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Assessing the Analytic Competency Gap for HR Professionals: Providing HR a Roadmap to Data-Driven Decision-Making

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by

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Abstract

Title: Assessing the Analytic Competency Gap for Human Resources Professionals: Providing a Roadmap to Data-Driven Decision-Making

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Human Resource (HR) professionals have fallen behind their peers in utilizing and leveraging analytics to enhance performance. Research indicates that HR professionals need a more prescriptive understanding of competencies required for analytics and the influence on job performance. This study utilizes a novel method to map a newly demanded skill set or competency cluster to a profession, filling a gap in the competency modeling literature for future state occupational needs. The developed and supported HR analytic competency cluster is logic, numeracy, and critical evaluation with special considerations for persuasion. This study utilized a structural equation model (SEM) to test the effect of these competencies on job performance. The HR analytic competencies predict increased job performance except for persuasion. Contrary to expectations, the analytic cluster of logic, numeracy, and critical evaluation mediated the impact of persuasion. Self-efficacy mediated competency impact on performance. The research increased our understanding of analytics on performance. Further, the study increased our knowledge of competencies in the behavioral model of job performance. The results have practical contributions, providing HR professionals with relevant information to inform their personal development.

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Dedication

I dedicate this dissertation to my husband Anthony Talerico. He was supportive when I thought I couldn't finish. When I was working on my dissertation, he would move heaven and earth to ensure I had the space to concentrate. Although I would drive him nuts, he was still willing to proofread. When I needed to buy a book or spend a small fortune on a survey panel, he made it happen. He sacrificed time and took on extra work around the house to ensure my success. I believe our wedding vow could be amended to state "through good times and bad, and through a dissertation" because such endeavors test love, patience, and compassion. He is my rock and my strength. Thank you for your love and support.

I also want to contribute this work to my parents. They taught me to work hard, have passion, and gave me the strength to see my commitments through. Without their nurture, support, and love, I wouldn't have made it to this point in my journey.

Chapter 1

Introduction

1.1 Background of the Study

For more than a decade, experts in the Human Resources (HR) discipline, professional organizations, and academia have championed analytics competency for HR professionals to enhance decision-making and HR performance (Ulrich, 2015; Rousseau & Barends, 2011; Huong Vu, 2017). The strategic push for the firm to develop insights for people decisions and drive Human Resource Management (HRM) practices reside in new HR professional competencies, specifically analytics (Levenson & Alexis, 2017; Fitz-enz, 2010; Kapoor & Kabra, 2014; Kryscynski et al., 2017). It is expected that HR professionals will be effective decision-makers and an asset to the firm if they position themselves to utilize and develop needed analytic skills (LaFevor, 2018). Ulrich and colleagues (2021b) explain that individual competencies are building blocks to business capabilities and advancing HR practices; HR must first work on the foundational building blocks to obtain desired firm success (Ulrich et al., 2021b). The research indicates HR professionals do not have the data skills or the ability to turn analysis results into insights for decision-making (Sinar et al., 2018; Angrave et al., 2016; Ulrich et al. 2021a), HR educational programs are not adept to the demand (Scanlan, 2007), and HR is not adopting analytics at the same pace as their peers in other business disciplines (Marler & Boudreau, 2017). The analytic gap being a hot topic, a promise of filling the need has resulted in the growth of graduate-level analytics programs. However, the schools toted to have analytic tracks, degrees, or certificates are among the elite in HR education and are at a graduate level (e.g., Rutgers and Cornell) (McIlvaine, 2019). On-demand professional programs tout analytics, but no evidence is provided to increase individual performance and variance in interpreted needs (e.g., Josh Bersin Academy, Academy to Innovate HR). The results of Kapoor and Kabra's (2014) work suggest that the future for HR professionals in analytics is high, with demand increasing and a limited supply of HR professionals with the needed skills. The research is unclear about what skills the HR professional needs for analytics, compounding the problem. A prescription is needed at an individual level to solve the discipline's Analytic Competency (AC) demand.

1.1.1 Analytic Competency Problem

Analytic competency in HR requires a baseline understanding of analytics, which has proven difficult (Marler and Boudreau, 2017). Definitions range from analytics being a process; multiple processes; the decision from an analysis; and a demonstration of insight from data directly contributing to business outcomes (Marler & Boudreau, 2017). The most prominent in the literature, Bassi et al. (2010) define HR analytics as "the application of a methodology and integrated process for improving the quality of people related decisions to improve individual and/or organizational performance" (p.11). Later Bassi (2011) provided a more robust definition that encapsulates the intent of this dissertation "an evidence-based approach for making better decisions on the people side of business and consists of an array of tools and technologies, ranging from simpler reporting of HR metrics to predictive modeling" (p.16).

Competency frameworks provide the knowledge, skills, abilities, and other characteristics (KSAOs) needed for effective job performance (Society for Human Resource Management, 2016). So far, analytic KSAOs in competency frameworks for HR suggest the need exists, but how AC is embedded and contributes to the HR professional's performance varies (Ulrich et al., 2015). The current competency frameworks in HR also differ in industry, professional, and academic views (Ulrich et al., 2017; Huong Vu, 2019). Yet AC is considered among the leading needs for HR in the future (Ulrich, Younger, & Brockbank, 2012; Ulrich & Dulebohn, 2015; Falletta & Combs, 2020).

Two KSAOs for conducting HR analytics are prominent in the literature: (i) logic or critical thinking and (ii) data analyses or numeracy (Fitz-Enz & Mattox, 2014; Soundararajan, 2017; Falletta & Comb, 2020; Boudreau & Ramstad, 2007; Waters et al., 2018; Ghazal, 2014). Logic is the essence of the "art" of analytics as prescribed by Fitz-Enz and Mattox (2014), akin to research design, inquisition, and developing insight and solutions (Soundararajan & Singh, 2017). Yet other researchers blend such KSAO's of logic with technical skills to conduct data analysis (e.g., statistical analysis), nesting the cognitive competency with the functional competency (Boudreau & Ramstad, 2007; Ulrich, 2021). The bifurcation in the literature (Bassi, 2015) suggests more research is needed to define and test logic functionality in a competency model (Margherita, 2021).

Another prominent KSAO is numeracy or data analysis. Still, the research is not consistent as to who, the HR professional or an external resource (e.g., data scientist or other business function such as finance or IT) performs the analysis (Boudreau & Ramstad, 2007; Kryscynski et al., 2017; Waters et al., 2018). Understanding who contributes to numeracy is essential to addressing differences in the literature as to how analytics successfully leads to insights; some researchers contending the connections between data to business insights cannot be reached with segmented skill sets (Kapoor & Kabra, 2014; Bassi, 2015). Researchers' have suggested that mature data analysis skills, such as statistical regression, provide more predictive and prescriptive solutions the HR professional can able to bring to the table to solve people problems in business (Lawler, Levenson, & Boudreau, 2004; Greasley, 2019; Kapoor & Kabra, 2014; Fitz-Enz & Maddox, 2014; Soundararajan & Singh, 2017). Great conceptually, but difficult to implement if the skills to conduct the data-analysis or numeracy abilities are not considered essential to the HR professional making the people decisions (Rasmussen & Ulrich, 2015; Angrave et al., 2016). The numeracy functionality in decision-making is a sought answer in decision science literature as well. Research in decision-making science suggests numeric skills will generate increased critical thinking and logic functions (Ghazal, 2014). Despite research supporting internalize numeracy skills, other researchers indicate external resources are more prone to help with numeracy skills in a team approach, suggestive that the breadth of KSAOs is too broad for an individual contributor (Boudreau & Ramstad, 2007; Simón & Ferreiro, 2018; Yeo & Carter, 2017). Due to the inconsistencies in numeracy demand (internal vs. external), the HR professional is left with no definitive answer as to what KSAO's they need to support the business. The disposition for and against numeracy in HR professional AC is merely speculation without directly linking to performance and decision-making functionality.

Besides logic and numeracy, other KSAOs are mentioned and utilized in various HR analytic process models or "recipe"; however, they are less consistent or formalized (Boudreau & Ramstad, 2007; Ulrich et al., 2017, Waters et al., 2018, Soundararajan & Singh, 2017; Fitz-Enz, 2010). Much of the other KSAOs focus on persuasion and effective organizational knowledge to sell analytics-based decisions to stakeholders (Boudreau & Ramstad, 2007; Waters et al., 2018; Fitz-Enz, 2010). Fitz-Enz and Mattox (2014) estimate from leadership interviews the skill mix for successful implementation of analytics. The non-logic and numeracy skills comprised 55% of the skill mix, contributing more than the prominent logic and numeracy skills (Fitz-Enz & Mattox, 2014). However, there has been no formal validated and empirical assessment for the contributions of the KSAOs. Given the estimated demand yet mixed presentation of these other less prominent skills, research is warranted to understand precisely how these skills contribute to HR performance.

1.1.2 Purpose for this Research

Academia is trying to solve the analytics competency problem. The lack of a formal framework to build the competency models is concerning (Margherita, 2021). Researchers propose we should now provide HR professionals with well-defined and theoretical bound competency models with empirical substantiation for them to take the evidence-based approach espoused in the literature (Marler & Boudreau, 2017; Margherita, 2021). Utilizing such a theoretical bound competency model will help elucidate competency components that may not be fully unearthed, providing a complete picture of the competency package (LeDeist & Winterton, 2005). Further, we should utilize the competency cluster to link analytics to performance (Marler & Boudreau, 2017; Boyatzis, 1982). HR has used academic models for HR organizational design to support competency demand (Mamman & Al Kulaiby, 2014; Lawler & Boudreau, 2015; Ulrich et al., 2021b). The discipline has not dedicated the same rigorous efforts to define the KSAOs for AC and prove their efficacy (Maurer, 2018; Sinar et al., 2018). Subsequently, HR professionals are hesitant to adopt AC and question the value of the insights from such practices (Angrave et al., 2016).

This dissertation is also motivated by the credibility problem of AC for HR professionals. In the business environment, an HR professional is taught to address problems through the root cause (Okes, 2019). The most frequently cited problem as to "how" to achieve analytics, according to Marler and Boudreau's (2017) meta-synthesis of the literature, is to address the individual skills in performing analytics. Yet, the recommendations for most research are at the organizational level (e.g., Marler & Boudreau, 2017; Vargas, 2018; Margherita, 2021), failing to address the root cause. For HR professionals to be motivated and have confidence in the KSAOs of analytics, we must have more than pontification, rather evidence that if professionals seek those skills, they will have a higher likelihood of success in their job (Rousseau & Barends, 2011; Boudreau & Jesuthasan, 2011). Further, the competency must be linked to individual performance to lend credibility to a skill set already in question (Ramussen & Ulrich, 2015; Angrave et al., 2016). In assessing the link to performance, HR professional skepticism of analytics and specific skills is broached head-on.

