	Multiracial	11	2.7
	7	Pacific Islander	0	0.0
	8	White or Caucasian	287	69.3
	9	Prefer Not to Answer	7	1.7
Salary	1	< $20,000	4	1.0
	2	$20,000 to $34,999	4	1.0
	3	$35,000 to $49,999	21	5.1
	4	$50,000 to $74,999	96	23.2
	5	$75,000 to $99,999	111	26.8
	6	$100,000 to $124, 999	81	19.6
	7	$125,000 to $149,999	38	9.2
	8	$150,000 to $174,999	25	6.0
	9	$175,000 to $199,999	11	2.7
	10	$\geq$ $200,000	23	5.6
Referral Source	1	Texas	352	85.1
	2	North Carolina	2	0.5
	3	Missouri	1	0.2
	4	Kentucky	3	0.7
	5	Pennsylvania	2	0.5
	6	Rhode Island	1	0.2
	7	Washington	1	0.2
	8	National	52	12.6

The majority of the respondents were female (n = 358, 86.5%) and the race/ethnicity of over two-thirds of the respondents were White/Caucasian (n = 287, 69.3%). The respondents reported that they received a wide range of annual salaries, ranging from < $20,000 (n = 4, 1.0%) to ≥ $200,000 (n = 23, 5.6%). The most frequent salaries, representing 50% of the respondents, were $50,000 to $74,999 (n = 96, 23.2%) and $75,000 to $99,999 (n = 111, 26.8%). The vast majority of respondents (n = 352, 85.1%) were referred to the survey by a professional association in Texas.

Table 4.2 presents the descriptive statistics for the interval level variables used as indicators of individual differences. The differences between the mean and median values reflected deviation from normality. As a result, the median values are used to summarize the variables since the median is a less biased estimate of central tendency than the mean when variables are skewed (Field, 2018). The ages of the respondents ranged from 21 to 71 years (median = 43.1 years). The Big Five personality traits with the highest scores measured with 5-point scales were Conscientiousness (median = 4.55) and Agreeableness (median = 3.85) and the lowest score was Neuroticism (median = 2.41). Although the rational decision style had a higher score (median = 4.16) than the intuitive style (median = 2.39), respondents' cognitive reflection conversely indicated a stronger leaning towards intuitiveness (median = 2) than reflectiveness (median = 1). Regarding information sources (measured on a 5-point scale), HRM professionals most frequently consult with professional HRM websites, webinars, and other HRM colleagues (median = 4 for each), and least frequently with consultants, academic journals, academic conferences, and academic scholars (median = 2 for each).

Table 4.2

Description of Interval Level Variables Used as Indicators of Individual Differences

Indicator	Min	Max	Median	Mean	SD
Age (Years)	21	71	43.1	44	10.9
Conscientiousness	2	5	4.55	4.43	0.61
Agreeableness	1	5	3.85	3.77	0.79
Openness	1	5	3.4	3.36	0.96
Extraversion	1	5	3.32	3.34	1.11
Neuroticism	1	5	2.41	2.46	0.92
Decision Style - Rational	1	5	4.16	4.22	0.48
Decision Style - Intuitive	1	5	2.39	2.47	0.67
Cognitive Reflection - Reflectiveness	0	3	1	0.95	1.10
Cognitive Reflection - Intuitiveness	0	3	2	1.62	1.09
Info source - HR websites	1	5	4	3.79	0.82
Info source - Online blogs/message boards	1	5	3	2.98	1.05
Info source - Webinars	1	5	4	3.49	0.82
Info source - Seminars	1	5	3	3.28	0.86
Info source - Professional conferences	1	5	3	3.08	0.94
Info source - Professional magazines	1	5	3	2.86	1.05
Info source - HR colleagues	1	5	4	3.83	0.90
Info source - Colleagues outside of HR	1	5	3	3.21	0.92
Info source - Consultants	1	5	2	2.28	1.01
Info source - Academic journals	1	5	2	1.95	0.93
Info source - Academic conferences	1	5	2	1.8	0.84
Info source - Academic scholars	1	5	2	1.7	0.79

Tables 4.3 and 4.4 present the descriptive statistics for the non-normally distributed indicators of the three dimensions of expertise. The differences between the mean and median values reflected deviation from normality. The median values are used to summarize the variables. All respondents had at least a high school or equivalent education. The most recurrent educational qualifications were a bachelor's degree (n = 205, 49.5%), followed by a master's degree (n = 148, 35.7%). The least common educational qualifications reported were a doctorate (such as a PhD or EdD) (n = 4, 1.0%), followed by a professional degree (such as an MD or JD) (n = 5, 1.2%). The majority of respondents possessed professional qualifications (i.e., certifications, credentials, or licenses) (73.2%) and reported that they were members of a national professional association (77.3%) and local professional association (81.2%). See Appendix G for a detailed description of the specific types of qualifications that respondents held, Appendix H for which national professional associations to which respondents belonged, and Appendix I for the various job titles of respondents.

Among the indicators of knowledge, the highest score was in the area of training and development (median = 77.22), and the lowest score was in the area of staffing (median = 33.91). The respondents reported a wide range of years of experience, ranging from zero to 53 years. The highest level of experience was indicated by the total number of years (median = 20.56), followed by years specifically within HRM (median = 14.16 years), and then years of experience in one's current job (median = 4.12 years). The total number of questions that respondents answered "Yes" to regarding whether they had certifications and belonged to any local and/or national associations ranged

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from zero to three (median = 2.46). Using a 5-point scale, the respondents reported a slightly higher level of adaptivity along the domain skills subscale (median = 4.41) than the innovative skills subscale (4.2). The overall adaptivity score was also high (median = 4.28).

Table 4.3

Coded Categorical Variables Used as Indicators of Expertise

Indicator	Code	Category	n	%
Education level	1	Less than high school	0	0
	2	High school or equivalent	9	2.2
	3	Some college but no degree	33	8
	4	Associate degree	10	2.4
	5	Bachelor's degree	205	49.5
	6	Master's degree	148	35.7
	7	Professional degree (e.g., MD, JD)	5	1.2
	8	Doctorate (e.g., PhD, EdD)	4	1
Certifications, credentials, or licenses	0	No	111	26.8
	1	Yes	303	73.2
National professional membership	0	No	94	22.7
	1	Yes	320	77.3
Local professional membership	0	No	78	18.8
	1	Yes	336	81.2

Table 4.4

Description of Interval Level Variables Used as Indicators of Expertise

Indicator	Min	Max	Median	Mean	SD
Knowledge - Training & Development	0	100	77.22	74.22	24.8
Knowledge - Management	12.5	100	68.94	67.81	15.9
Knowledge - General Employment	0	100	61.71	61.23	18
Knowledge - Overall HRM	11.4	94.3	57.03	56.82	11.5
Knowledge - Compensation and Benefits	0	87.5	53.27	51.99	18.2
Knowledge - Staffing	0	100	33.91	35.54	17
Experience - Total (years)	0	53	20.56	21.43	10.4
Experience - HRM (years)	0	53	14.16	15.37	9.39
Experience - Current job (years)	0	43	4.12	6.54	6.81
Knowledge - Certifications and Associations	0	3	2.46	2.31	0.91
Adaptivity - Overall	3	5	4.28	4.31	0.39
Adaptivity - Domain Skills	1.8	5	4.41	4.34	0.45
Adaptivity - Innovative Skills	3	5	4.2	4.28	0.43

Table 4.5 presents the descriptive statistics for the non-normally distributed indicators of the three dimensions of overconfidence. The differences between the mean and median values reflected deviation from normality. Consequently, the median values are used to summarize the variables. Among the indicators of overestimation (subjective scores minus actual scores), the highest scores were in the HRM knowledge areas of staffing (median = 42.73) and general employment (median = 23.47). The lowest (i.e., most calibrated) score was in the area of training and development (median = -2.39).

Table 4.5

Description of Interval Level Variables Used as Indicators of Overconfidence

Indicator	Min	Max	Median	Mean	SD
Overestimation - Training & Development	0	100	-2.39	-2.37	21.2
Overestimation - Management	-90	67	8.36	7.77	25.4
Overestimation - General Employment	-46	92	23.47	22.87	21.3
Overestimation - Overall HRM	-59	78.6	25.8	24.66	18.1
Overestimation - Compensation & Benefits	-62	82.5	16.09	15.22	29.1
Overestimation - Staffing	-67	100	42.73	39.67	25.9
Overprecision - Training & Development	-100	100	-0.63	-0.16	29.6
Overprecision - Management	-90	70	12.32	9.43	26.1
Overprecision - General Employment	-62	100	23.5	22.76	21.8
Overprecision - Overall HRM	-36	78.6	26.7	25.48	18.3
Overprecision - Compensation & Benefits	-62	86	18	16	29
Overprecision - Staffing	-67	100	44.4	40.77	25.8
Overplacement - Training & Development	1	5	3.29	3.29	0.89
Overplacement - Management	1	5	3.58	3.54	0.92
Overplacement - General Employment	1	5	3.66	3.66	0.84
Overplacement - Overall HRM	1	5	3.68	3.66	0.8
Overplacement - Compensation & Benefits	1	5	3.09	3.08	1.02
Overplacement - Staffing	1	5	3.43	3.43	0.91

Among the indicators of overprecision (subjective scores minus actual scores), the highest scores were in the areas of staffing (median = 44.4) and overall HRM knowledge (median = 26.7). Interestingly, the area of training and development was the

lowest overestimation score as well as the lowest overprecision score (median = -0.63), meaning that respondents were relatively calibrated when asked to assign a confidence score. Among the indicators of overplacement, measured with a 5-point scale, the highest scores were in the areas of overall HRM (median = 3.68) and general employment (median = 3.66), and the lowest score was in the area of compensation and benefits (median = 3.09).

Validation of the Measurement Model

Table 4.6 presents the matrix of the cross-loadings of the factor loading coefficients for all of the indicators used in this study to identify the six reflective latent variables. Each coefficient represented the strength and direction of the correlations between the 31 indicators versus the six factors, on a standardized scale from -1 to 0 to +1. The strongest loading coefficients ≥ 0.5 (0.50 to 0.99) confirmed that the reflective latent variables consisted of six mutually exclusive factors (Adaptivity, Experience, Knowledge, Overestimation, Overprecision, and Overplacement). Discriminant validity was confirmed because the strongest factor loadings of the indicators used to identify each of the six factors were consistently greater than the cross-loadings of the coefficients on the alternative five factors.

Table 4.7 displays the results of tests to validate the variables used in PLS-SEM. The high values of the Composite Reliability Coefficient (0.82 to 0.88) indicated good internal consistency reliability. The Average Variance Explained (AVE) by the indicators that constituted each variable are also presented. The high AVE values ≥ 50% (50.3% to 88.6%) confirmed adequate convergent validity of all the variables.

Table 4.6

Matrix of Cross-loadings of Factor Loading Coefficients to Identify Reflective Latent Variables

Indicator	Reflective Latent Variables					
	Adaptivity	**Experience**	**Knowledge**	**Over-estimation**	**Over-placement**	**Over-precision**
Adaptivity: Domain Skills	**0.89**	0.02	0.52	0.14	0.01	0.13
Adaptivity: Innovative Skills	**0.87**	0.02	0.51	0.04	-0.02	0.01
Experience: Current Job (Years)	-0.05	**0.50**	0.04	0.09	0.15	0.12
Experience: HRM (Years)	-0.05	**0.94**	0.16	0.26	0.37	0.27
Experience: Total (Years)	-0.01	**0.94**	0.15	0.22	0.26	0.24
Knowledge: Certifications & Associations	0.11	0.19	**0.51**	0.10	0.22	0.12
Knowledge: Compensation & Benefits	0.09	0.14	**0.64**	-0.36	0.05	-0.34
Knowledge: General Employment	0.09	0.17	**0.66**	-0.32	0.19	-0.27
Knowledge: Management	0.11	0.06	**0.53**	-0.39	-0.03	-0.37
Knowledge: Overall HRM	0.12	0.16	**0.99**	-0.59	0.07	-0.55
Knowledge: Staffing	0.01	0.13	**0.63**	-0.38	0.00	-0.37
Knowledge: Training & Development	0.14	-0.02	**0.57**	-0.33	0.06	-0.32
Overestimation: Compensation& Benefits	0.01	0.10	-0.39	**0.68**	0.24	0.63
Overestimation: General Employment	-0.01	0.11	-0.51	**0.65**	0.18	0.62
Overestimation: Management	-0.05	0.25	-0.53	**0.87**	0.44	0.83
Overestimation: Overall HRM	0.04	0.31	-0.16	**0.61**	0.36	0.59
Overestimation: Staffing	0.04	0.08	-0.32	**0.60**	0.21	0.55

Overestimation: Training & Development	-0.02	0.14	-0.36	**0.57**	0.11	0.53
Overplacement: Compensation & Benefits	0.09	0.16	-0.01	0.33	**0.52**	0.34
Overplacement: General Employment	0.05	0.24	0.03	0.29	**0.79**	0.35
Overplacement: Management	0.04	0.30	0.01	0.32	**0.84**	0.39
Overplacement: Overall HRM	0.19	0.09	0.10	0.14	**0.51**	0.18
Overplacement: Staffing	0.15	0.34	0.16	0.27	**0.77**	0.33
Overplacement: Training & Development	0.07	0.05	0.13	0.04	**0.54**	0.06
Overprecision: Compensation & Benefits	0.02	0.12	-0.36	0.63	0.30	**0.65**
Overprecision: General Employment	-0.01	0.14	-0.47	0.65	0.24	**0.68**
Overprecision: Management	-0.02	0.26	-0.50	0.83	0.47	**0.87**
Overprecision: Overall HRM	0.05	0.31	-0.12	0.56	0.40	**0.61**
Overprecision: Staffing	0.02	0.06	-0.31	0.55	0.25	**0.59**
Overprecision: Training & Development	0.01	0.18	-0.36	0.55	0.17	**0.59**

Note. Strong factor loadings > 0.5 highlighted in **bold** confirmed the construct validity of the latent variables.

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Table 4.7

Validation of the Latent Variables

Latent Variable	Average Variance Explained (AVE) %	Composite Reliability
Adaptivity	79.4	0.88
Experience	88.6	0.94
Expertise	50.3	0.82
Knowledge	57.5	0.83
Overconfidence	70.9	0.83
Overestimation	58.1	0.84
Overplacement	59.4	0.82
Overprecision	56.2	0.83

Evaluation of the Structural Model

Because the measurement model was valid, it was appropriate to evaluate the structural models used to test the five hypotheses. Figure 4.1 features the path diagram with the path coefficients to test H1; Figure 4.2 exhibits the path diagram with the path coefficients to test H2, H3, and H4; and Figure 4.3 presents the path diagram with the path coefficients to test H5 (all three of these figures are presented at the end of this section). Table 4.8 showcases the results of *t*-tests using the bootstrapped data obtained with 5000 random sub-samples. All of the path coefficients (β) were significantly different from zero ($p < .05$). Hypothesis 1 was supported because the path coefficient between Expertise $\rightarrow$ Overconfidence was statistically significant ($\beta = 0.126$; $t = 2.11$; $p = .035$). The proportion of variance explained indicated a very strong effect of expertise on overconfidence ($R^2 = 98.6\%$), implying that this relationship demonstrates substantial practical significance.

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Table 4.8

Statistical Significance of Path Coefficients to Test H1

Path	β	SE	t	p
Knowledge → Expertise	0.822	0.139	5.93	<.001*
Experience → Expertise	0.133	0.062	2.16	.031*
Adaptivity → Expertise	0.464	0.127	3.64	<.001*
Overestimation → Overconfidence	0.442	0.027	16.38	<.001*
Overprecision→ Overconfidence	0.437	0.032	13.71	<.001*
Overestimation→ Overconfidence	0.250	0.021	11.68	<.001*
Expertise → Overconfidence	0.126	0.059	2.11	.035*

Note. * Indicates that the path coefficient is significantly different from zero ($p <$ .05).

Table 4.9 displays the path coefficients to test H2 and H3. H2 was supported because all of the path coefficients between expertise and individual differences were statistically significant ($p < .001$), including the overall relationship ($\beta = 0.863$, $p < .001$). H3 was not supported since none of the path coefficients between individual differences and overconfidence were statistically significant ($p > .05$).

Table 4.10 presents the Z statistics and p-values to test H4 using Sobel tests. The hypothesis was not supported, indicated by $p > .05$ for all of the Z statistics. The conclusion is that there was insufficient statistical evidence to determine if individual differences had any mediating effects on the relationships between expertise and overconfidence.

Table 4.11 depicts the statistics to test H5. The hypothesis was not supported, indicated by $p > .05$ for all of the *t*-test statistics. The mediating effects were not significantly different from zero. The conclusion is that there was insufficient statistical evidence to determine if individual differences had any moderating effects.

Table 4.9

Statistical Significance of Path Coefficients to Test H2 and H3

Path	β	SE	t	p
Personality traits → Expertise	0.362	0.094	3.82	<.001*
Age → Expertise	0.829	0.047	17.45	<.001*
Decision-making styles → Expertise	0.301	0.084	3.58	<.001*
Individual differences → Expertise	0.863	0.030	28.78	<.001*
Personality traits → Overconfidence	0.010	0.008	1.28	.201
Age → Overconfidence	0.015	0.016	0.95	.342
Decision-making styles → Overconfidence	0.120	0.071	1.68	.093
Individual differences → Overconfidence	0.040	0.032	1.23	.395

Note. * Indicates that the path coefficient is significantly different from zero ($p < .05$).

Table 4.10

Sobel Tests for Mediation to Test H4*

Hypothesized Mediator	Z	p
Personality traits	1.19	.234
Age	0.94	.349
Decision-making styles	1.53	.126
Cognitive reflection	1.07	.285
Information sources	1.02	.308

Note. * Path coefficient statistics are not relevant to testing mediation; therefore, those are not displayed for H4.

Table 4.11

Moderation Analysis to Test H5

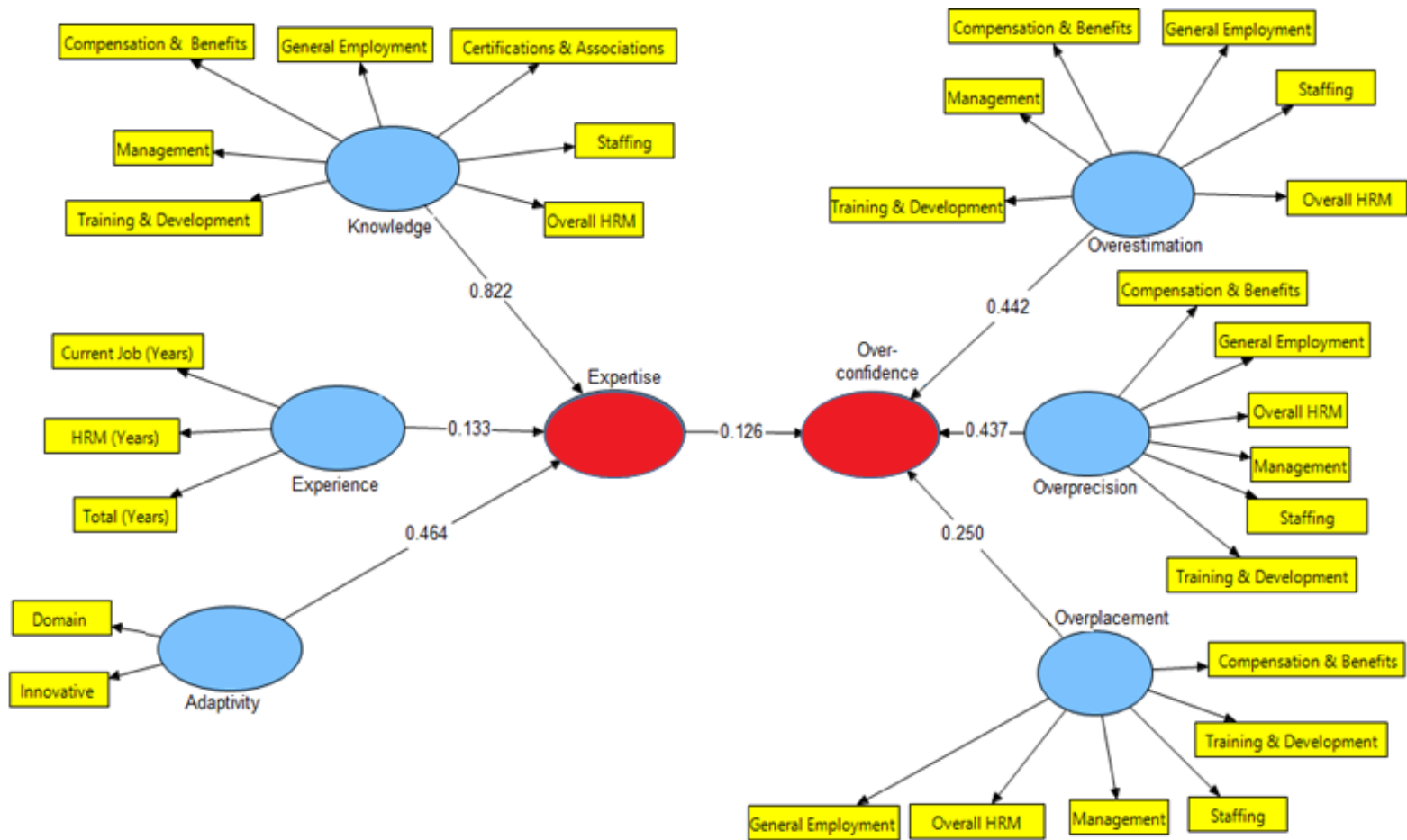| Moderating Effect	β	SE	t	p
Expertise x Gender	0.001	0.003	0.35	.726
Expertise x Race/Ethnicity	0.006	0.014	0.42	.674
Expertise x Salary	0.044	0.035	1.25	.211
Expertise x Individual Differences	0.023	0.025	0.92	.357