In the root cause dive into why the competency problem persists in HR analytics, another purpose emerges for this research - how to appropriate model and develop new competency clusters needed in a profession. Current modeling processes have a different purpose - provide firms with a means to identify, measure, train, promote, retain, build competency structures, support organizational change based on the job currently being performed (Scott & Reynolds, 2010; Campion et al., 2011). However, what happens when you have a new process, task, or responsibility not previously performed adequately in that discipline? The following problems permeate the modeling process when assessing for emergent or enabling competency needs: current methods assume the job is being performed well in its current state and can be observed (Champion et al. 1999; Shippmann, 2010); the methods assume consensus among subject matter experts; and the approach does not require holistic assessment (LeDeist & Winterton, 2005). The growth of competency modeling, in general, without appropriate evaluations of the modeling process (Stone et al., 2013) has resulted in active models on the market with a multitude of issues –lagging presentation, orthogonal presentation, conflated competencies, and mixing of tasks, behaviors, and competencies. Contributing to these errors, many models and their authors fail to meet seminal guidelines to test the model for efficacy in job performance (e.g., McCartney et al., 2021) (McClelland, 1973; Stone et al., 2013).

Further motivating this research is the need to integrate decision science into the methodology. HR builds on the premise for AC in decision science, calling on evidence- and data-driven decision-making for HR performance (Boudreau & Jesuthasan, 2011; Ulrich et al., 2015; Kryscynski, 2017; SHRM, 2016). Roberts (2007), an originalist, juxtaposes evidenced-based decisions on improved HR outcomes. Today, the concept that decision-making is vital to performance is the base assumption of most HR literature driving analytic capability demand (Rousseau & Barends, 2011; Boudreau & Jesuthasan, 2011; Noe et al., 2017; Lengnick-Hall et al., 2009; van den Berg, Stander, & van der Vaart, 2020). Despite also having the time to mature, limited academic research solidifies the connection with analytics and decision science literature. The investigations so far are limited to case-study and assess analytics at an organizational level (e.g., Severson, 2019; Rousseau & Barends, 2011; Boudreau & Jesuthasan, 2011; van der Togt, 2017), not empirically assessing the relationships the authors are claiming between analytics, decision-making, and performance.

The assumption - accurate decision-making enhances performance - plagues not only HR literature but larger bodies of industrial/organizational (I/O) psychology research and decision-making science (Dalal et al., 2010). Not until recently has research worked to answer the call to connect these two streams. Zhu et al. (2020) and Seong and Hong (2018) join decision-making and performance, focusing on group decisions and participation. Zhu et al.'s (2020) research highlight the importance of individuals in decision-making and why we should explore rational decision-making mechanisms. This limited branch, which connects the decision science and I/O streams, does not take a business discipline approach nor addresses an environment where rational decision-making processes are questioned. This gap makes the HR discipline and professionals a prime subject for assessment. How does a rational approach work in a field where HR professionals are characterized as non-conforming to the traditional business (rational) decision-making mold?

1.1.3 Research Questions and Outcomes

This dissertation will develop an AC model on a well-defined competency framework, assess relationships and power of AC in HR practitioner decision-making accuracy and job performance. The research questions that drive this research are:

1. *What* analytic competencies are needed from HR professionals to drive higher job performance?
2. *How* do these analytic competencies drive higher job performance?

Upon building the model of competencies on a supported theoretical bedrock, this study will explore inconsistency regarding the depth of some specific skills needed or not. Specifically, the concept that the AC is more of a state of mind, as championed by Fitz-enz (2010) and Boudreau and Ramstad (2007) camp. The "state-of-mind" school of thought focuses on critical thinking and the ability to problem solve as the vital capability to successfully implement analytics (Fitz-enz, 2010; Boudreau & Ramstad, 2007; Petra, 2016). The "state of mind" school of thought is in direct conflict with Sinar et al. (2018), who argue that AC is composed of more tangible and specific data skills, and it is with these skills an HR professional builds an ability to garner predictive and prescriptive insights. It is expected this research will contribute to professional development and help HR professionals understand which AC KSAOs are valuable for their individual performance. HR professionals who question the contribution of numeracy competency or the contribution of people-data to decisions will have a more substantial resource to inform whether or not they pursue such skills in the future. The use of competency frameworks to build the AC model will embed the evidence-based approach desired by professionals within their own practice.

Academic contributions include expanding our knowledge of competency and its attribution to job performance, enhancing the competency modeling process for enabling competencies, implications of behavioral and cognitive approaches to HR job performance, and creating a bridge between I/O and decision science literature. The lack of academic rigor in previous competency research was cited in Marler and Boudreau (2017) and is a defined need. This research could validate the concept of data-driven and evidence-based decision-making for HR professionals in HRM, a popular but not empirically tested theoretical driver for AC (Rousseau & Barends, 2011; Boudreau & Jesuthasan, 2011). Finally, understanding the relationship between numeracy and critical thinking in decision-making is of emergent interest. This research will contribute to understanding that relationship in the context of HR job performance.

1.2 Organization of the Remainder of the Study

The subsequent chapter provides a literature review of important topics regarding this study in preparation for methods development. Chapter 2 will first describe the research gap after an in-depth review of the literature on competency, analytics, performance, and decision-making. Chapter 2 will conclude with building a set of comprehensive HR analytic competencies, with the hypothesized path relationships to decision-making and job performance. Chapter 3 provides the structural model and methods for testing the model. The method for testing the model will be Structural Equation Modeling (SEM) because of the method's ability to handle the complexity of the competency structure and the latent variables. Chapter 4 will assess the model and results of the SEM analysis. Chapter 4 also has a defense and analysis of a revised SEM model, as well as mediation analyses. Finally, Chapter 5 will include a discussion and implications from the study outcomes.

Chapter 2

Literature Review

2.1 Overview

The literature review will introduce the topic of competency, providing a foundation for understanding how and why competence models are utilized. Then the review will take focused dive into the current state of analytics and AC. The subsequent sections will focus on the dependent variables' decision-making and job performance. Finally, the review will wrap up with the gap in the research that is driving the need to identify formal HR AC Cluster modeled on a defined framework for competency.

2.2 Competency

2.2.1 Competency Modeling

Competency models allow organizations to influence behavior and expect such behaviors to be associated with maximum performance (Sanchez & Levine, 2016). Most competency modeling processes focus on modeling to support the HRM (e.g., providing a tool for identifying candidates for hire, assessing, training, developing, promoting talent within the organization) (Lucia & Lepsinger, 1999; Stone et al., 2013; Shippmann, 2000). Competencies as a source of job performance were by McClelland's (1973) *Testing for Competence rather than "Intelligence."* McClelland made a direct plea for change in assessing job performance capabilities because of the lack of criterion testing (testing for the actual needs of the job), effective communication measures, and operational conditions (McClelland, 1973). At the time of McClelland's work, academic measures and intelligence psychometrics amassed most of the literature. McClelland (1973) argued intelligence measures have limited validity and evidence for predicting job performance despite the intense study of intelligence.

Scott and Reynolds (2010) explain the rich history of how competency modeling, job analysis, competence dictionaries, and taxonomies flourish from McClelland's spark. In addition to the other seminal works reviewed, is a notable giant Prahalad and Hamel (1990); however, the work focused on the firm's core competencies for organizational level performance, not an individual performance which is the focus of this dissertation.

McBer/McClelland's Competency framework emerged under the formal title *Scaled Competency Dictionary* in 1996 (Scott and Reynolds, 2010). Their competency modeling process originated from a different definition of competence with hidden factors such as motive, traits, and self-concept were part of the competence model. The process for building the competence model stemmed from behavioral event interview-based studies. Subsequently, the dictionary included personal orientations (e.g., achievement, helping orientations) (Spencer & Spencer, 1993; Raven, 2001). However, as Raven (2001), explains this model loses ground because the fundamentals of competence are too generalized and not helpful in an applied setting.

In modern competency modeling, Campion and Shippmann dominate the process modeling research (McCartney et al., 2021; Shippmann, 2010; Stone et al., 2013). In both Campion and Shippmann methods, the focus is on competence as composing of KSAOs; the definition used in this dissertation. The modeling process derives competencies from the organizational level mission, values, and strategy, filtering down to the job families and the subsequent technical and leadership behaviors that will lead to measurable performance and metrics, which are expected to reflect improved organizational performance (Campion et al., 2011). According to Campion et al. (2011), future-oriented needs are best modeled through a literature review of emergent competency literature, business strategy analysis for future needs, and the use of Subject Matter Experts to identify competencies.

In addition to firm-level recommendations for competency modeling, Campion is an influential figure of O*Net, the largest discipline-based taxonomy and working list of job content, referenced as the KSAOs. O*Net maintains a comprehensive list of single occupational taxonomy, or occupational titles, last updated in 2019. The O*Net model has six working domains – worker characteristics, worker requirements, experience requirements, occupational requirements, workforce characteristics, and occupation-specific information from which KSAO's are defined (O*Net, n.d.; Peterson et al., 2001). O*Net retains some of the motivational influences of McClelland, but in the context of the job values. However, O*Net attributes this contribution to Lofquist & Dawis (1969) work values model (O*Net, n.d.; Campion et al., 1999). O*Net utilizes statistical random sampling of firms to obtain data on sample job incumbents for each occupation through structured questionnaires that cover the employee's background, education and training, knowledge, work activities, work context, and the worker's style.

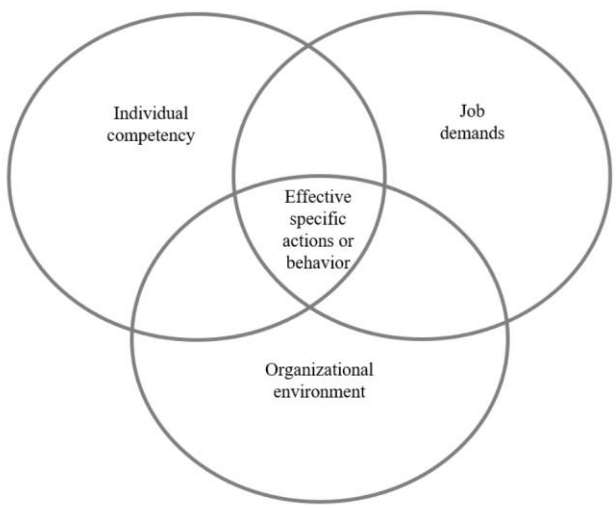
O*Net was quite revolutionary at inception, providing a means to capture the evolution of work and the depth of the job-person fit with different "windows" on the world of work (Peterson et al., 2001). O*Net is prescribed as a tool for helping the United States (US) understand the rapidly changing nature of work and it is utilized for the development of the workforce (O*Net, n.d.). However, job demands are shifting at an accelerated pace, requiring constant upskilling (Cheremond, 2019). The once contemporary O*Net has database components that represent laggard indicators because its methods only occasionally sample current job incumbents and periodically assess new occupations and titles. The lagging nature is exemplified in the new HR analytic role; no taxonomy was defined for an HR analyst with tasks similar to those in postings of HR analytic professionals in Kapoor and Kabra (2014), nor fully representative of the HR competency model defined in McCartney et al. (2021). Nonetheless, some features of O*Net that could be valuable to future competency modeling are not yet captured in academic channels. The value of obtaining insights from the related or cross-occupational references (Peterson et al., 2001) will be essential for adapting to future demands as jobs continue to evolve even more rapidly (Cheremond, 2019).