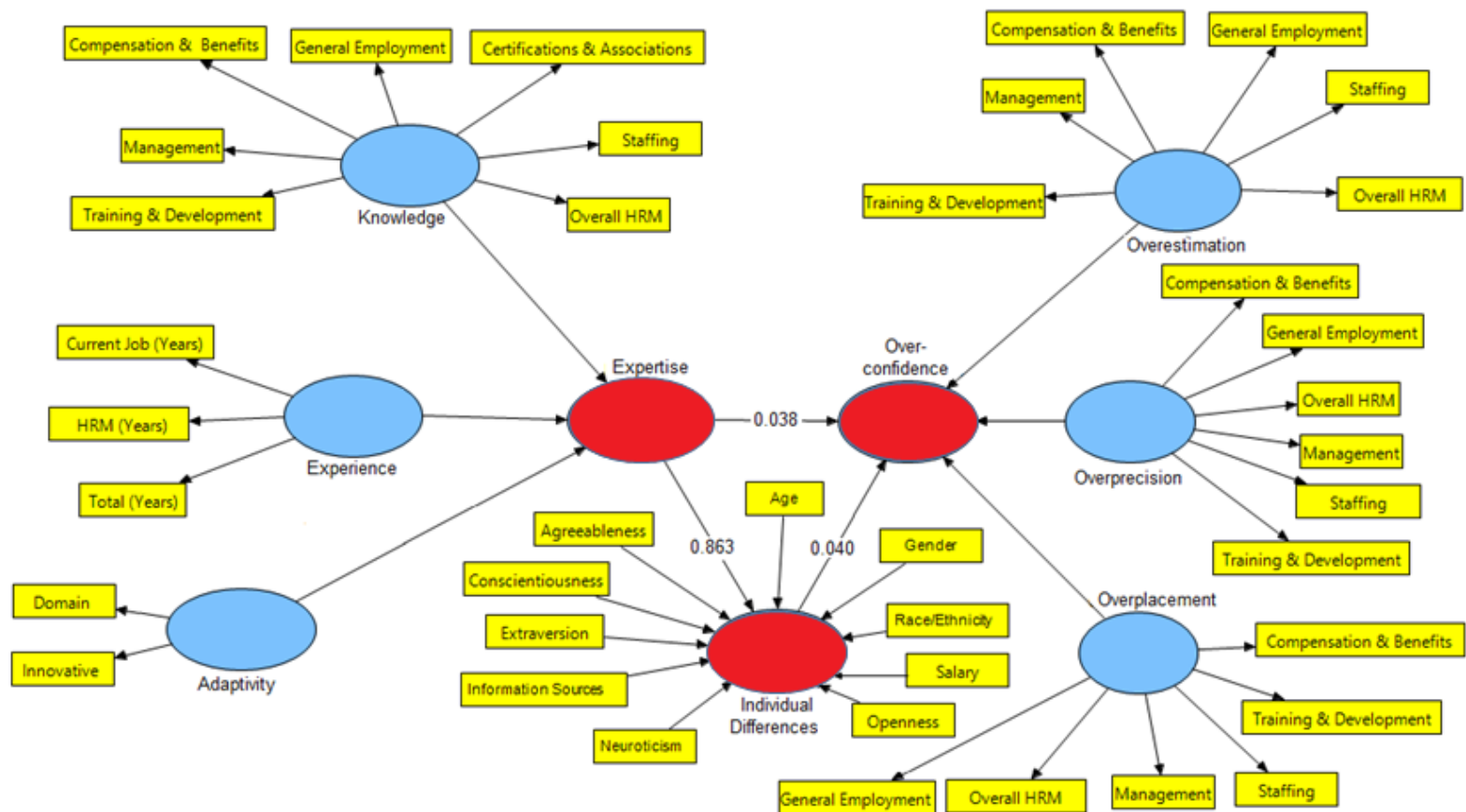*Figure 4.1.* PLS-SEM path diagram with the path coefficients to test H1

Figure 4.2. PLS-SEM path diagram with the path coefficients to test H2, H3, and H4

Note. H4 was also tested by Sobel tests and no statistically significant mediators were detected. This path diagram confirms that the mediation effect ($\beta = 0.038$) is not significant.
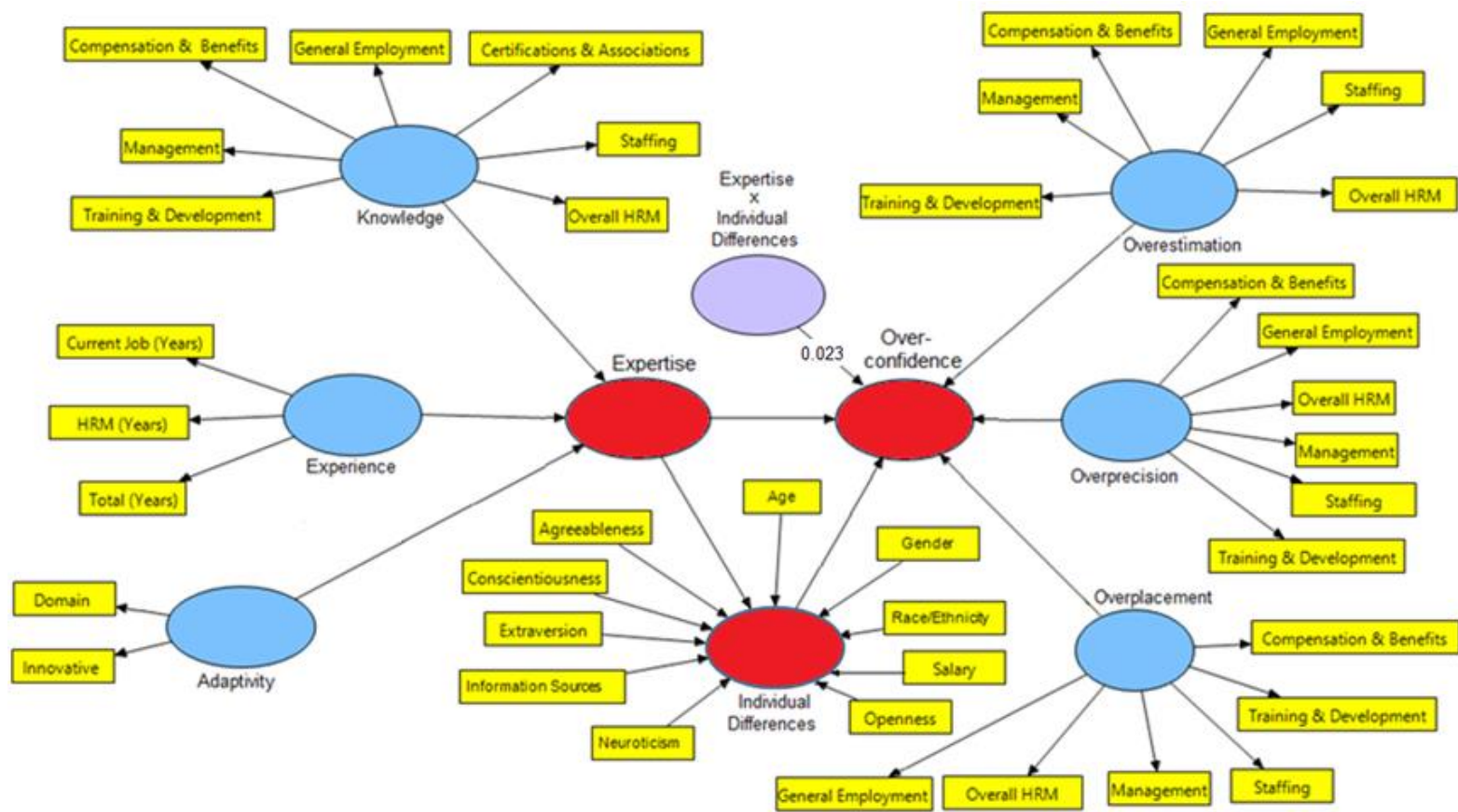
Figure 4.3. PLS-SEM path diagram with the path coefficients to test H5

Note. The moderating effect is the path coefficient between overconfidence and the product of expertise x individual differences.

Summary

In this chapter, the results of the descriptive statistics, validation of the measurement model (i.e., factor analysis), and evaluation of the structural model (i.e., path analysis, mediation analysis, and moderation analysis) were reported. The measurement model was validated, as were the structural models representing the (a) relationships between expertise and overconfidence and (b) individual differences and expertise. Therefore, two of the five hypotheses were supported. A more detailed discussion about these findings, the implications of these results on theory and practice, and recommendations for future research are presented in Chapter V.

CHAPTER V

DISCUSSION, IMPLICATIONS, RECOMMENDATIONS, AND CONCLUSION

This chapter begins with a discussion of the results of the study in relation to the research hypotheses and extant literature. Based on these findings, the implications for theory, research, and practice are provided. The current study can best be described as (a) an overconfidence study (b) conducted through an HRD lens (c) as applied specifically to the context of HRM professionals. Therefore, implications focus on these three areas, with particular emphasis given to HRD. This chapter concludes with an examination of the limitations of the study as well as a recommended agenda for future research.

Discussion

The purpose of this quantitative study was threefold: (a) to explore the relationships among expertise, overconfidence, and individual differences related to HRM professionals; (b) to ascertain the impact that individual differences have on the relationships between expertise and overconfidence; and (c) to determine the extent to which individual differences influence the relationships between expertise and overconfidence. Expertise (the independent variable) was represented by the dimensions of knowledge, experience, and adaptivity. Overconfidence (the dependent variable) consisted of overestimation, overprecision, and overplacement. Finally, individual differences (the mediating and/or moderating variables) were expressed through personality traits, decision-making styles, and demographic characteristics.

Research Questions and Hypotheses

My study was positioned within the larger body of decision-making research (Kahneman, 2011; Koriat, Lichtenstein, & Fischhoff, 1980). The three theoretical resources that provided a framework were the theory of bounded rationality, the biases and heuristics program (which is a term that refers to a collective network of connected research), and cognitive-experimental self-theory (CEST). The following three overarching questions guided this study:

1. What are the relationships among the various dimensions and components of expertise, overconfidence, and individual differences?

2. What is the impact of individual differences on the relationships between expertise and overconfidence?

3. To what extent are the relationships between expertise and overconfidence influenced by individual differences?

To explore these three research questions, five hypotheses were developed. The first three hypotheses related to the first research question, the fourth hypothesis corresponded with the second research question, and the fifth hypothesis pertained to the third research question. These hypotheses were tested in Chapter IV, the results of which are summarized in Table 5.1.