Shippmann et al.'s (2000) work also reflected a lagging analysis. Like Campion, Shippmann et al. (2000) started with a job content analysis. Other influential modelers do the same (e.g., Lucia & Lepsinger, 1999), which leads to only understanding the work as it is currently performed. The nature of the job content analysis delimits one from analyzing and fully defining future-state nascent jobs, for which performance measures are often not yet well defined. All these models assume one can observe the superior performance of the job, which is an issue in HR where performance is not meeting expectations (Giannantonio & Hurley, 2002; Maurer, 2018). Given that this dissertation seeks to define and measure a particular set of poorly performed skills, we must look at modeling differently. Stone et al.'s (2013) conclusions support such an endeavor, finding competency modeling research stagnant and not adequate for the demands of an evolving workforce.

This research returns to the fundamental theory of competence for job performance to develop a basic understanding. Boyatzis (1982), a seminal author who answered the call for competence-based job performance measures, built a simple model to describe the intersection of inputs that drive job performance. Similarly, this dissertation focuses on a specific cluster of KSAOs for job performance. Boyatzis (1982) created a model for job performance grounded in behavior theory, utilizing Lewin's heuristic formula that job performance (behavior) is a function of the person and their environment (Lewin, 1936). Boyatzis's (1982) job performance model and behavioral approach are foundational to understanding how AC drives job performance. Boyatzis's (1982) model is a Venn diagram of job demands, individual competency, and organizational environment collectively linked to the professional's effective specific actions or behaviors.

Figure 1

Boyatzis (1982) Model of Job Performance



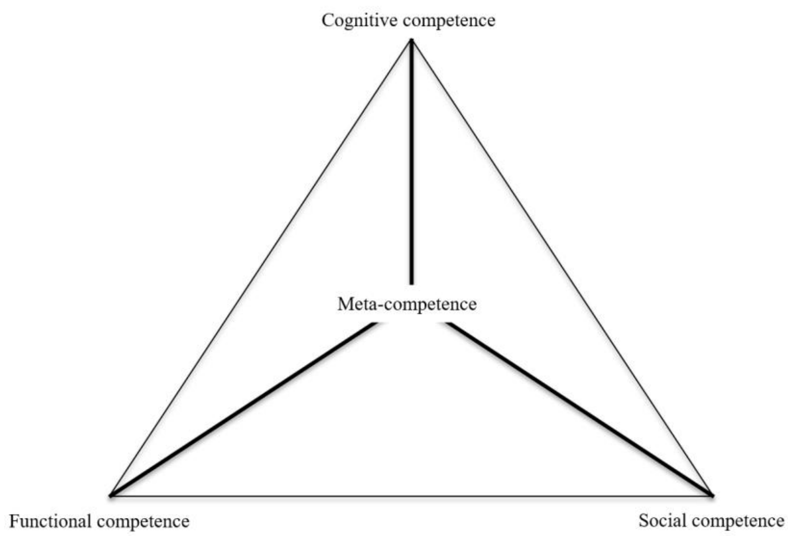
Consider HR job performance in the context of Boyatzis's (1982) model. HR's job demands and organizational environment require a regular redesign of the job to adapt the people and organizations to dynamic economic and social changes (Ulrich et al., 2021b). The current HRM literature indicates that the organizational environment is more competitive for talent. Job demands have increased with expectations to glean insights from the data housed in Human Resource Information System (HRIS), executives wanting HR professionals to provide consultation based on decision science, rather than their gut (Boudreau and Ramstad, 2007; Kryscynski et al., 2017; Maurer, 2018). In the competency shift, an incongruence has emerged, leaving executives perceiving that HR professionals cannot fill the AC void and some HR professionals questioning if the void can be filled (Brown, 2017; Chen, 2015; Maurer, 2018). The larger body of HR competency models have evolved to incorporate the new individual competency of AC, but in varying forms (e.g., either called out as a separate competency or nested in other competencies such as business acumen, critical evaluation, or mobilizing information) within models from 2010 through 2021 (Huong Vu, 2017; Ulrich, 2021b; Ulrich et al. 2017; SHRM, 2016). Some researchers argue the emergence of a new occupation and unique competency set to handle the demand of analytics in HR (McCartney et al., 2021; Kapoor & Kabra, 2014). While others argue there is inadequate evidence and information on what competencies are needed and how to apply them for the current HR occupations (Bassi et al., 2010; Margherita, 2021; Ulrich et al., 2021). Based on this literature review, theoretical application, and the mixed results within the HR profession, this study aims to demonstrate the analytic competencies as a cluster for generalized HR decision-making, similar to how Boyatzis (1982) addresses the leadership competency cluster. Taking a generalized approach and modeling the competencies as a cluster provides more agility and flexible application as needed within the firm. Consequently, the HR AC cluster could be applied to different HR segments while the profession's occupational design is in flux.

This research sought to assess future competency with a holistic framework understanding the dynamic HR environment and limitations of current modeling processes. Much of the competency literature reviewed thus far is from the US domain, and a holistic view requires broadening the horizon to international research. Different geographical influences on competency modeling drove variance and alternative perspectives on competency theories. For example, much of the model developed in the UK was from vocational practice, public policy, and economic changes where demand for increased skill and qualifications among the labor force drove modeling practices. In contrast, the US was prompted by academic influence from psychology behavior theory. Meanwhile, other European models recognized the value of functional and cognitive models and merged them to create multi-dimensional frameworks (Le Deist & Winterton, 2005). Le Deist and Winterton (2005) sought to develop a holistic model, as depicted in Figure 2, which reconciled the emerging schools of thought from the US, UK, France, Germany, and Austria. Le Deist and Winterton (2005) incorporated the US behavioral approach, the UK's functional approach, and the multi-dimensional aspect of France, Germany, and Austria. The resulting model became the framework for future competency research for understanding competency gaps (Persaud, 2020; Siveyra, Herrero, & Perez, 2021). Hence, the LeDeist and Winterton (2005) framework is the prime resource for building new competency sets when a complete picture is not available in the job as it is performed. The final framework included four dimensions as described below:

1. Cognitive competency: defined as the conceptual occupational competency that covers knowledge and understanding;
2. Functional competency: defined as the operational occupational typology for applied skills;
3. Social competency: defined as the operational personal typology to include behavior and attitudes considerate of social context; and
4. Meta-competency: defined as the conceptual personal typology that provides for how one learns and uses of learning (LeDeist & Winterton, 2005).

Figure 2

LeDeist and Winterton (2005) Holistic model of competence (p. 40)



2.2.2 HR Competency Models

In addition to generalized modeling literature, HR has a subset of literature focused on the profession's competencies. HR competency models are abundant and can vary. One broadly accepted model for western practitioners within the profession is the Society for Human Resources (SHRM) competency model, which utilizes methodology guidance from Campion and Shippmann (Lockwood et al., 2018; SHRM, 2016). The SHRM model incorporates the multiple functions of HR and the different levels (functional vs. strategic). SHRM suggests that the implementation of competencies is dependent on both HR professional's career position and function (e.g., utilization of competencies to make strategic decisions will happen more so with an executive or senior level). SHRM (2016) also suggests that the model supports HR professionals from all geographies because of their global membership. The nine competencies of the SHRM model include: leadership and navigation, business acumen, ethical practices, relationship management, consultation, critical evaluation, global and cultural effectiveness, HR expertise, and communication. Out of the nine, two competencies partially prescribe the need for an analytical skill set. The critical evaluation competency requires measurement and assessment skills, problem-solving, and research methodology, all of which are rooted in analytic behaviors (SHRM, 2016). The business acumen competency comprises sub-competencies in HR and organizational metrics, analytics, and business indicators (SHRM, 2016).

On the academic side of the house, Ulrich and colleagues have studied HR competencies extensively, completing study cycles every five years, exposing the gaps in skills as well as declared emerging competency needs (Ulrich & Dulebohn, 2015; Ulrich, Younger, & Brockbank, 2008, 2012; Ulrich et al., 2012; Ulrich et al., 2021a). Ulrich and colleagues' work, known as the Human Resource Competency Study (HRCS), utilizes subject matter experts to develop a 120-item survey. The HRCS study also incorporates 360 performance interviews and assess the defined competencies against business outcomes. The results from the HRCS study are used to inform the competency model for the current cycle (Ulrich & Dulebohn, 2015; Ulrich, Younger, & Brockbank, 2008, 2012; Ulrich et al., 2012; Ulrich et al., 2021). In addition, Ulrich et al. (2015) also provided a synthesis from academic, professional associations, and industry on HR competencies. The result of the synthesis was organized on six core domains: business (e.g., business acumen, business partner); personal (ethics, self-awareness, trusted); HR tools, practices and process (talent management, employee engagement); HR information system and analytics (data-driven mindset, process excellence); change (change leader, collaborative, resolver of issues, be business psychologists); and organizational and culture (culture leader/ champion, organizational design).

Since Ulrich and colleagues' synthesis, they have continued their research and issued revised HRCS models in 2017 and 2020. The 2017 competency model was organized on two competency types – enabling and foundational proposed to enhance the sub-competencies of the strategic positioner, paradox navigator, and credible activist. The enabling competencies included strategic enabling competencies and foundational enabling competencies. The foundational competencies emphasized emergent skills relative to analytics, specifically Analytics Designer and Interpreter, and Technology and Media Integrators. The Technology and Media Integrator utilizes technology to drive high-performing organizations, and the Analytic Designer and Interpreter use analytics to improve decision-making. Detailed more as a person than a competency, the analytic designer gets the correct data, develops an HR scorecard, looks for insights, creates interventions for people processes, and then assesses the impact on the business. Ulrich explains that learning the basics of statistics and research methodology, seeing patterns in data to tell a story, and then using data to demonstrate results is needed to be an Analytics Designer (Ulrich et al., 2017). At the time of the study, Ulrich et al. (2017) considered information management and integration, and employee performance in HR analytics were high priority actions for HR organizations to focus on improving HR professional skills.

In the 2020 competency study, the HR competency model was restructured and on a focal outcome of Simplifying Complexity. The final architecture had the competencies of Mobilizing Information, Accelerating Business, Advancing Human Capability, and Fostering Collaboration connected on the Simplifying Complexity objective (Ulrich et al., 2021b). The focus of the 2020 model moved from conducting analysis to leveraging data and information analysis to make better decisions. Ulrich and colleagues explain that the mobilized information competency is the practice of effectively collecting data, knowing the correct data to use, and then using data and information (both through technology and analysis) to develop insights that inform business decisions (Ulrich et al., 2021b). The model then requires the HR professional to have the ability to present a clear and concise summary (referring back to the objective to simplify complexity) of relevant information that drove the recommendations and conclusions reached by the HR professional.

The Ulrich model shifted from conducting analysis and technical prowess to focusing on the desired critical thinking and insights developed from the analysis outcomes. The shift in language from technical and analytic focus is due to the need to derive results from the analysis. The transition from such technical competence is also due to the demand on HR to spotlight the professional's organizational behavior skills to keep the workplace conflict-free. The increased need for organizational behavioral skills is attributed to the increasingly divided US political environment seeping into the workplace, making diversity and inclusiveness a priority (Ulrich et al., 2021; Milligan, 2020). However, the Ulrich research team cautions practitioners not to lose sight of the economic value of AC (through the Mobilizing Information competency) to their job performance. Mobilizing Information competency positively impacted business practices more than other competencies, such as fostering collaboration, which is abuzz among practitioners (Ulrich et al., 2021b).

Although Ulrich and colleagues are the prominent academic figures in HR competency literature, new researchers are entering the field. McCartney et al. (2021) utilized the Campion et al. (2011) process for creating a competency model specifically for the HR Analysts role. The results of the HR analyst study comprised of six distinct competencies: consulting, technical knowledge, data fluency and data analysis, HR and business acumen, research and discovery, and storytelling and communication. McCartney et al. (2021) argue against Ulrich et al. (2021ab) that technical skills do not have broad reach within the HR discipline. However, this argument may be due to the stagnant approach to competency modeling (Stone et al., 2013).

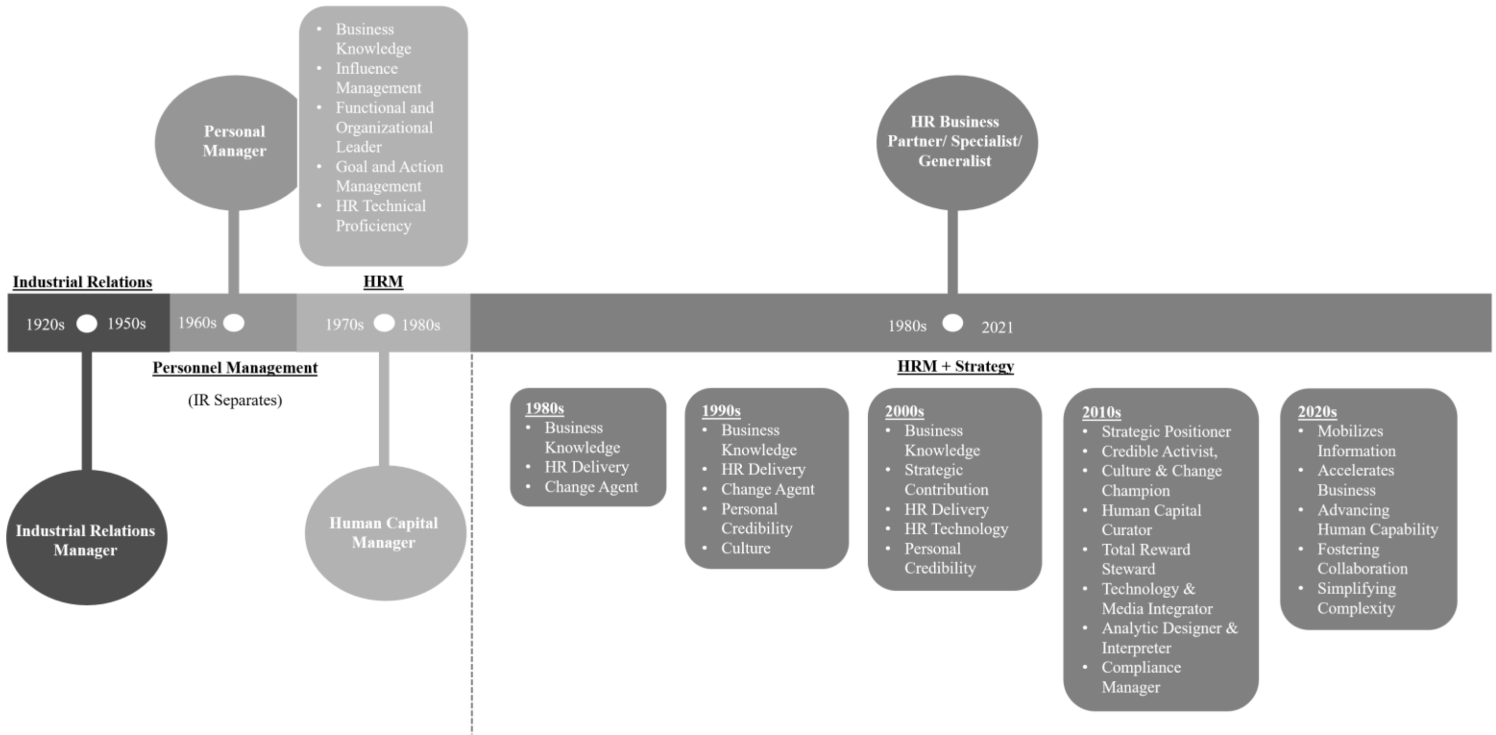
Academic and professional partnerships grew in the competency model evolution, resulting in unified collaborative models between the SHRM and Ulrich camps periodically through the historical chronology. Today SHRM and other professional organizations sponsor the HRCS research and utilize the HRCS research in part to inform and support professional models. However, organizations such as SHRM do not wholly accept the model in the current professional organization material (Ulrich et al., 2021b; SHRM, 2016; Huong Vu, 2017). SHRM has a platform of commercial products built on its proprietary competency structure. To support SHRM's independent model and learning products, they perform their own studies, informed by academic literature and rigorous independent analysis, and utilize professional member participants (SHRM, 2016; SHRM, 2015). SHRM utilizes Campion et al. (2011) and Shippmann et al. (2000) methods, which are predominately functional with behavioral outcomes. However, both Campion and Shippmann lack the multidimensional aspects of LeDeist and Winterton's (2005) framework, which is holistic and well-tailored to advancing new skill sets.

The literature also indicates that the demands of HR competencies and the availability of needed skills vary by country. Mamman and Al Kulaiby (2014) suggest that the strategic partner role (where AC demand is recommended in some literature streams) is the least performed in the developing country of Sultanate Kingdom of Oman. Also conflicting, Ulrich et al. (1995) found an increased need for business knowledge outside the United States, whereas Han et al. (2006) found no evidence for business knowledge in a Taiwanese high technology company. Welch and Welch's (2012) research indicated predominantly organizational behavior and operational HR-based skill demand, such as a “welfare officer,” for HR professionals supporting international projects. Likewise, Coetzer and Sitlington (2013) suggest a need for KSAO’s in emotional intelligence over intellectual skills. The international investigation is void of AC-specific research. Talerico’s (2021) research, utilizing HRCS data and building on Kryscynski et al. (2017) AC research, found a slight significant increase in perceived AC for HR professionals in developing countries versus developed countries, opposite the expected findings given the demand for soft skills in international research.

Figure 3 depicts the historical evolution of HR competency models. The figure consists of four eras: Industrial Relations, Personnel Management, HRM, and the most recent HRM era incorporating strategic HRM (Kaufman, 2014). The organizational environment in each of these eras uniquely influenced the needs of the HR professional and the HR demands. Figure 3 follows the HRM lineage and does not encompass the entire labor branch, a declining function (Friedman, 2009) and not relative in the literature to this study's interest. Figure 3 does not contain non-competency features that emerged in model illustrations of the 2010s onward to create an economic depiction of the competency evolution. Although the complete competency illustrations provide HR professionals and academia with an example of how HR practices link to the business, they are unnecessary for this figure. This figure aims to demonstrate the changing needs of the competencies themselves. Further, it is to provide how the HR role has been redesigned iteratively in the modern era of HR for the dynamic nature of the job. The figure presentation is consistent with previous works and has taken a similar approach to compare and review competency models (Huong Vu, 2017; Ulrich et al., 2015).

Figure 3

Historical Evolution of HR Competency Models with Eras and Titles



Note. Adapted from Greenough (2018), Huong Vu (2017), Kaufman (2014), Kaufman (2019), Ulrich et al. (2017), and Ulrich et al. (2021a).

The HR profession was born out of conflict with labor and management. The outcome of this conflict was a labor movement where unions, legislation, and labor economics produced competency demands for tactical skills in negotiations and labor planning. The Industrial Relations Manager was the product of labor relations demands (Kaufman, 2014). However, the labor relations competencies were not formalized in a model; instead, they were captured post-mortem in historical documentation (e.g., Kaufman, 2014).

An outgrowth of industrial psychology and the emergence of organizational behavior science, HR shifted to personal management in the 1960s (Kaufman, 2014). HR professionals continued to focus on employee management, but the framework shifted to goodwill methodology and handling employee productivity in new ways. Labor relations and labor economic skills were still in high demand but split into a separate role to maintain union activity, a predominant force until the late 1970s (Kaufman, 2014). HR professionals incorporated selection tests and developed incentive pay methods based on influential psychology research (Kaufman, 2014). However, no formal competency structure existed for professionals, and much of the literature came from the profession and experiences in the field (Kaufman, 2014).

The formalization of HRM in the 1970s and 80s is concurrent with the growth of competency-based job performance (Kaufman, 2014; Boyatzis, 1982). The 1970s and 80s were a transitional period to the modern HR structure

(Kaufman, 2014). The first competency model for professionals was developed to inform and grow professional skills based on an amalgamation of emerging business strategy theory and the value of human capital to firm performance; continued growth of organizational behavior and leadership literature to improve employee relations and productivity; and the onset of more robust HR processes, policies, and practices within the firm (Kaufman, 2014; Kaufman, 2019; Huong Vu, 2019; Greenough, 2018; Barney, 1991).

Part of the growth of these competency models and demand from the 1980s onward is attributed to the Resource-Based View (RBV) and Core Competence. The ability of a firm to enhance competitiveness through its people became a platform of inertia for competency modeling (Boudreau & Jesuthasan, 2011; Boudreau and Ramstad, 2007; Parahad & Hamal, 1990; Kryscynski et al., 2017; Barney, 2001; Barney & Wright, 1998; Bharadwaj, 2000; Le Deist & Winterton, 2005; Shippmann et al., 2000). The RBV wave defined competence at multiple levels, not just at an individual level (Parahad & Hamal, 1990; Shippmann et al., 2000). However, the term competence for the organizational level is countered by Ulrich and colleagues (2021b), who clarify that competencies are individual-level KSAOs, whereas capabilities are an organizational-level form of abilities. However, because of the RBV influence, the research has remained predominately at the firm level. As a result, the literature has limited application for individual development, a defined need, and leaves a gap in applied research on the successful implementation of competency models (Marler & Boudreau, 2017; Bassi, 2011; Levenson, 2004).

During the development of modern HRM, also emerged the discipline of human resource development (HRD). McLagan (1989) subscribed three elements of HRD – training and development, organizational development, and career development. The functions of HR to support the resource development, HRM, and the information systems of the organization were illustrated on the HR wheel. Consequently, the HR wheel has become a functional reference for subsequent HR research (McGuire, 2011). Functions, in addition to HRD, include: organization/job design, human resource planning, performance management, talent selection and staffing, compensation and benefits, employee assistance, labor relations, and HR research and information systems (McGuire, 2011).