Table 5.1

Summarized Results of the Hypotheses

Hypothesis	Results
H1: Expertise will be positively related to overconfidence.	S
H2: Expertise will be positively related to individual differences.	S
H3: Individual differences will be positively related to overconfidence.	N
H4: Individual differences will have a mediating effect on the relationships between expertise and overconfidence.	N
H5: Individual differences will have a moderating effect on the relationships between expertise and overconfidence.	N

Note. **S (blue font)** means the hypothesis is fully supported; **N (red font)** means the hypothesis is not supported. No hypotheses were partially supported.

Hypothesis 1: Expertise Will Be Positively Related to Overconfidence

Hypothesis 1 was supported. Based on the results of the PLS-SEM, all of the path coefficients for the dimensions of expertise (i.e., Knowledge → Expertise, Experience → Expertise, and Adaptivity → Expertise) and overconfidence (Overestimation → Overconfidence, Overprecision → Overconfidence, and Overestimation → Overconfidence) were significantly and positively related. The strongest path coefficient for expertise was knowledge ($\beta = 0.822$; $t = 5.93$; $p < .001$), followed by adaptivity ($\beta = 0.464$; $t = 3.64$; $p < .001$), and then experience ($\beta = 0.133$; $t = 2.16$; $p = .031$). This shows that although all three dimensions of expertise were significant, the weakest relationship was with experience. This finding supports the assertion by some HRD researchers that although experience might be a fundamental element of expertise, it is not generally considered to be the most consequential

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component of it (Herling, 2000; Swanson, 2003a). All three dimensions of overconfidence were strongly and positively related in the following order: overestimation ($\beta = 0.442$; t = 16.38; p < .001), then overprecision $\beta = 0.437$; t = 13.71; p < .001), and finally overestimation $\beta = 0.250$; t = 11.68; p < .001).

In addition to the constructs of expertise and overconfidence being validated, the hypothesized relationship between expertise and overconfidence was also confirmed. The overall composite relationship ($\beta = 0.126$; t = 2.11; p = .035) was found to be significantly positive, indicating that the directionality of expertise and overconfidence is the same. This finding reinforces and is aligned with previous claims that experts tend to be more overconfident than novices (Camerer & Johnson, 1991; Glaser, Langer, & Weber, 2005; Kirchler & Maciejovsky, 2002; Önkal, Yates, Simga-Mugan, & Öztin, 2003; Russo & Shoemaker, 1992). Therefore, my study contributes to the debate among overconfidence scholars by lending support to the notion that expertise is not a mitigant or calibrant against overconfidence.

Hypothesis 2: Expertise Will Be Positively Related to Individual Differences

Hypothesis 2 was also supported. Path coefficients for individual differences (Personality traits → Expertise, Age → Expertise, and Decision-making styles → Expertise) were all statistically significant and positive. The strongest path was between age and expertise ($\beta = 0.829$; t = 17.45; p < .001), followed by personality traits ($\beta = 0.362$; t = 3.82; p < .001), and then decision-making styles ($\beta = 0.301$; t = 3.58; p < .001). This indicates that these individual differences are associated with varying degrees of expertise. Although a central focus of the current study was to explore the

role that individual differences have on overconfidence (as well as the potential mediating and/or moderating effects of individual differences on the relationship between expertise and overconfidence), this finding presents opportunities to study the direct relationship between individual differences and expertise.

Hypothesis 3: Individual Differences Will Be Positively Related to Overconfidence

The findings of the current study revealed that no significant relationships exist between individual differences and overconfidence. None of the path coefficients for individual differences (Personality traits → Overconfidence, Age → Overconfidence, and Decision-making styles → Overconfidence) were statistically significant. Therefore, Hypothesis 3 was not supported. This is in concurrence with studies that did not find evidence that overconfidence was exhibited differently based on personality (Larrick, Burson, & Soll, 2007; Moore & Healy, 2008), and in contrast to studies that did identify differences based on personality (Campbell, Goodie, & Foster, 2004; Kausel, Culbertson, & Madrid, 2016; Larkin & Leider, 2012).

Additionally, my study offers evidence that one's dominant or preferred style of decision-making (rational style versus intuitive style) does not meaningfully reduce or diminish one's overconfidence. Rational decision-making purportedly results in less biased and higher quality decisional outcomes than intuitive decision-making (Kirkpatrick & Epstein, 1992; Pacini & Epstein, 1999). However, at least in the context of the overconfidence effect, this assumption was not empirically sustained. Therefore, the current study bolsters past research that found that cognitive biases can be equally ubiquitous among both rational and intuitive decision-makers (Lu, 2015).

Hypothesis 4: Individual Differences Will Have a Mediating Effect on the Relationships Between Expertise and Overconfidence

To test whether the continuous or interval level variables of individual differences (personality traits, age, decision-making styles, cognitive reflection, and information sources) affect the relationships between expertise and overconfidence, a mediation analysis was conducted. However, the mediation analysis did not find that individual differences were the underlying cause of the correlation between expertise and overconfidence, either completely or partially. Consequently, the correlation between expertise and overconfidence exists in isolation and is not explained by the indirect relationship of individual differences.

As a result, Hypothesis 4 was not supported. This implies that it is actually the differences in expertise factors, rather than individual differences, that contribute to associated differences in overconfidence. Therefore, no causal inferences could be made that individual differences are responsible for the relationships between expertise and overconfidence. This finding points to a universal overconfidence effect that is unaffected by individual differences.

Hypothesis 5: Individual Differences Will Have a Moderating Effect on the Relationships Between Expertise and Overconfidence

To examine whether the categorical variables of individual differences (gender, race/ethnicity, and salary) control the strength and/or direction of the relationships between expertise and overconfidence, a moderation analysis was performed. No moderating effects or interactions were detected among these individual differences.

Therefore, Hypothesis 5 was not supported, indicating that the magnitude and trajectory of the correlation between expertise and overconfidence were unrelated to and independent from individual differences. This finding also points to the overconfidence effect being a universal phenomenon and that individual differences do not influence the observed relationships between the expertise and overconfidence of HRM professionals.

Discussion Summary

Although expertise is positively and significantly associated with both overconfidence and individual differences, the relationship between individual differences and overconfidence is irrelative and negligible. Together, the results of the five hypotheses lend support to the postulation that the overconfidence effect may be a universal bias, thereby confirming past studies (Benoît, Moore, & Dubra, 2015; Johnston & Fowler, 2011; Odean, 1998). Moreover, overconfidence appears to be more strongly displayed as expertise increases, validating research that found experts to be more susceptible to the overconfidence effect (Camerer & Johnson, 1991; Glaser et al., 2005; Kirchler & Maciejovsky, 2002). Finally, my study established that overconfidence was not manifested differently by virtue of individual differences (Larrick et al., 2007; Moore & Healy, 2008).

<div align="center">

Theoretical Implications

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This study advances HRD and overconfidence scholarship and mutually benefits each area of research. As such, the theoretical implications for both HRD and overconfidence research are discussed. First, my study successfully made a theoretical contribution to the overconfidence literature from an HRD perspective. The

overconfidence effect is a multidisciplinary area of inquiry, but HRD had previously made little exploration into it. Likewise, the multidimensionality of expertise had not been given adequate attention by overconfidence researchers. Expertise had often been oversimplified as either knowledge (Huang, Tan, & Faff, 2016; Lambert, Bessière, & N'Goala, 2012; Lassoued, Phillips, Smyth, & Hesseln, 2019) or experience (Bédard & Chi, 1993; Kirchler & Maciejovsky, 2002; Menkhoff, Schmeling, & Schmidt, 2013). My study helped bridge these gaps by relying heavily on HRD expertise literature to enrich overconfidence scholarship. I accomplished this by developing and validating a robust construct of expertise that was used to evaluate overconfidence. As a result, I extended what was formerly a narrow perspective of expertise by overconfidence scholars.

Secondly, although the results of my study do not likely settle any theoretical disputes among overconfidence scholars or reconcile discrepant conclusions, my work does at least contribute to the body of knowledge and to ongoing academic debates, especially regarding (a) the universality versus conditionality of the overconfidence effect and (b) the achievable versus chimerical nature of expert calibration. My research adds to the accumulating evidence that the overconfidence effect is a universal bias, individual differences do not meaningfully govern overconfidence, and experts may actually be even more prone to exhibiting overconfidence than novices.

Finally, my study suggests that being a rational decision-maker does not abate the prevalence or intensity of the overconfidence effect compared with being an intuitive decision-maker. This finding disconfirms the theoretical assertion that intuitive-

experiential processing is interminably and inherently more susceptible to judgment errors and lower decisional quality than analytical-rational processing (Kirkpatrick & Epstein, 1992). Although some studies have found that intuitive thinkers are more vulnerable to certain biases (Epstein, 2003), other studies have found that rational thinkers can also be more prone to exhibiting other biases (Wong, Kwong, Ng, 2008). My research revealed no statistically significant differences between rational and intuitive thinkers and their susceptibility to the overconfidence effect, which is consistent with studies that identified that intuitive and rational thinkers can be equally predisposed to biases (Lu, 2015). These conflicting results raise questions about the presumed locality of biases as being exclusively contained within the intuitive system. Rather, it seems more likely that biases may occupy and saturate both systems.

Research Implications

Two major research implications arose from my study. First, a revised multidimensional construct of expertise as displayed through the dimensions of knowledge, experience, and adaptivity was empirically validated. As a result, HRD researchers who are interested in researching expertise may adopt this construct as operational. Even though there is some overlap with the construct proposed by Swanson and Holton (2009) with the dimensions of knowledge and expertise, the third dimension of my construct (adaptivity) is more comprehensive than theirs (problem solving). Overconfidence researchers may similarly embrace this construct of expertise, especially because past overconfidence studies have often treated expertise as one-dimensional.