The modern era of HRM incorporates new callings for HR professionals. Due to the multitude of processes and the HRM system's growing complexity, the HR professional's role could take varying forms (Greenough, 2018; Kaufman, 2019). To handle this growth, HRM turned to a shared services model with specialists in specific processes or functions such as compensation or talent acquisition, and the new business partner role arose to tailor and align the policies, processes, and practices of the HRM system to business objectives (Noe et al., 2017). The HR professional must now work as change and culture agents to prevent conflict rather than manage it (Ulrich et al., 2015; Huong Vu, 2017). In addition, HR professionals are expected to leverage the cornucopia of people data and technology in their HRM to enhance people decisions within the business (Ulrich, 2021a; Huong Vu, 2017; Margherita, 2021). Today HR professionals are expected to have the knowledge and skills to play in the calculative world of business and simultaneously be able to proactively manage the emotive and least predictable resource – the people.

2.3 Analytics

HR competency literature has called for more research and understanding of a specific competency encompassing analytics. The penetration of KSAOs for analytics in the HR field is less than desired (Kapoor & Kabra, 2014). Without explicit KSAOs, the toolbox for AC is empty and an ambiguous concept. The current research offers different perspectives on AC, yet ironically fails to prescribe direct KSAOs that are the most effective in fulfilling competency intent. Outside of HR, competency models for analytics are also in their infancy. However, the extant literature can be utilized to curate a more refined competency profile and define through this study the best KSAOs to guide HR professionals in the future (Campion et al., 2011).

The next segment will summarize analytics literature, starting with the emerging value of analytics in HR, critical thinking processes, data-driven processes, and review the current debate between the frameworks. Embedded within the summary is also research on analytic KSAOs both in and outside of HR. Analytics will wrap up with technological considerations and implications.

2.3.1 Value of Analytics

Evidence-Based HR. The value of analytics is best explored by understanding what drove interest in HR analytics. The emergence of analytics in competency models aligns with an ever-increasing interest in evidence-based HR. Boudreau and Jesuthasan (2011) assign principles to evidence-based HR, and Logic-Driven Analytics was the foundational principle. The concept of evidence-based practice, popularized in medicine, proved effective in HR practices once applied, despite an uphill battle to get HR professionals on board. Evidence-based process improvements – structured interviews (versus unstructured), scientifically designed employee surveys, and research-driven goal setting methods in performance management – demonstrated immense value but remain the exception and not the norm to HRM (Boudreau & Jesuthasan, 2011). The finance discipline has taken a similar decision-science approach and implemented evidence-based methodologies to substantiate analytic utilization and capabilities to enhance professional skills (Yeo and Carter, 2017).

Data-driven decision-making. Data-driven HRM gained popularity in the same period as evidence-based HR. Historical chronology is a bit more challenging to find, most researchers noting an evolution in generalized terms. This study took a structured review of the literature utilizing keywords “data-driven decision-making" and "HR" by year till results populated within the discipline. Likewise, the search included other terminology variations with and without hyphenation, human resources spelled out, and human capital instead of HR. The investigation was conducted in a general database search, Business Source Complete, and EBSCO databases. The first article that alluded to data-driven decision-making, but did not state it expressly, was Murphy and Zandvakili (2000) in their push for data- and metric-driven approach for HR to inform decisions. Although Murphy and Zandvakili (2000) do not directly put the two terms together, they link the practice to effective decision-making within the article. Seven years later, Roberts' (2007) professional article and his presentation of data-driven human capital decisions formally connect data-driven decision-making in HR. Roberts (2007) suggests that HR has more power than ever with its current HRIS to crunch data to make decisions on more than just intuition alone. Roberts (2007) memorialized the terminology and conversations among thought leaders at the time; he spoke formally of dashboards, workforce analytics, and the rationale behind the move to meet the firm's demand. Roberts (2007) foreshadows a problem that is still part of the debate today: *how* to make data-driven decision-making. At the time, Roberts' (2007) opinion was that HR professionals do not have the skill set to perform the advanced analysis to gain insights into the data.

2.3.2 The Analytic Divide

The convergence of evidence-based HR and data-driven decision-making is in analytics is an interesting debate. The definition of analytics is not synonymous in evidence and data-driven research. Evidence-based decision-making calls for a critical thinking approach that often incorporates data and information for the HR professional to leverage with a vague answer to how that data is crunched. Whereas data-driven decision-making derives an understanding of analytics from the levels of data analysis, and through advancing stages, one can obtain insights and prescriptive solutions. The process and approach to analytics is a highly debated topic because ownership of data analysis can be delegated in an evidence-based approach but is an essential skill in a data-based approach.

Bassi (2015) takes up the debate of who should perform analytics and cautions against leaning on other functions such as IT or finance, as it will be the partnership of the people knowledge and analytic skill that will reap the greatest contribution to human resource decisions. The results of Kapoor and Kabra's (2014) synopsis of the AC gap suggests the skills are needed in-house. Kapoor and Kabra (2014) demonstrated the value of analytics within the HR professional, reporting two times more likely to improve their recruiting efforts and leadership pipelines, 2.5 times more likely to have better talent mobility, and three times more likely to realize efficiency gains. Kapoor and Kabra (2014) find HR professionals focus on the wrong data (inputs vs. outputs); lack effective recording methods; lack the numeracy skills that result in predictive analytics; skills are too compartmentalized; and the right combination of technologists and analyst skills are lacking.

Huselid and Becker (2005), in opposition, stated that the HR professional should redefine what matters for competitive advantage, focusing on the decisions and insights from the data. Doing so requires understanding the statistics and data enough to come to sound conclusions, but one does not need to be a statistician. Huselid and Becker (2005) utilize the book and movie *Moneyball* as a case study to demonstrate how HR should be strategic managers making solid conclusions and then determining what and how to measure facets of the firm that lead to the successful execution firm's strategy through HRM. McCartney et al. (2021) followed Huselid and Becker's (2005) argument to promote the existence of a separate occupation in HR, specifically for analytics, allowing HR business partners to focus on the decisions from the analysis.

Simón and Ferreiro (2018) pose a third solution versus the black and white internal versus external numeracy skill set in the HR profession. Simón and Ferreiro (2018) suggest a collaboration between professional and academia for workforce analytics; combining the knowledge of HR practices, the firm, and its environment from the HR professional; and the social science methods, questions mindset, and independent thinking of the academic researcher. However, Simón and Ferreiro's (2018) proposal suggests the HR professional neither has critical thinking nor numeracy skills. Instead, the HR professionals have organizational knowledge, stakeholder understanding/ influence, and complete the decision-making tasks derived from the analysis and insights of the academic researcher. Therefore even the prowess of merely having an inquisitive mindset is questioned as an AC skill within HR professionals. Valadares de Oliveira and Handfield (2018) take a similar approach to supply chain analytics and recommend a team approach with data scientists for statistical capabilities, supply chain experts to bring in deep business knowledge, and analytic interpreters with business acumen and IT capability to coordinate the information between data scientists and supply chain experts.

Research suggests HR should be cautious in dismissing the value of numeracy skills. Disciplines outside of HR are also vying to take the lead in analytics to support decision-making in all aspects of business ahead of their peers (Mandal, 2018; Yeo & Carter, 2017). Proponents for IT ownership of analytics explain that their specialization in advanced analysis techniques – machine learning, AI, data extraction, data cleaning, cloud computing – are essential for generating insights and recommendations (Persaud, 2020). Meanwhile, proponents of the finance discipline believe that since they are the purveyors of financial data, they will be better positioned to make business-enhancing decisions with analytics (Yeo & Carter, 2017). The fight to be the discipline of choice suggests that analytics' influence on business leaders is profound. HR professionals may want to weigh heavily before taking their preverbal hat out of the ring. HR must also consider if such skills have broader implications than just strategic decisions. Laursen (2011), from the sales and marketing perspective, suggests analytics are essential for individual contributors because the use of such KSAOs helps with both micro and macro decision-making.

2.3.3 Analytics - Critical Thinking Process Models

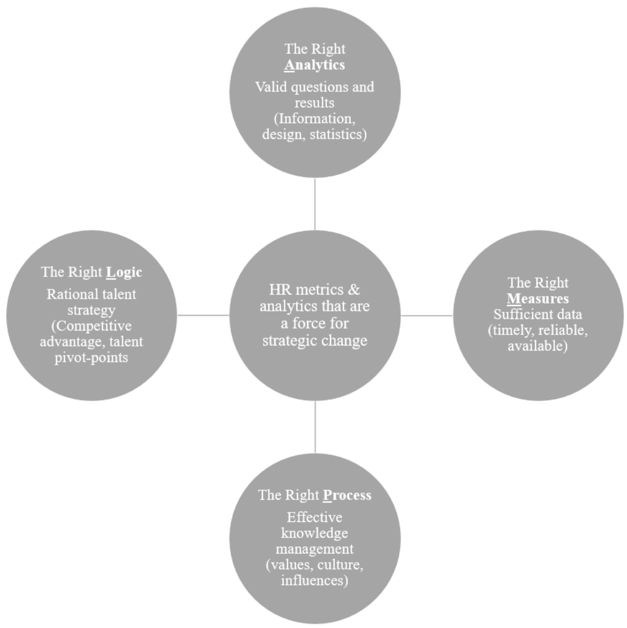
Different analytic process models emerged as a result of the two approaches (evidence vs. data). The prescribed solutions in the critical thinking models consider analytics a sum of both critical processing and technical analysis. The authors in a critical thinking framework insist it is not just about data. Instead, data is the source of analytic value and processing (Ulrich & Duhlebon, 2015; Boudreau & Jesuthasan, 2011; Boudreau & Ramstad, 2007). In the next section the analytic models are grouped by critical thinking and data analysis processes to demonstrate the contrast between analytics and the weighted value of data analysis and technical skills.

The most commonly referenced model is the Logic, Analytics, Measures, and Process or LAMP framework, depicted in Figure 4, by Boudreau and Ramstad (2007) (Marler & Boudreau, 2017). This model's purpose was two-fold: 1) provide *light* on how HR perceived its role in supporting the business, focusing on a talentship approach that leans on the firms to own its talent decisions, and 2) guide HR professionals on how to implement analytics in strategic HR problems.

Although self-described as a measurement system in Boudreau and Ramstad (2007), the model has been adapted for its insights to analytic competencies (Kryscynski et al., 2017; Marler & Boudreau, 2017).

Figure 4

Boudreau and Ramstad's (2007) Light the LAMP (p.193)



The model recognizes the need for technical analysis in their Analytics component but focuses on metrics outcomes in terms of impact, effectiveness, and efficiency for creating better decisions for the firm. Laursen (2011) took a similar approach in the sales and marketing discipline, focusing on decision-making for the greatest impact; such decisions influenced customer retention and profitability instead of employees. When Boudreau and Ramstad (2007) dive into the model's analytic processing component, the skills' specificity is missing and relegated to others. The specific examples of who completes that analytics function (described in the LAMP framework as the source of inquiry, research design, and statistical analysis) are from outside the firm and not the HR professionals themselves (e.g., social scientist and PhD-level trained researchers, engineering resources, or outside consultants) (Boudreau & Ramstad, 2007). Boudreau and Ramstad (2007) stated that the resources could be within HR but skim over this crucial detail of achieving analytic KSAOs or describe what they are specifically. The LAMP framework starts to align well with the Le Deist and Winterton (2005) concept of competence combining cognitive and social needs of HR to have a complete package, in that the technical knowledge alone does not work independently of other competencies needed to inform decisions. However, LAMP falls short of a full Le Deist and Winterton (2005) competency framework, missing meta-competence and functional competence concepts present in Analytic process models.

The LAMP model was the guiding framework for Kryscynski et al.'s (2017) study of AC. A generalized study of AC, Kryscynski et al. (2017) suggests that AC enhances HR performance. However, the Kryscynski et al. (2017) research was limited in the questions already presented in the HRCS and did not assess the individual constructs of the LAMP model. Kryscynski et al. (2017) evaluated perceived analytic skills from the LAMP model within HR professionals. The authors identified three survey questions from the HRCS considered to have a high association with the *right analytics* from the LAMP model: 1) Does the HR professional translates data into useful insights for [Organization Name], 2) Does the HR professional effectively uses HR analytics to create value for [Organization Name], and 3) Does the HR professional accurately interpret statistics. Notably, none of these questions indicate the ability to perform statistical analysis or research design (as depicted in the model illustration), leaving a mystery about how such data is turned into insight.

Fitz-Enz (2010) prescribes a model of analytics that has some resemblance to Boudreau and Ramstad (2007) yet is different and likely aligns to the "fuzzy" concepts depicted in LeDeist and Winterton (2005) that can often frustrate those looking for concrete constructs. Fitz-Enz (2010) concludes that there is an art – the mental framework to create a logical design, and there is the science – the statistical and mathematical analysis. Both art and science are needed to form analytics. The output of both is required to arrive at a decision that influences the strategic, operational future of the firm. In both Fitz-Enz's (2007) and Boudreau and Ramstad's (2007), the proposed models are based on expertise; no empirical evidence was presented.

Patre (2016) took a different approach, suggesting the six thinking hats method borrowed from De Bono (1985). Patre (2016) defends this approach to help the HR professional move away from "adversarial thinking" to a pragmatic and systematic methodology that promotes problem-solving, decision-making, and innovative solutions (p. 192). The approach suggests there are six fundamental elements of effective thinking, demonstrated with each "hat". The hats prescribed are as follows:

1. Blue hat thinking: The Planner—managing and controlling the thinking
2. White hat thinking: The Prober—focusing on the facts
3. Red hat thinking: The Partner—using intuition and feelings
4. Yellow hat thinking: The Provider—generating positive ideas
5. Black hat thinking: The Preventer—evaluating the risks and potential problems
6. Green hat thinking: The Proposer—searching for solutions to overcome barriers

Patre (2016) then demonstrates the 6-hats tool in the problem of analytics in HR. Patre (2016) "green hat" outcome included a proposal to increase HR analytics skills by: improving data literacy training in employee development programs, hiring HR personnel with analytic backgrounds, rotations for HR professionals in other departments that utilized data analysis (e.g., finance and marketing), and incorporating analytics within the job description. Petra (2016) also stated that it is not about advanced techniques but about creating new insights and removing bias. Consequently, Patre's (2016) perspective is that the analytic competency demands are not a singular construct, supportive of a holistic initiative and cluster modeling. Patre's (2016) manuscript was the most unconventional. However, the weighted focus on critical thinking processes proved relevant enough to include in this summary.

2.3.4 Analytics – Data-Driven Models

This latter summary of analytic data processing models specifically addresses models that prescribe how one uses data in decision-making. Unlike the critical thinking models, these models have demonstrated more consistency across the literature.

It is appropriate to start with the forefather of HR analytics Fitz-Enz (Caudron, 2004). For clarification, Fitz-Enz (2010) and data-driven model peers find analytics is more than data processing (Soundararajan & Singh, 2017; Ulrich & Duhlebon, 2015; Boudreau & Jesuthasan, 2011; Boudreau & Ramstad, 2007). However, the models demonstrate the contradiction of how insight is achieved from the evidence versus data process models. In Fitz-Enz's (2010) evolution of human capital metrics, he defines four levels: transactional monitoring (human resources activity reports), human resources management (performance monitoring), business metrics (tying HR metrics to the business), and predictive analytics (foretelling effects). To obtain these outputs, Fitz-Enz (2010) defines five steps of analytics: recording, relating the data to organizational goals, benchmarking, descriptive analytics, and finally predicting with prescriptive analytics. These steps, according to Fitz-Enz, have obtained higher value in informing business-people decisions as one rises through each step.

Meanwhile, a consensus has developed across HR specific and business literature regarding the classification of analytics into three general categories: descriptive, predictive, and prescriptive (Lawler, Levenson, & Boudreau, 2004; Greasley, 2019; Kapoor & Kabra, 2014; King, 2016; Fitz-Enz & Maddox, 2014). According to Greasley's (2019) definitions, descriptive analytics are used for reports and visual displays to explain or understand past and current business performance; predictive analytics have the ability to predict future performance; and prescriptive analytics have the ability to recommend an action from predictive analytics. There are variations of these accepted classifications as well. Power (2016), from the IT discipline, prescribes analytical data models as retrospective, predictive, and prescriptive. Whereas Laursen (2011) describes data as leading, lagging, and learning information from the sales and marketing discipline.

Many of the process models utilize analytic classifications in their illustrations. For example, Fitz-Enz and Mattox (2014) provide a refined model using the three classifications along with their process map, Table 1.

Table 1

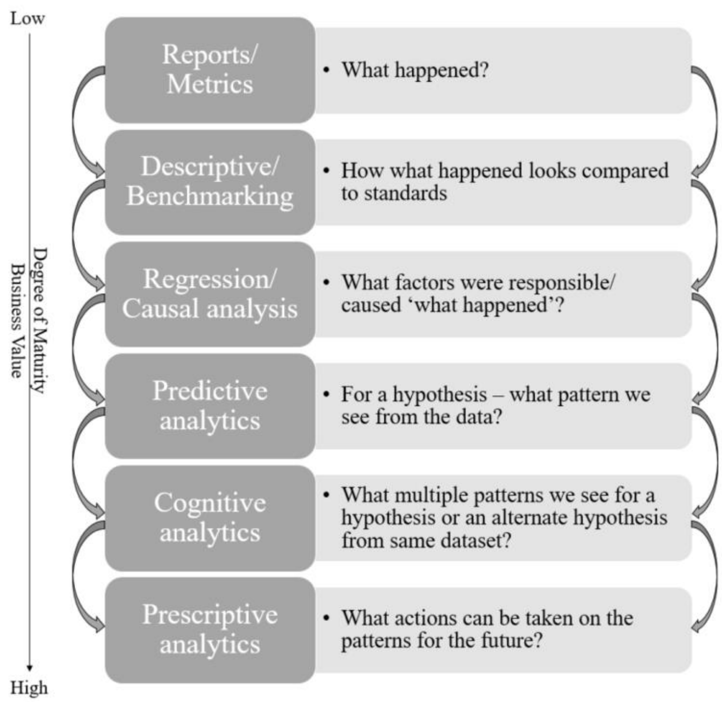
Fitz-Enz and Mattox (2014) Analytic Process Model (p. 9)

Descriptive	Organize – collect and validate data. This initial step features static data and provides an essential need of data for analysis, Fitz-enz (2014) describes as the fundamental problem to analytics.
	Display – often in dashboards and reports aggregates the data to see trends. Descriptive, but a stepping stone to predictive and prescriptive analytics.
Predictive	Relate – demonstrating a connection and shows an effect for future opportunities to create an impact. This level introduces some predictive value
	Model – Designing a testable experiment from which one could prove or disprove how complex interactions occur in one's hypothesis.
Prescriptive	Evaluate – Applying statistical or methodological means to validate the model. From these results, the firm can record financial impact and make recommendations corresponding with the results, reaching maturity with prescriptive functionality.

Boudreau, Cascio, and Fink (2010) proposed a continuum of analytical sophistication akin to the other data-based analytic models– Reporting, Metrics, and Insight & Impact. Boudreau and Jesuthasan (2011) add to Boudreau et al. (2010) continuum defining in new terms of counting, clever counting, insight, and influence; each level builds upon the previous. Through their research experience, Boudreau and Jesuthasan (2011) state that the most challenging hurdle to overcome right now is obtaining insight and influence. Boudreau et al. (2010) does not call out predictive and prescriptive analytics by name. However, predictive and prescriptive levels are implied in the concepts of insight and influence (i.e., insight and influence use trends to understand what is driving behavior, and then HR prescribes solutions based on these needs to manage people outcomes in the future). Similarly, Soundararajan and Singh (2017) illustrate a continuum with ratios and metrics on the low end of the spectrum of complexity and predictive and prescriptive analytics on the high end. However, in a more explicit explanation, Soundararajan and Singh (2017) illustrate their value chain and bring together the classifications along with the specific value and function of each data analysis step, resulting in a more robust understanding of how one obtains maturity in analytics. Soundararajan and Singh's (2017) illustration is recreated in Figure 5 to understand the intersection of classification, purpose, analytic process, and linkage to both business value and maturity in one comprehensive view.

Figure 5

Soundararajan and Singh (2017) Analytics Value Chain (p. 9)



Soundararajan and Singh (2017) emphasize that, within the pursuit of utilizing data to achieve success in the organization, one must not lose sight of the question driving the analytic inquiry, the importance of finding the correct data, and letting the question drive the method of analysis not the desire for advance analysis. This advice hearkens back to the critical thinking models. The assumption of effective inquiry (analogous to logic in Boudreau and Ramstad [2007]) suggests that both models seek to illustrate a comprehensive analytics model from different perspectives. The critical thinking approach focuses on a sophisticated research process that obtains insights from a nebulous, albeit imperative data source and analysis. Whereas the data models are centered on the data-processing techniques as a source of insight and solutions, data-analysis maturity and prescriptive capabilities growing hand-in-hand, with the contradicting caveat the problem dictates the analysis methodology. Does this mean there are problems we are not looking for a prescriptive answer? The evidence- versus data-driven paradox is influential to competency modeling because how we conduct analytics influences the competencies needed.

2.3.5 Analytic Competency Models

As previously noted, there is a dearth of competency modeling to perform the analytic processes as described. Therefore, this section of the research took a broader approach and expanded the literature review scope to include recommended "recipe," suggested skills, and research outside the area of HR.

Fitz-Enz and Mattox (2014) derived from executive insights a "recipe" to create impact from analytics: 30% data (accurate and current), 5% stakeholdering (let the executives make a hypothesis), 15% analysis (statistical acumen required), 20% storytelling (compelling explanation of insights), 20% implementation (insights to action), and 10% embedment (accountability and follow-up) (p.50).

Soundararajan and Singh (2017) prescribed a skill base essential to successfully integrating and performing analytics. There is terminology in the skill set that resembles critical thinking model concepts; however, they are inconsistent in interpretation. For example, *analytics* from LAMP is similar to *measures* in Soundararajan and Singh (2017).