Finally, based on the aggregate findings of my five research hypotheses, a revised concept map of the relationships among expertise, overconfidence, and individual differences emerged (see Figure 5.1). This contribution serves as a model of expert overconfidence that future researchers can use. This model displays the positive relationship between expertise and individual differences, and between expertise and overconfidence. Additionally, it shows that there is not a perceptible relationship between individual differences and overconfidence as initially hypothesized.
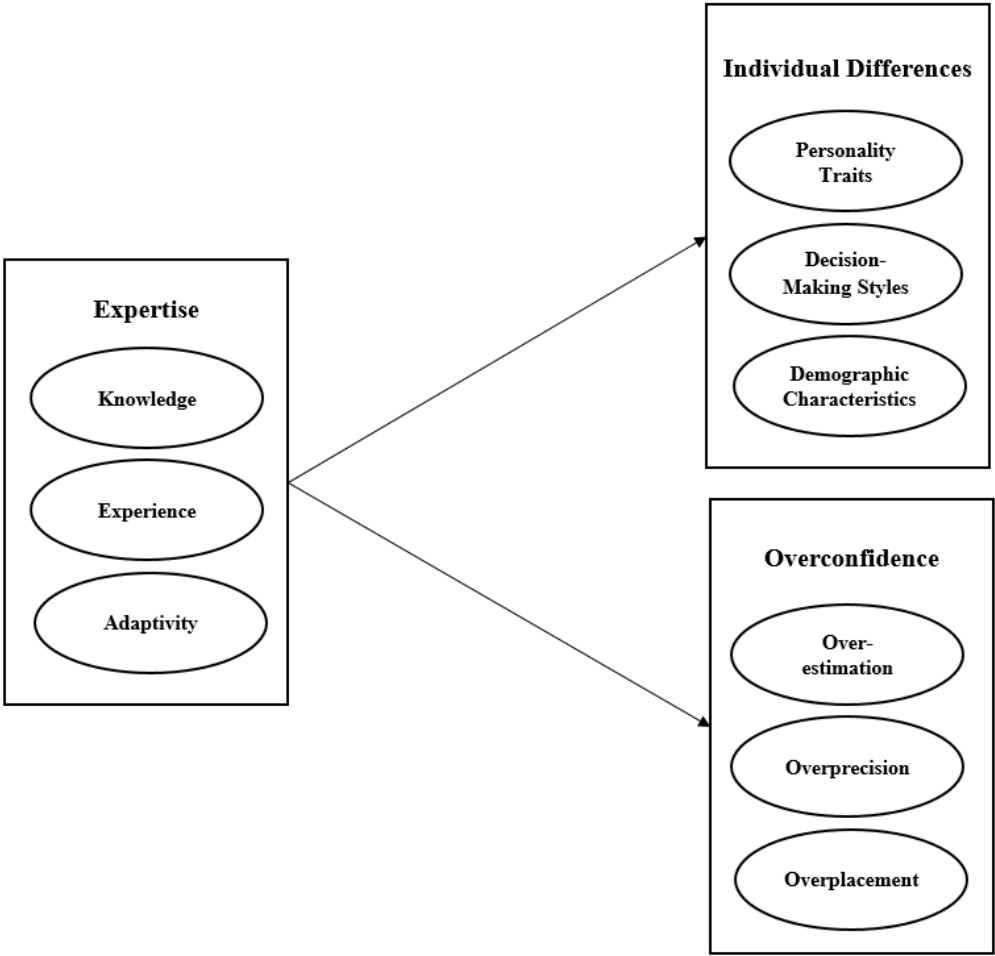
Figure 5.1. Model of expert overconfidence

Practical Implications

The finding from this study that expert calibration is not an intrinsic condition or feature of expertise is not just theoretically implicative, but practically as well. The applied implications of this cannot be overstated. The potential consequences of expert overconfidence are significant and can lead to numerous harmful workplace outcomes, including poor hiring decisions (Kausel et al., 2016), labor strikes (Babcock & Olson, 1992), and lawsuits (Moore & Healy, 2008). HRM professionals are often relied upon to help organizations mitigate risk and navigate the complexity behind difficult organizational decisions, so expert overconfidence among HRM professionals could potentially limit their effectiveness in being able to accomplish this.

My study confirmed that HRM professionals do not always adopt evidence-based practices, rarely consult academic sources, and often maintain beliefs that are at odds with research findings (Allen, Bryant, & Vardaman, 2010; Rynes, Colbert, & Brown, 2002). This can result in HRM professionals embracing practices that do not effectively add value to an organization (and that could potentially even be unfavorable to an organization) (Buyens & Verbrigghe, 2015). In my study, not only did HRM practitioners embrace beliefs that were counter to evidence-based best practices, but they were also overconfident about the accuracy of their knowledge. In other words, in addition to their subjective confidence about their knowledge being inflated compared with actual scores, the HRM practitioners in this study also overestimated the precision of their knowledge. The overconfidence effect offers a possible explanation for why HRM professionals frequently base their decisions on their own judgment rather than on

evidence and why they might be unaware that their existing knowledge is deficient (Miller & Geraci, 2014; Zacharakis & Shepherd, 2001).

Even though the focus of my study was on HRM professionals, overconfidence is not just limited to HRM practitioners. Overconfidence has been observed across many different professional fields and settings (Koehler, Brenner, & Griffin, 2002). As a result, it is a widespread phenomenon that is not unique to HRM professionals. HRM professionals have a dual opportunity to not just contend with this bias within their own ranks, but to also effectively manage and alleviate it across the organization. Because organizational success depends upon the accuracy of the accumulated decisions of multiple stakeholders, HRD also has a collaborative role to play in helping HRM practitioners (as well as other professionals) grapple with the organizational consequences of the overconfidence effect. It is imperative for HRD researchers and practitioners to strive to develop strategies and interventions to safeguard organizations against overconfidence. Understanding the pervasive nature and effect of biases is at the core of HRD activities and is essential for advancing HRD research and practice (Chermack, 2003a, 2003b; Korte, 2003). Therefore, HRD has a shared interest and responsibility to assist organizations with the practical development of decision-making competencies and techniques that countervail the adverse effects of biases, including the overconfidence effect (Ceschi, Costantini, Phillips, & Sartori, 2017).

Another implication of this study is that the overconfidence of experts casts doubts on the purported ways in which experts are differentiated from novices. For example, education and professional qualifications (e.g., credentials and certifications)

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are often regarded as objective measures and factors of expertise (Germain & Tejeda, 2012). It has commonly been maintained that possessing increased levels of education and professional training validate and certify expertise and result in better performance outcomes (Babcock, 2016; Blackwell, 2015; Daniels, 2011; Germain & Tejeda, 2012; McLean & Akdere, 2015). However, because experts are more susceptible to the overconfidence effect than novices, it challenges the notion that education and professional designations inherently mitigate biased thinking or create higher quality and better calibrated decisions.

Finally, this study calls into question the presumed effectuality of confidence. Having a high degree of confidence has conventionally been considered to be a desirable and enhancive attribute, correlative with performance, and concomitantly linked with achievement and success (Gudmundson & Lechner, 2013). Furthermore, individuals who prominently display self-confidence are often regarded by others as being experts in their fields, even though self-confidence is not a verifiable characteristic of expertise and can even lead to illusions and misattributions of expertise (Germain & Tejeda, 2012). Because confidence has been shown to be a potentially deceptive and unreliable indicator of expertise, it should not be unconditionally or uncritically accepted as a positive trait or predictor of successful outcomes. Instead, subjective confidence assessments should be cautiously evaluated against objective standards of performance.

Limitations and Agenda for Future Research

There are limitations in this study; however, each limitation offers an opportunity for future research. Therefore, my discussion about the study limitations and areas for

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future investigation goes hand in hand. First, my study was intentionally bounded in a specific context (HRM) and focused exclusively on the population of HRM professionals. Accordingly, the results of this study are not inferable or generalizable to other fields of professional practice. A prospective study, therefore, could focus on the hypothesized relationships among expertise, overconfidence, and individual differences appertaining to other contexts and populations. Nevertheless, given that knowledge is domain-specific, the knowledge instrument of this study could readily be replaced with knowledge instruments corresponding with other applicable domains; this study could be replicated by scholars with other professional populations in mind.

A second limitation is that the HRM knowledge instrument used in this study was developed in 2002 and has not been updated since (Rynes et al., 2002). This may signal a possible degree of deterioration over time of the domanial representativeness, scope, and amplitude of the instrument. Domain-specific knowledge is dynamic and must be continually cultivated and renewed in response to environmental changes and developments (Grenier & Kehrhan, 2008; Jeong, McLean, McLean, Yoo, & Bartlett, 2017; Swanson & Holton, 2009). As a consequence, researchers have an opportunity to develop or revise an HRM instrument that reflects and encompasses more recent scholarship and emergent knowledge areas, such as strategic HRM, technology and people analytics, employer branding, employee engagement and belonging, and diversity, equity, and inclusion (DEI).

A third limitation is with the identification and selection of the relevant theories that guided the current study. Although a theoretical framework allows a researcher to

rigorously formulate research questions, intentionally narrow the boundaries of inquiry, explain and predict observations, and challenge and extend existing theories, it represents just one of an infinitesimal number of ways of structuring and organizing knowledge. This means that there are other approaches I could have taken and other theories I could have utilized to investigate the same phenomenon. The theoretical framework was anchored in the broader context of decision-making research. However, this does not constitute a definitive paradigm through which to conclusively examine the topics of interest. Future studies could consider other bodies of knowledge that I did not explore, including theories of intelligence, attention, learning, and motivation.

Fourth, the current study was limited by the statistical techniques employed, specifically PLS-SEM. Even though PLS-SEM is a powerful multivariate technique and it was combined with bootstrapping to further strengthen its quality and precision, it is still a non-parametric approach to data analysis. Non-parametric tests are usually, though not always, less powerful than parametric tests (Fraenkel, Wallen, & Hyun, 2019). Nonetheless, PLS-SEM typically produces comparable results as its parametric counterpart (CB-SEM) (Awang, Afthanorhan, & Asri, 2015). PLS-SEM is also newer than CB-SEM, so it has had to overcome misconceptions by some methodologists that as a non-parametric technique it is less effective relative to CB-SEM (Hair, Hult, Ringle, & Sarstedt, 2017; Hair, Ringle, & Sarstedt, 2011; Henseler et al., 2014). Because PLS-SEM has risen in popularity, acceptance, and endorsement among researchers over the last few years, the non-parametric nature of this technique has become far less of a concern (Hair et al., 2017; Hair, Howard, & Nitzi, 2020; Hair & Sarstedt, 2019).

Regardless, researchers could design a future study in a manner that could be evaluated through parametric analyses, including CB-SEM.

A fifth limitation is related to the quantitative research design and (post)positivist orientation of the current study. A key standard of quantitative research is to focus on findings that are statistically significant and widely applicable. Even though the methodological and epistemological choices I made helped me achieve the objective of this study and yielded important and compelling conclusions, a tradeoff with having adopted this approach was that deep, rich, and personal human experiences were not captured. The aim of qualitative research on the other hand is not usually to generalize, but rather to intensively explore a phenomenon in the form of descriptive accounts and thick narratives, and from the perspectives of others (Merriam & Grenier, 2019; Polit & Beck, 2010). Based on the theory-building and construct validation I accomplished in this study, I would encourage qualitative researchers to expand upon my work and thoroughly delve into the untold stories and lived experiences of HRM professionals. Approaching the current study from a qualitative lens could undoubtedly generate new and perceptive insights.

In addition to the above agenda proposed based on the study limitations I identified, there are other opportunities for future research. First, expertise and individual differences could be studied with respect to how they relate to other biases and heuristics. Second, the current study utilized a cross-sectional survey, so a future study could explore the relationships among expertise, overconfidence, and individual differences via repeated observations (a longitudinal study). Third, the individual

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differences I identified (personality traits, decision-making styles, and demographic characteristics) do not account for the full spectrum of human variability. Hence, there is a need for future research to identify other indicators of individual differences and to test whether there are mediating and/or moderating effects of those individual differences. Fourth, based on the findings from this study, even though individual differences were not shown to have a significant impact or effect on overconfidence, there was evidence of a positive relationship between individual differences and expertise. Therefore, future studies could examine this more closely.