- Critical Thinking – inquisition and questioning regarding a business problem; ability to develop a hypothesis related to the business problem; ability to make associations with HR datasets to business outcomes; upon conducting an analysis develop insights; and ability to establish a controlled study;
- Sell the Solution – ability to demonstrate for the business the value of a subsequent action from those insights;
- Measure – familiarity with standard HR ratios and metrics (e.g., tooth to tail, time to fill); utilize current data sources and technology to retrieve relative data; obtain cross-functional data; use software tools (excel and statistical tools) to conduct relative analysis such as descriptive statistics, SEM, statistical process control, and regression to identify trends and key factors.

Other business units have also assessed AC, and external literature provides insight for AC development. Valadares de Oliveira and Handfield (2018), through expert interviews, define three AC skill sets for Supply Chain – Business Analytics, Statistics, and Information Technology. Refreshingly, Valadares de Oliveira and Handfield (2018) test these skills in a structured model. Statistical skills loaded higher than the other two skill sets on the model, and all three have a significant contribution to AC. Performance in the supply chain was defined as real-time supply chain capabilities, and results indicate higher performance capabilities. Likewise, Persaud (2020) assessed the competencies of Big Data Analytic (BDA) professionals through job posting content analysis, executive interviews, and a review of BDA programs at major colleges and universities. The text mining and interviews gleaned a need for BDA professional competency, similar to HR, in the following: an ability to present and communicate findings in a salient manner; tailor solutions and recommendations to the needs of the business; utilize technical and business knowledge to generate valuable insights from data; and statistical analysis. Unique from HR, Persaud (2020) identified IT technical skills in machine learning, artificial intelligence, data extraction, data cleaning, and cloud computing as essential competencies for BDA professionals. Power (2016) performed a job content analysis of data scientist roles with similar results from Persaud (2020). Power's (2016) competency results included: relating insights from the data to business impact, a storytelling capability, an inquisitive mindset to identify problems and test hypotheses, and statistical knowledge.

2.3.6 AC in the Spotlight

In general, empirical research on analytics is quite limited. The literature review was considered semi-systematic methodology, which allowed for assessing a topic that has been conceptualized differently and studied, in this case by professional venues and academic HR, business, and psychology disciplines

(Snyder, 2019; Wong et al., 2013). The structured review included HR AC term searches in professional publications such as SHRM, academic HR journals, psychology databases such as PsychInfo, and business databases such as Business Source Complete. Explicit and implicit competency references in analytic process guides (e.g., Waters et al., 2018; Boudreau & Ramstad, 2007; Falletta & Comb, 2020) were incorporated. The output of a semi-systematic methodology includes a thematic analysis, provided in Table 2. The process for thematic selection started with the current meta-synthesis on HR analytic research and competency summaries to include Marler and Boudreau (2017) and Huong Vu (2017). Critical authors in the HR competency domain were reviewed, and seminal manuscripts were searched for additional contributions or resources. Literature from these reviews were analyzed for AC-specific variables and implications. Some articles in the meta-syntheses were excluded if AC was not inclusive or the articles were more than ten years old and were no longer current. As part of this robust literature review, the contemporary academic HR AC literature that explicitly touches on KSAOs (sans generalized competency models) is summarized in Table 2. Most were not explicitly intended for competency building; however, salient results were pulled to inform the competency model.

Table 2 foreshadows current challenges in the literature. The level of analysis is predominately at the firm level. Research to date has not assessed the specific KSAO's of analytics for job performance or decision-making and the contributions those KSAO’s make toward performance. Individual-level research is often based on firm-level theoretical underpinnings.

Table 2

Summary of *HR Analytics Literature*

Author, Year	Level of Analysis	RQs	Theory	Method	Findings
Kryscynski et al. (2017)	Individual	Is there a positive relationship between HR Analytic ability and performance, Use of Analytic tools, lower job levels, and generalists	LAMP framework; Resource-Based View (RBV)	Quantitative- Factor Analysis	A Positive Relationship between HR Analytic ability associated with LAMP (Logic, Analytics, Measures, and Processes) and performance. The role was significant for specific specialists, such as talent management. The use of analytic tools and job level were not significant predictors of performance
Angrave et al. (2016)	Firm	Will HR create transformative change and influence through HR analytics?	RBV; Institutional Isomorphism Theory	Conceptual	There are not enough operationally and strategically methods and approaches for analytic implementation
Douthitt & Mondore (2013)	Firm	How to use analytics?	HR Scorecard for Competitive Advantage	Qualitative – Case Study	Successful implementation of a Scorecard (deliverables, processes, alignment, & results); integrate data systems; firm buy-in are needed for AC to increase firm performance
Rasmussen & Ulrich (2015)	Individual and Firm	What is the definition of HR Analytics?	Strategic HRM; Cognitive Dissonance	Literature Review	There is no one universal definition. There is a need to understand how to achieve analytics in HR and recommend to reskill/upskill HR professionals
Karwehl & Kauffeld (2021)	Firm to Individual	How does one use competency management for AC	RBV	Conceptual; Literature Review	Data-driven approach and firms-specific competency model should be developed for tailored individual assessments; orchestration will result in firm-level advantages

Author, Year	Level of Analysis	RQs	Theory	Method	Findings
Aral et al. (2012)	Firm	Does an incentive-based compensation structure enhance HR analytic performance?	Agency Theory	Quantitative	Demand for HR technology use increases when performance pay and HR analytic practices already exist; When implemented as a triad HR technology, analytics, and an incentive system, there is a significant positive increase in productivity
Barišić et al. (2019)	Firm	What is the relationship of HRIS use and organizational performance?	Strategic HRM	Quantitative	HRIS intensity is positively related to organizational performance. Findings relative to technical competence demands.
Coetzer & Sitlington (2013)	Individual in a group setting	What knowledge, skills, and attitudes should a strategic HRM student acquire?	Strategic HRM	Qualitative – Delphi Study	HR skills identified in this study: Knowledge of how HR metrics can be used to evaluate HR's contribution to organizational performance; ability to identify and analyze critical internal and external factors influencing management choices in HRM; positive political skills (e.g. persuasion) to influence HR decisions.
Kapoor & Kabra (2014)	Firm	Identify trends in analytic adoption	Drucker's Competitive Advantage	Quantitative – Job Description Content Analysis & Survey to college programs	Job description requirements include the following for future analysts: strong business acumen, data analysts, strong communicator, team player, & change agent
Severson (2019)	Firm	What does it feel like to lead evidence-based HR?	Evidence-Based Decision-Making	Qualitative – Case Study	The retail and healthcare firm demonstrated positive performance upon the use of evidence-based methods

Author, Year	Level of Analysis	RQs	Theory	Method	Findings
Simón & Ferreiro (2018)	A retail store as a unit-level within the firm	How can collaboration between researchers and HR professionals may fill the research-practice gap?	No referenced theory	Qualitative – Case Study	The case study resulted in some evidence-based decisions. However, reluctance by the HR professionals to gather data impeding the potential for additional insights
van der Laken (2018)	Firm	What is the current state of people analytics? How can people analytics make HRM more evidence-based	RBV; Evidence-Based Decision Making	Qualitative – Case Study	Demonstrate a link between people analytics and how it can help the firm make evidence-based decisions.
van der Togt & Rasmussen (2017)	Firm	What is the future value of HR analytics?	Evidence-Based Decision-Making	Qualitative – Case Study	HR Analytics adds value once pre-conditions are met of necessary analytic skills. In the interim academic-HR collaboration was used to help fill the gap.
McCartney et al. (2021)	Individual	What are the competencies for the emerging HR analyst?	Human Capital Theory	Campion et al. (2011) Competency Modeling	HR analyst has the following competencies – Storytelling & Communication, Consulting, Research & Discovery, Technical Knowledge, HR & Business Acumen, & Data Fluency & Analysis

2.3.7 Analytics and Technology

The means to achieve analytics are interwoven with technology. Technological tools house data, clean data, provide analysis, and in some cases, even prescribe outcomes (Eubanks, 2019; Levenson & Alexis, 2017; Lunsford & Phillips, 2018). In HR, information technology tools are commonly part of the HRIS. Tansley and Watson (2000) define HRIS as systems for HR information storage, processing, and reporting people data as a competitive advantage tool. Continued research supports that higher utilization of HRIS, measured by the number of functionalities implemented, positively impacts organizational performance (Barisic, Poor, & Bach, 2019). HR professionals have products available for a myriad of applications for the different HR functions – Applicant Tracking Systems, Learning Management Systems, and core HR functions such as payroll and benefits administration (Eubanks, 2019). Lunsford and Phillips (2018) researched the available technology based on the different analytics levels in advance of needed research on the intersection of technology and analytics. Some software tools were part of HRIS systems, and some tools identified for advanced HR analytics were statistical software programs or focused analytic programs (Lunsford & Phillips, 2018). The research gap on individual tool utilization and competency requires future research (Margherita, 2021; Lunsford & Phillips, 2018).

Other technologies, such as a Business Intelligence (BI) system, can link technologies together, provide metric capabilities, and advance predictive features (Lunsford & Phillips, 2018; Laursen, 2011). BI systems are utilized for enterprise analytics and are not specific to a subset of businesses but have reported other HR analytic technology functionality discussed in Lunsford and Phillips (2018). BI systems track and visualize key performance indicators (KPIs), forecasting, scenario analysis, and conduct simulation. Pape (2016) assessed HR analytics from the BI systems perspective. Pape (2016) annotates that emerging BI systems targeted toward HR, such as Fusion, OrgVue, SuccessFactors, and WorkDay, are expected to grow HR's capability. Pape (2016) cautions that BI systems rely on the HR professional knowing the questions or hypotheses they want to answer and the kind of analysis they want to perform. Uniquely, AI-based tools find the associations in data, make connections, assess causality, and derive answers to questions the HR professional poses to the software (Pape, 2016). Pape's (2016) results indicated that the following HR processes are primary candidates for advanced analytic applications: recruitment, succession planning, learning and development, performance management, induction, offer and contract, and exit. Insight processes such as focused analytics and workforce planning were secondary priorities (Pape, 2016).

Despite the value of advanced analytic technologies, few companies have implemented such tools (Levenson & Alexis, 2017). Why? HR professionals need to see through the cloud of data to make sense of it all and, just as importantly, a practical means to assess the best solutions. Vargas et al. (2018) found lower adoption and self-efficacy in HR analytic tool adoption among females. Sex is an important variable as the HR profession is female dominate. Vargas et al. (2018) suggested the findings aligned with previous research where females were limited by their own beliefs of mastering skills such as data analysis (Bandura, 1977; Bandura, 1997; Bandura, 1982; Talukder & Quazi, 2011). Levenson and Alexis (2017) describe six problems to solve for an effective application of analytic technologies: 1) lack of a defined analytics strategy, 2) increased measurement does not guarantee actionable insight, 3) incremental vs. step-change improvements, 4) devotion to searching out needles in haystacks, 5) lack of basic data hygiene, and 6) have a healthy skepticism of the data. The solutions are pragmatic but not always well executed. Examples include: investing the time to clean the data, back-planning from the desired end-state, and being forward-thinking about the data, rather than looking in the past (Levenson & Alexis, 2017). Lunsford and Phillips (2018) describe barriers from their research: lack of correction technologies, leadership not understanding analytics, and appropriate talent to manage data. Similar technology adoption pains were described in the finance discipline. In their international study among accountants and financial analysts, Yeo and Carter (2017) identify a lack of system-specific analysis tool proficiency, such as SAP and ERP software. Further, a murky and potentially legal issue with technology, specifically AI in HR, is the potential of discrimination embedded in the algorithm, even if unintentional (Köchling & Wehner, 2020; Eubanks, 2019).