Fifth, as this study shows, the relationships between expertise and overconfidence were significant and positive. A possible subsequent study could be for deeper analysis into what, how, when, why, and to what extent factors of expertise relate to, interact with, and influence overconfidence. Sixth, while this study found that HRM practitioners often maintained beliefs that were contrary to evidence-based practices, it would be interesting to examine the degree to which other professionals also adopt practices that are misaligned with the findings of research. Relatedly, this study confirmed that HRM professionals least frequently consumed and consulted academic and scholarly information sources, perhaps contributing to why they do not always base their practices on research. Therefore, future studies could focus on how to bridge this researcher-practitioner gap and how researchers might present the findings of their research in ways that are more approachable, digestible, and illuminative for practitioners. Finally, because of the overall theoretical, research, and practical implications of my study, future HRD researchers should focus on developing and

evaluating debiasing strategies and interventions aimed at reducing the harmful effects of overconfidence.

Conclusion

The overconfidence effect has long been regarded by researchers within the social, behavioral, and management sciences as a widespread phenomenon occurring across a wide spectrum of professional settings. Despite the multidisciplinary interest the overconfidence effect has garnered by researchers, it had not been extensively studied by HRD scholars. This study aimed to intentionally examine the overconfidence effect within an HRD lens by developing and validating a robust construct of expertise as expressed through the dimensions of domain-specific knowledge, experience, and adaptivity. The specific population of interest in this study was HRM professionals.

This dissertation consisted of five chapters. In Chapter I, an overview of the study was offered. This introduction included the background of the study, the problem identified, the purpose of the study, theoretical framework that guided the study, the keys concepts under study, and research questions and hypotheses. In addition, this chapter highlighted the research design and justified the significance of the study. This chapter concluded by specifying the operational definitions, delimitations, assumptions, and organization of the study.

In Chapter II, I thoroughly reviewed and critiqued the relevant literature, identified the gaps that informed my current study, identified themes and relationships that emerged from the literature, and appraised the importance of this study for HRM professionals. The three theoretical resources that guided the study were the theory of

bounded rationality, the heuristics and biases program, and cognitive-experiential self-theory (CEST). The two major bodies of literature I reviewed were expertise and the overconfidence effect. Even though expertise had previously been addressed within the overconfidence literature, it was only superficially covered. Therefore, I relied heavily on HRD expertise literature to develop a multidimensional construct of expertise. Based on the literature, I proposed conceptual relationships among expertise, overconfidence, and individual differences.

In Chapter III, I described in detail the research methods and methodology I employed to test the hypotheses of the current study. An online survey was designed and administered to gather data from 414 HRM practitioners affiliated with HRM professional associations in the United States. After I pre-screened the data for quality and completeness, the data were analyzed through descriptive statistics, PLS-SEM (which incorporates both factor and path analyses), mediation analysis, and moderation analysis. Additionally, I discussed how I ensured the validity and reliability of the study.

In Chapter IV, I presented the results of the statistical analyses. The results of these analyses validated the constructs of expertise and overconfidence. Additionally, the measurement model was validated through factor analysis and the structural model was evaluated through path analysis, mediation analysis, and moderation analysis. Although the hypothesized relationships between (a) expertise and overconfidence and (b) expertise and individual differences were supported, the (c) relationships between individual differences and overconfidence, as well as the (d) mediating and (e) moderating effects of individual differences were not supported.

Finally, in Chapter V, the results of the study were summarized and discussed in relation to the research hypotheses and relevant literature. Findings validated path models for expertise and overconfidence and found the relationships between these two to be statistically and positively associated. As such, expertise was identified as a good predictor of overconfidence. However, individual differences were ultimately determined to not be related to overconfidence or to be mediators and/or moderators of the relationships between expertise and overconfidence. The theoretical, research, and practical implications of these findings were addressed in detail as they relate to the areas of HRD, overconfidence, and HRM. This chapter concluded with the limitations of the current study and recommendations for future research.

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APPENDIX A

SCREENSHOTS FROM ONLINE QUALTRICS SURVEY

You are invited to participate in a study being conducted by Anthony Hunt, PhD student in the Human Resource Development (HRD) program at Texas A&M University. Please review the Informed Consent document. If you wish to participate, please select **"I Agree"** and click on the arrow on the bottom right of the screen to be taken to the survey.

Informed Consent Form.pdf ▾

TEXAS A&M UNIVERSITY HUMAN RESEARCH PROTECTION PROGRAM
INFORMED CONSENT SCRIPT

Title of Research Study: Exploring the Expertise of Human Resource Management (HRM) Professionals

Doctoral Student: Anthony Hunt

Principal Investigator: Jia Wang, PhD

Why am I being asked to take part in this research study?

You are invited to participate in this study because we are trying to learn more about factors that relate to the expertise of human resource (HR) professionals.

"I Agree" to participate in the study.

"I Disagree" to participate in the study.

→

Are you at least 18 years old?

Yes

No

→

What is your age (in years)?

From which HR group did you access this survey?

Do you hold any professional certifications, credentials, or licenses?

Yes

No

Are you a member of any national professional associations?

Yes

No

Are you a member of any local professional associations?

Yes

No

→

Which professional certifications, credentials, or licenses do you hold? Select all that apply.

Professional in Human Resources (PHR)	Certified Employee Benefit Specialist (CEBS)
Senior Professional in Human Resources (SPHR)	Certified Benefits Professional (CBP)
SHRM-Certified Professional (SHRM-CP)	Certified Staffing Professional (CSP)
SHRM-Senior Certified Professional (SHRM-SCP)	Project Management Professional (PMP)
Global Professional in Human Resources (GPHR)	Certified Public Accountant (CPA)
Certified Professional in Learning & Performance (CPLP)	License to practice law
Certified Compensation Professional (CCP)	Other

Of which national professional associations are you a member?

Society of Human Resource Management (SHRM)

College and University Professional Association for Human Resources (CUPA-HR)

Association for Talent Development (ATD)

WorldatWork

Academy of Human Resource Development (AHRD)

International Public Management Association for Human Resources (IPMA-HR)

International Foundation of Employee Benefit Plans (IFEBP)

Project Management Institute (PMI)

Other

→

How many years of experience do you have in your current or most recent role?

How many total years of professional experience do you have in HR?

How many years of professional experience do you have in total (both inside and outside of HR)?

Which of the following best describes your current employment status?

Employed full-time (30+ hours per week)	Student
Employed part-time (fewer than 30 hours per week)	Retired
Unemployed and currently looking for work	Self-employed
Unemployed and currently not looking for work	Unable to work

→

Which best describes your current or most recent position?

Academician	Legal Counsel
Administrative Assistant	Manager or Sr. Manager
Administrator	Partner, Principal
Assistant or Associate Vice President	President, CEO, Chairperson
Chief HR Officer	Representative, Associate
Consultant	Specialist
Coordinator	Senior/executive leader outside of HR
Director, Asst/Assoc Director, or Sr. Director	Supervisor
Generalist	Vice President or Senior Vice President
HR Business Partner	Other

Please indicate your current annual salary in U.S. dollars.

Under $20,000	$100,000 to $124,999
$20,000 to $34,999	$125,000 to $149,999
$35,000 to $49,999	$150,000 to $174,999
$50,000 to $74,999	$175,000 to $199,999
$75,000 to $99,999	$200,000 and above

How often do you leverage the following resources to stay current in the HR field?

	Never	Rarely	Sometimes	Frequently	Always
Professional HR websites (e.g., SHRM)	○	○	○	○	○
Online blogs or message boards	○	○	○	○	○
Webinars	○	○	○	○	○
Seminars	○	○	○	○	○
Professional conferences	○	○	○	○	○
Professional magazines	○	○	○	○	○
Other HR colleagues	○	○	○	○	○
Colleagues outside of HR (e.g., legal)	○	○	○	○	○
Consultants	○	○	○	○	○
Academic journals	○	○	○	○	○
Academic conferences	○	○	○	○	○
Academic scholars	○	○	○	○	○

→

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With which gender do you most identify?

Female

Male

Transgender Female

Transgender Male

Gender Variant / Non-conforming

Prefer Not to Answer

Other

What is your race / ethnicity? Select all that apply.

African American or Black	Multiracial
American Indian or Alaska Native	Pacific Islander
Asian American or Asian	White or Caucasian
Hispanic or Latin American	Prefer Not to Answer
Middle Eastern	Other

What is the highest level of education you have completed?

Less than high school	Bachelor's degree
High school diploma or equivalent (e.g., GED)	Master's degree
Some college but no degree	Professional degree (e.g., MD, JD, DDS, DVM)
Associate degree	Doctorate (e.g., PhD, EdD)

→

Please use the slider scale from 1 to 100 to indicate what percentile you rate yourself in each area. The higher the number means the more highly you rate yourself.

| 0 | 20 | 40 | 60 | 80 | 100 |

Management practices

General employment practices

Training & employee development

Staffing

Compensation & benefits

Overall HR knowledge

Please use the slider scale from 1 to 100 to answer how confident/certain are you in each of the following areas. The higher the number means the more confidence/certainty you have.

0	20	40	60	80	100

Management practices

General employment practices

Training & employee development

Staffing

Compensation & benefits

Overall HR knowledge

Compared with other HR professionals, how knowledgeable are you in the following areas?

	Extremely less knowledgeable	Somewhat less knowledgeable	About the same	Somewhat more knowledgeable	Extremely more knowledgeable
Management practices	○	○	○	○	○
General employment practices	○	○	○	○	○
Training & employee development	○	○	○	○	○
Staffing	○	○	○	○	○
Compensation & benefits	○	○	○	○	○
Overall HR knowledge	○	○	○	○	○

→

The next few sections will ask if you think each HR-related statement is True or False. Although you may respond that you are Uncertain, please try to answer as best as you can given your knowledge, experience, and beliefs about each statement.

Management Practices

	True	False	Uncertain
Leadership training is ineffective because good leaders are born, not made.	O	O	O
The most important requirement for an effective leader is to have an outgoing, enthusiastic personality.	O	O	O
Once employees have mastered a task, they perform better when they are told to "do their best" than when they are given specific, difficult performance goals.	O	O	O
Companies with vision statements perform better than those without them.	O	O	O
Companies with very low rates of professional turnover are less profitable than those with moderate turnover rates.	O	O	O
If a company feels it must downsize employees, the most profitable way to do it is through targeted cuts rather than attrition.	O	O	O
In order to be evaluated favorably by line managers, the most important competency for HR managers is the ability to manage change.	O	O	O
On average, encouraging employees to participate in decision making is more effective for improving organizational performance than setting performance goals.	O	O	O

General Employment Practices

	True	False	Uncertain
Most managers give employees lower performance appraisals than they objectively deserve.	O	O	O
Please select "Uncertain" for quality control	O	O	O
Poor performers are generally more realistic about their performance than good performers are.	O	O	O
Teams with members from different functional areas are likely to reach better solutions to complex problems than teams from a single area.	O	O	O
Despite the popularity of drug testing, there is no clear evidence that applicants who score positive on drug tests are any less reliable or productive employees.	O	O	O
Most people overevaluate how well they perform on the job.	O	O	O
Most errors in performance appraisals can be eliminated by providing training that describes the kinds of errors managers tend to make and suggesting ways to avoid them.	O	O	O

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Training & Employee Development

	True	False	Uncertain
Lecture-based training is generally superior to other forms of training delivery.	O	O	O
Older adults learn more from training than younger adults.	O	O	O
The most important determinant of how much training employees actually use on their jobs is how much they learned during training.	O	O	O
Training for simple skills will be more effective if it is presented in one concentrated session than if it is presented in several sessions over time.	O	O	O

→

Staffing

	True	False	Uncertain
The most valid employment interviews are designed around each candidate's unique background.	O	O	O
Although people use many different terms to describe personalities, there are really only four basic dimensions of personality, as captured by the Myers-Briggs Type Indicator (MBTI).	O	O	O
On average, applicants who answer job advertisements are likely to have higher turnover than those referred by other employees.	O	O	O
Being very intelligent is actually a disadvantage for performing well on a low-skilled job.	O	O	O
There is very little difference among personality inventories in terms of how well they predict an applicant's likely job performance.	O	O	O
Although there are "integrity tests" that try to predict whether someone will steal, be absent, or otherwise take advantage of an employer, they don't work well in practice because so many people lie on them.	O	O	O
One problem with using integrity tests is that they have high degrees of adverse impact on racial minorities.	O	O	O
On average, conscientiousness is a better predictor of job performance than is intelligence.	O	O	O
Companies that screen job applicants for values have higher performance than those that screen for intelligence.	O	O	O

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Compensation & Benefits

	True	False	Uncertain
When pay must be reduced or frozen, there is little a company can do or say to reduce employee dissatisfaction and dysfunctional behaviors.	O	O	O
Most employees prefer to be paid on the basis of individual performance rather than on team or organizational performance	O	O	O
Merit pay systems cause so many problems that companies without them tend to have higher performance than companies with them.	O	O	O
There is a positive relationship between the proportion of managers receiving organizationally based pay incentives and company profitability.	O	O	O
New companies have a better chance of surviving if all employees receive incentives based on organization-wide performance.	O	O	O
Talking about salary issues during performance appraisals tends to hurt morale and future performance.	O	O	O
Most employees prefer variable pay systems (e.g., incentive schemes, gain sharing, stock options) to fixed pay systems.	O	O	O
Surveys that directly ask employees how important pay is to them are likely to overestimate pay's true importance in actual decisions.	O	O	O

→

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When answering the following questions, please consider how you have responded to projects within the last two years within your current or most recent role.

During past projects...

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I was able to develop and integrate new knowledge with what I learned in the past.	O	O	O	O	O
I concerned myself with the latest development in the domain of my discipline.	O	O	O	O	O
I gained a better understanding of concepts in my discipline.	O	O	O	O	O
I realized that the knowledge in my discipline keeps on developing.	O	O	O	O	O
I realized that I need to learn continuously to become and stay an expert in my field.	O	O	O	O	O
I showed that I am willing to keep on learning new aspects related to my discipline.	O	O	O	O	O
I applied my knowledge in new and unfamiliar situations in areas related to my discipline with a degree of success.	O	O	O	O	O
Please select "Disagree" for quality control	O	O	O	O	O
I focused on new challenges.	O	O	O	O	O
I was able to keep on performing at a high level when confronted with unfamiliar situations or tasks.	O	O	O	O	O
I was able to apply my knowledge flexibly to the different tasks within the project.	O	O	O	O	O

When answering the following questions, please consider how you make decisions.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I prefer to gather all the necessary information before committing to a decision.	O	O	O	O	O
I thoroughly evaluate decision alternatives before making a final choice.	O	O	O	O	O
In decision making, I take time to contemplate the pros/cons or risks/benefits of a situation.	O	O	O	O	O
Investigating the facts is an important part of my decision making process.	O	O	O	O	O
I weigh a number of different factors when making decisions.	O	O	O	O	O
When making decisions, I rely mainly on my gut feelings.	O	O	O	O	O
My initial hunch about decisions is generally what I follow.	O	O	O	O	O
I make decisions based on intuition.	O	O	O	O	O
I rely on my first impressions when making decisions.	O	O	O	O	O
I weigh feelings more than analysis in making decisions.	O	O	O	O	O

→

In this next section, please answer these three basic problems.

A bat and a ball cost $1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost?

$0.09

$0.01

$0.05

$0.10

If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?

20 minutes

500 minutes

100 minutes

5 minutes

In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

36 days

12 days

24 days

47 days

→

In this **final** section, here are a number of personality traits that may or may not apply to you. Please indicate how well the following statements describe your personality. Please note the slight change in the 5-point scale for these questions.

I see myself as someone who:

	Disagree strongly	Disagree a little	Neither agree nor disagree	Agree a little	Agree strongly
Is reserved	O	O	O	O	O
Is generally trusting	O	O	O	O	O
Tends to be lazy	O	O	O	O	O
Please select "Agree a little" for quality control	O	O	O	O	O
Is relaxed, handles stress well	O	O	O	O	O
Has few artistic interests	O	O	O	O	O
Is outgoing, sociable	O	O	O	O	O
Tends to find fault with others	O	O	O	O	O
Does a thorough job	O	O	O	O	O
Gets nervous easily	O	O	O	O	O
Has an active imagination	O	O	O	O	O

→

Would you like to be entered into a raffle for a chance to win one of four (4) $50 Amazon gift cards?

Yes

No

→

Optional: If you would like to be entered into a drawing for one of four (4) $50 Amazon gift cards for your participation, please enter your email address below. Your responses will remain private and anonymous. Your email address will be used for the drawing only and will not be linked to your responses, shared with anyone else, or used for any other purpose.

→

Thank you for participating in my study! I greatly appreciate your time.

Your responses have been recorded.

COPYRIGHT PERMISSIONS

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UNIVERSITY.

Anthony Hunt <tonykhunt@tamu.edu>

Permission to Use the Adaptive Expertise Inventory
3 messages

Anthony Hunt <tonykhunt@tamu.edu>
To: katerina.carbonell@northwestern.edu

Wed, Dec 27, 2017 at 2:35 PM

Dr. Bohle-Carbonell:

I am a PhD student in the Human Resource Development program at Texas A&M University in College Station, TX. I am in the process of writing my dissertation titled *Exploring the Relationships Among the Overconfidence, Expertise, and Individual Differences of Human Resource Professionals.*

I am writing you because I would like your permission to use the **Adaptive Expertise Inventory** from the following published source:

Carbonell, K. B., Könings, K. D., Segers, M., & van Merriënboer J. J. G. (2016). Measuring adaptive expertise: Development and validation of an instrument. *European Journal of Work and Organizational Psychology, 25*(2), 167-180.

Proper credit and acknowledgement will be included in the dissertation. Furthermore, the dissertation will be made available to the public online through Texas A&M University Libraries and will be microfilmed and sold on demand by ProQuest/UMI.

I would greatly appreciate your permission to use this questionnaire in my research. If I do have your permission, please indicate so by replying to me at tonykhunt@tamu.edu. Also, please do not hesitate to contact me if you have any questions at all.

I thank you in advance for your help and I hope you have a very wonderful upcoming year.

Most Sincerely,

Anthony Hunt

Katerina Bohle Carbonell <katerina.carbonell@northwestern.edu>
To: Anthony Hunt <tonykhunt@tamu.edu>

Thu, Dec 28, 2017 at 1:44 PM

Hello Anthony,

You have an interesting dissertation project. I give you permission to use the Adaptive Expertise Inventory. Please inform me about your results or let me know once your dissertation is done.

Small remark, my family name is Bohle Carbonell. Correct citation would begin with Bohle Carbonell, K. ….

Best,
Katerina

Anthony Hunt <tonykhunt@tamu.edu>

Permission to Use the Decision Styles Scale

3 messages

Anthony Hunt <tonykhunt@tamu.edu>   Wed, Dec 27, 2017 at 2:46 PM
To: khamilton@ist.psu.edu

Dr. Hamilton:

I am a PhD student in the Human Resource Development program at Texas A&M University in College Station, TX. I am in the process of writing my dissertation titled *Exploring the Relationships Among the Overconfidence, Expertise, and Individual Differences of Human Resource Professionals.*

I am writing you because I would like your permission to use the **Decision Styles Scale** from the following published source:

Hamilton, K., Shih, S-I, & Mohammed, S. (2016). The development and validation of the rational and intuitive Decision Styles Scale. *Journal of Personality Assessment, 98*(5), 523-535.

Proper credit and acknowledgement will be included in the dissertation. Furthermore, the dissertation will be made available to the public online through Texas A&M University Libraries and will be microfilmed and sold on demand by ProQuest/UMI.

I would greatly appreciate your permission to use this questionnaire in my research. If I do have your permission, please indicate so by replying to me at tonykhunt@tamu.edu. Also, please do not hesitate to contact me if you have any questions at all.

I thank you in advance for your help and I hope you have a very wonderful upcoming year.

Most Sincerely,

Anthony Hunt

Katherine Hamilton <khamilton@ist.psu.edu>   Thu, Dec 28, 2017 at 12:15 PM
To: Anthony Hunt <tonykhunt@tamu.edu>

Anthony,
Thanks for expressing an interest in our work. Yes, you have my permission to use the scale. Please use the following citations when referring to the scale.

Hamilton, K., Shih, S., & Mohammed, S. (2016). The development and validation of the rational and intuitive decision styles scale. Journal of Personality Assessment, 98, 523-535.

Hamilton, K., Shih, S., & Mohammed, S. (2017). The predictive validity of the decision styles scale: An evaluation across task types. Personality and Individual Differences, 119, 333-340.

Let me know if you have any other questions on the measure. Best of luck with your research.

-Katherine

Permission to Use HR Beliefs Questionnaire

3 messages

Anthony Hunt <tonykhunt@tamu.edu>
To: sara-rynes@uiowa.edu

Wed, Dec 27, 2017 at 2:54 PM

Dr. Rynes-Weller:

I am a PhD student in the Human Resource Development program at Texas A&M University in College Station, TX. I am in the process of writing my dissertation titled *Exploring the Relationships Among the Overconfidence, Expertise, and Individual Differences of Human Resource Professionals.*

I am writing you because I would like your permission to use the questionnaire from the following published source:

Rynes, S. L., Colbert, A. E., & Brown, K. G. (2002). HR professionals' beliefs about effective human resource practices: Correspondence between research and practice. *Human Resource Management, 41*(2), 149-174.

Proper credit and acknowledgement will be included in the dissertation. Furthermore, the dissertation will be made available to the public online through Texas A&M University Libraries and will be microfilmed and sold on demand by ProQuest/UMI.

I would greatly appreciate your permission to use this questionnaire in my research. If I do have your permission, please indicate so by replying to me at tonykhunt@tamu.edu. Also, please do not hesitate to contact me if you have any questions at all.

I thank you in advance for your help and I hope you have a very wonderful upcoming year.

Most Sincerely,

Anthony Hunt

Rynes-Weller, Sara L <sara-rynes@uiowa.edu>
To: Anthony Hunt <tonykhunt@tamu.edu>

Wed, Dec 27, 2017 at 3:43 PM

Dear Anthony,

By all means, feel free to use the questionnaire. We no longer have any hard copies (and never DID have an electronic version) of the questionnaire so you'll have to re-create it from the items listed in the HRM article. That's inconvenient, but not insurmountable.

Best of luck with your dissertation!

Sara

APPENDIX C

IRB APPROVAL OF EXEMPT RESEARCH

Ā̵M | **TEXAS A&M**
U N I V E R S I T Y

EXEMPTION DETERMINATION
(Common Rule –Effective January, 2018)

August 19, 2019

Type of Review:	Submission Response for Initial Review Submission Form
Title:	Exploring the Relationship between the Overconfidence and Expertise of Human Resource Management (HRM) Professionals
Investigator:	Jia Wang
IRB ID:	IRB2019-0901M
Reference Number:	095966
Funding:	Internal
Documents Reviewed:	• IRB Application (Human Research) - (Version 1.2) • Simple Survey Consent Script - Anthony Hunt - (Version 1.0) • Recruitment email - (Version 1.0) • Dissertation survey 8.2019 - (Version 1.0)
Review Category	Category 2: Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met: i. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects; ii. Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation.

Dear Jia Wang:

The HRPP determined on 08/19/2019 that this research meets the criteria for Exemption in accordance with 45 CFR 46.104.

This determination applies only to the activities described in this IRB submission and does not apply should any changes be made. If changes are made you must immediately contact the IRB. You may be required to submit a new request to the IRB.

Your exemption is good for three (3) years from the Approval Start Date. Thirty days prior to that time, you will be sent an Administrative Check-In Notice to provide an update on the status of your study.

If you have any questions, please contact the IRB Administrative Office at 1-979-458-4067, toll free at 1-855-795-8636.

Sincerely,
IRB Administration

APPENDIX D

RECRUITMENT LETTER

Hello,

My name is Anthony Hunt and I am a PhD student in Human Resource Development (HRD) at Texas A&M University. I am conducting research about factors that relate to the expertise of HR professionals, such as experience, exposure to various areas within HR, personality, and approaches to decision-making.

I am reaching out to you because I would like to invite the members of your association to participate in my study, and would greatly appreciate it if you would distribute my survey on my behalf to your members. Participation is voluntary, confidential, convenient, and will only take about 15-20 minutes.

The link to my survey can be found at <SURVEY LINK>.

If you have any questions, please do not hesitate to contact me at (512) 922-1807 or at tonykhunt@tamu.edu.

Thank you very much for your time and consideration. I look forward to hearing from you.

Most Sincerely,
Anthony Hunt
PhD Student
Texas A&M University
TAMU IRB #20XX-XXXX Approved: XX/XX/XXXX

APPENDIX E

INFORMED CONSENT FORM

TEXAS A&M | UNIVERSITY.

TEXAS A&M UNIVERSITY HUMAN RESEARCH PROTECTION PROGRAM
INFORMED CONSENT SCRIPT

Title of Research Study: Exploring the Expertise of Human Resource Management (HRM) Professionals

Doctoral Student: Anthony Hunt

Principal Investigator: Jia Wang, PhD

Why am I being asked to take part in this research study?

You are invited to participate in this study because we are trying to learn more about factors that relate to the expertise of human resource (HR) professionals.

You were selected as a possible participant in this study because of your identified association and/or involvement with the field of HR. You must be 18 years of age or older to participate.

Why is this research being done?

The survey is designed to ask you questions about your professional expertise, such as your experience, exposure to various areas within HR, and your approach to making decisions.

How long will the research last?

It will take approximately 15-20 minutes to complete the survey.

What happens if I say "Yes, I want to be in this research"?

If you decide to participate, please indicate so by selecting the **"I Agree"** button at the bottom of this form. Once you submit your consent to participate, you will be able to proceed to the questionnaire.

What happens if I do not want to be in this research?

Your participation in this study is voluntary. You can decide not to participate in this research and it will not be held against you. You can leave the study at any time.

Is there any way being in this study could harm me?

There is a risk of discomfort, as some of the questions are sensitive. You can skip any question you do not wish to answer, or exit the survey at any point.
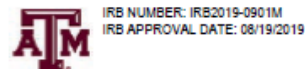
<u>**INFORMED** C<small>ONSENT</small> S<small>CRIPT</small></u>

What happens to the information collected for the research?

You may view the survey host's confidentiality policy at:
https://www.qualtrics.com/privacy-statement/

You have the option to enter your email address to be entered into one of four (4) drawings for a $50 Amazon gift card. If you decide to enter, your email address will be stored separately from your survey data, and is only being collected for payment purposes. All information will be kept on a password protected computer and is only accessible by the research team.

The results of the research study may be published but no one will be able to identify you.

What else do I need to know?

If you are selected as a winner of one of the four (4) $50 Amazon gift cards, the electronic gift card will be sent to the email address you provide at the end of the survey. This is optional if you do not want to provide your email address.

Who can I talk to?

Please feel free to ask questions regarding this study. You may contact us later if you have additional questions or concerns. You may contact the doctoral student, Anthony Hunt, at 1-512-922-1807 or by email at tonykhunt@tamu.edu, or the principal investigator, Dr. Jia Wang, at 1-979-862-7808 or by email at jiawang@tamu.edu.

You may also contact the Human Research Protection Program at Texas A&M University (which is a group of people who review the research to protect your rights) by phone at 1-979-458-4067, toll free at 1-855-795-8636, or by email at irb@tamu.edu for:

- additional help with any questions about the research
- voicing concerns or complaints about the research
- obtaining answers to questions about your rights as a research participant
- concerns in the event the research staff could not be reached
- the desire to talk to someone other than the research staff

If you want a copy of this consent for your records, you can print it from the screen.

> ➢ If you wish to participate, please click the **"I Agree"** button and you will be taken to the survey.

> ➢ If you do not wish to participate in this study, please select **"I Disagree"** or select **X** in the corner of your browser

APPENDIX F

TESTS FOR NORMALITY AND SKEWNESS

Latent Variables		Indicators	Shapiro-Wilk statistic	p	Skew-ness
Individual Differences		Age	0.982	<.001*	+0.26
		Agreeableness	0.936	<.001*	-0.85
		Conscientiousness	0.834	<.001*	-1.05
		Extraversion	0.946	<.001*	-0.10
		Neuroticism	0.951	<.001*	+0.39
		Openness	0.961	<.001*	-0.24
		Information Sources	0.991	.013	+0.17
		Rational Decision Style	0.969	<.001*	+0.53
		Intuitive Decision Style	0.940	<.001*	-0.16
Expertise	Adaptivity	Domain & Innovative	0.968	<.001*	-0.18
	Experience	Current job (years)	0.775	<.001*	+2.06
		HRM (years)	0.957	<.001*	+0.73
		Total (years)	0.917	<.001*	+0.34
	Knowledge	Compensation & Benefits	0.948	<.001*	-0.31
		General Employment	0.922	<.001*	-0.30
		Management	0.930	<.001*	-0.47
		Staffing	0.947	<.001*	+0.50
		Overall HRM	0.985	<.001*	-0.33
		Training and Development	0.840	<.001*	-0.85
		Certifications & Associations	0.736	<.001*	-1.14
Overconfidence	Over-estimation	Compensation & Benefits	0.992	.025	-0.60
		General Employment	0.991	.015	-0.12
		Management	0.997	<.001*	-0.60
		Staffing	0.977	<.001*	-0.62
		Overall HRM	0.975	<.001*	-0.58
		Training and Development	0.994	.102	-0.05
	Over-precision	Compensation & Benefits	0.992	.020	-0.22
		General Employment	0.987	<.001*	-0.24
		Management	0.969	<.001*	-0.71
		Staffing	0.974	<.001*	-0.65
		Overall HRM	0.985	<.001*	-0.42
		Training and Development	0.991	.013	+0.11
	Over-placement	Compensation & Benefits	0.910	<.001*	-0.05
		General Employment	0.872	<.001*	-0.22
		Management	0.882	<.001*	-0.44
		Staffing	0.858	<.001*	-0.01
		Overall HRM	0.890	<.001*	-0.39
		Training and Development	0.891	<.001*	+0.05

Note. * Indicates strong deviation from normality (p < .001)

APPENDIX G

DESCRIPTION OF PROFESSIONAL QUALIFICATIONS

Category	n	%
Professional in Human Resources (PHR)	186	61.4
Senior Professional in Human Resources (SPHR)	68	22.4
SHRM-Certified Professional (SHRM-CP)	128	42.2
SHRM-Senior Certified Professional (SHRM-SCP)	68	22.4
Global Professional in Human Resources (GPHR)	7	2.3
Certified Professional in Learning & Performance (CPLP)	3	1.0
Certified Compensation Professional (CCP)	10	3.3
Certified Employee Benefit Specialist (CEBS)	1	0.3
Certified Benefits Professional (CBP)	4	1.3
Certified Staffing Professional (CSP)	1	0.3
Project Management Professional (PMP)	2	0.7
Certified Public Accountant (CPA)	2	0.7
License to practice law	4	1.3
Other	62	20.5

Note. There were 303 HRM professionals with credentials. Respondents were able to select multiple options. Therefore, n exceeds 303 and % exceeds 100.

APPENDIX H

DESCRIPTION OF NATIONAL ASSOCIATIONS

Category	n	%
Society for Human Resource Management (SHRM)	307	95.9
College and University Professional Association for Human Resources (CUPA-HR)	2	0.6
Association for Talent Development (ATD)	20	6.3
WorldatWork	20	6.3
Academy of Human Resource Development (AHRD)	1	0.3
International Public Management Association for Human Resources (IPMA-HR)	2	0.6
International Foundation of Employee Benefit Plans (IFEBP)	2	0.6
Project Management Institute (PMI)	3	0.9
Other	32	10.0

Note. There were 320 HRM professionals who were members of a national association. Respondents were able to select multiple options. Therefore, n exceeds 320 and % exceeds 100.

APPENDIX I

DESCRIPTION OF RESPONDENT JOB TITLES

Category	n	%
Academician	1	0.2
Administrative Assistant	4	1.0
Administrator	5	1.2
Assistant or Associate Vice President	1	0.2
Chief HR Officer	16	3.9
Consultant	22	5.3
Coordinator	8	1.9
Director, Assistant/Associate Director, or Sr. Director	79	19.1
Generalist	58	14.0
HR Business Partner	61	14.7
Legal Counsel	1	0.2
Manager or Sr. Manager	82	19.8
Partner, Principal	5	1.2
President, CEO, Chairperson	7	1.7
Representative, Associate	4	1.0
Specialist	1	0.2
Senior/executive leader outside of HR	1	0.2
Supervisor	25	6.0
Vice President or Senior Vice President	7	1.7
Other	26	6.3