As experienced by the researcher, the market can be just as tricky to navigate. The current commercial IT tools are not easily identified and compared; HR professionals often have to research trade websites, sign confidentiality agreements, conduct multiple demonstrations, and piece-meal together a picture of what each tool can effectively perform and the number of resources needed to build, implement, and maintain the data within the program. The risk of implementing expensive programs and being unsuccessful at meeting planned goals is high for HR professionals and, unfortunately, happens frequently (Human Resource Director, 2017; Gartner, 2016). When considering the limitations and costs in reputation and program investment, it is easy to understand the hesitation of implementing information technology for HR analytics.

2.4 Job Performance

The driving force for analytics is the promise of enhanced job performance. According to Campbell (1990), job performance relates to the act of doing a job, and job performance is a complex activity, not a single action. For HR professionals, this could not be more true as their role can include a multitude of activities: analyzing jobs and design of work, recruitment and selection, training and development, performance management, compensation and benefits, employee relations, developing personnel policies, maintaining employee data and information systems, maintaining legal compliance, and supporting the business strategy (Noe et al., 2017). In addition, HR job tasks are diverse and require professionals to have multiple skill sets. With this complexity, how do we assess job performance? The literature has taken several different approaches. However, this dissertation focuses on a Person-Environment (P-E) approach because the theoretical relationship to competency modeling and the empirical research is robust. The subsequent sections will assess the current literature and options for understanding job performance and why the P-E approach was the most viable.

In contrast to P-E, personality and job satisfaction are less substantial predictors. Judge et al. (2001) reviewed the literature on the job satisfaction-job performance relationship. Previous studies attempted to assess the relationship in a multitude of ways job satisfaction on performance, performance on job satisfaction, an interaction effect between the two, and the influence of potentially confounding third variables (e.g., Strauss, 1968; Fishbein, 1973; Eagly & Chaiken, 1993; Kinicki & Fugate, 2018; Shore & Martin, 1989; Schwab & Cummings, 1970). The results linking job satisfaction to performance are mixed and controversial (Judge et al., 2001; Kinicki & Fugate, 2018; Ostroff, 1992).

Research on personality similarly has a large body of research but is not a large contributor to performance. He et al.'s (2019) meta-analysis consistently finds, of the personality factors, conscientiousness has a positive aspect to job performance across occupations. However, personality traits as a whole contribute a small percentage to specific task performance, accounting for only 5% (He et al., 2019). Meanwhile, research that takes a P-E approach has a robust relationship to performance (Mumford et al., 2017; Raffiee & Byun, 2020).

Boyatzis (1982) created a model for job performance grounded in behavior theory, utilizing Lewin's heuristic formula that the job performance (behavior) is a function of the person and their environment (Lewin, 1936). Today, the Person-Environment (P-E) fit or Person-Organization fit is the formalized moniker utilized to express Lewin's (1936) theory (Mumford et al., 2017; Raffiee & Byun, 2020). P-E continues to be relevant and is explored through competencies, job requirements or criteria, and organizational factors. This approach is aligned with a series of studies that derive KSAOs and utilize criterion testing to predict job performance and is considered the standard for occupational practice (Farr & Tippins, 2010; Scott & Reynolds, 2010).

In the research of job performance and competency, the literature supports the proposed model. Baczynska and Thornton (2017) utilized intelligence typology[1] (analytical, practical, and emotional) for their competency variable and tested the dependent variable manager performance in leadership, initiative, goal orientation, change orientation, and employee development. Baczynska and Thornton (2017) research supported a relationship with analytical and practical

[1] In Baczynska and Thornton (2017) work intelligence typology are Ability (in KSAOs) indicators needed for leadership job performance. Since McClelland's (1973) work intelligence literature matured and grew intelligence from a singular typology to multi-typology consisting of more than mental acuity.

intelligence, not emotional intelligence. Subsequently, the KSAOs related to solving problems through inductive and deductive reasoning are strong indicators of job performance. Other research on job performance in the context of the P-E is also promising. Choi et al. (2020) found a link between P-E fit indirectly linking self-efficacy through informal learning on job performance. Choi et al.'s (2020) research is also topical as the self-efficacy variable on job performance results are also relevant to the final research model.

2.4.1 HR Job Demands and Environment

The rest of the environment and job demands of HR must be understood to illustrate the importance of AC on job performance (Boyatzis, 1982). Therefore the following section summarizes the current HR environment regarding the HRM system and expectations from the discipline. Then the review will narrow in focus on the job demands that emerge for professionals to effectively perform in the occupation, with a subsequent section on the intersection between the two.

HR Environment. How HR is structured and supports the business contributes to roles and competency demands. The consensus in HR literature is that HRM systems consist of three key elements – policies, practices, and processes. HR professionals orchestrate the system's development, use, and facilitate the advancement of human capital (Schuler, 1992; Noe et al., 2017). Schuler had a 5-P model that incorporated philosophies and programs, but as the field of Strategic HRM developed, policies, practices, and processes became embedded and codified in textbooks (Noe et al., 2017). There is a distinct environmental demand in the literature for Strategic HRM, where HR professionals are a vital link between the people and the business needs of the future (Schuler, 1992). Therefore, HR professionals' decisions in implementing the HRM are influential and consequential for both the firm and its employees.

HR is purportedly organized to enhance strategic HRM. The environmental demands on HR to utilize HRM (decisions on policies, practices, and processes) to increase business capabilities drives much of the literature on AC (Boudreau & Jesuthasan, 2011; Boudreau and Ramstad, 2007; Parahad & Hamal, 1990; Kryscynski et al., 2017; Barney, 2001; Barney & Wright, 1998; Bharadwaj, 2000; Le Deist & Winterton, 2005; Shippmann et al., 2000). The HR environment and organizational design research suggests a disconnect as to where decision support is housed and implemented. Despite some contention in the field (Kaufman, 2015), the accepted model of current HR organizational design is where an HR business partner (HRBP) links the people to the business and makes strategic decisions, and HR specialists tend to the specific HR process administration (LaFevor, 2018; Noe et al., 2017). However, Scully and Levin's (2010) research on shared service trends described HR analytics and reporting as one of the shared services functions, an argument defended by McCartney et al. (2021). No matter the organizational placement, the research suggests the process is rarely outsourced and preferred in-house (Scully & Levin, 2010) and, as a result, is crucial for HR professional development.

HR Job Demands. SHRM (2020) identifies roles and positions as influential factors in job performance. Right now, HR and academics are not consistent as to who and where within HR AC is needed; therefore, this dissertation contends such an endeavor to assess AC should happen with eyes wide open. From the sales and marketing discipline, Laursen's (2011) work suggests that AC is essential to all roles because decision-making and problem-solving are ubiquitous, rather the scope and magnitude changes. Although some research contends HRBPs need to be a source of analytic capability (LaFevor, 2018; Scanlan, 2007; Sinar, Ray, & Canwell, 2018), another trend is emerging where the analytics role is delegated to a specialist function (McCartney et al., 2021). The argument for/against HR job needs is similar to that of HR organizational design conflict. Kryscynski et al. (2017) found AC associated with higher performance in specific specialist roles over the HRBP role. The results of Kapoor and Kabra (2014) suggest analytic specialist roles are a stand-alone occupation in some companies, based on job postings. However, a search of standard occupational tools indicates that the emerging HR analytic occupation is not yet memorialized as a formidable standard (O*Net, 2020).

HR Environment and Job Demands. The HR environment, supposedly organized to support business decision-making, is not aligning with the job demands. As a result, HR finds itself in an identity crisis and a stark debate about what activities increase value and how HR professionals can enhance the firm's abilities (Flynn, 2014). The identity crisis is no small problem; HR is an overhead function, and such notions of value to the business support the existence of the HR function and this dissertation. Chen’s (2015) research spotlights the issue, with respondents indicating their roles are still primarily transactional and not impacting the boardroom. Chen (2015) described HR as “pigeon-holed in a very tight, tactical box, but viewed as generally irrelevant or lacking in major influence when it comes to strategic issues that the top the board’s agenda” (p. 36).

Chen’s (2015) work also brings us to the second tenet in the literature; HR professionals as a decision-maker. Much of the drive for AC is in data-driven decision-making (Ulrich & Dulebohn, 2015; Giannantonio & Hurley, 2002; Maurer, 2018; Levenson & Alexis, 2017). Although the positionality of HR and its place at the executive table is in flux, the avant-garde and value of the data-driven approach are expected, and as current research suggests, a destination where contributions as decision-makers are significant to HR professional performance (LaFevor, 2018; Kryscynski et al., 2017; Ulrich & Dulebohn, 2015; Ulrich, Younger, & Brockbank, 2008). High-risk decision propensity is a deflating variable to job performance unless a high level of performance management supports the risk demands (Glaser et al., 2016). The perceived risk of potential failure in implementing analytics and desire for sustaining job performance may confound HR adoption.

HR is being redesigned to meet the needs of the future (Huong Vu, 2017; Kaufman, 2019; Ulrich et al., 2021b). Currently, HR professionals are uncertain of AC's value in performing their occupational duties (Ulrich & Duhlebohn, 2015). The HR professional skepticism is expected given the initial negative impact job redesign has on performance (Siengthai & Pila-Ngarm, 2016). The importance of social capital, or developing relationships, has proven vital to organizational fit and performance (Raffiee & Byun, 2020), and a function of HR roles that professionals lean on as the precipice to their value, given the validated need (Welch & Welch, 2012; Coetzer & Sitlington, 2013; Ulrich, 2021a; Ulrich, 2021b). The argument against AC may also be a form of cognitive dissonance for HR professionals to avoid the changing climate to a more technical skill set (Rasmussen & Ulrich, 2015). However, given the work of Baczynska and Thornton (2017), it may be just as imperative for HR professionals to demonstrate AC for their performance as a change and performance management agent.

In conclusion, the HR environment and job demands are focused on strategic people decisions, but the organizational structure and roles are in flux. HR decisions are far-reaching, but the competencies to support those decisions are not defined. Finally, the dynamic nature of the HR discipline, HR professionals are not assured that the value of AC is definite and long-standing.

2.5 Decision-Making

The decision sciences focus on decision-making rather than job performance. However, due to the significance of data- and evidence-driven decision-making have on the overarching HR competency models in the literature (Ulrich et al., 2015; Kryscynski, 2017; SHRM, 2016), the decision-making variable receives focused attention in this section. Brown (2017) explains from an HR professional perspective - imagine making a people decision at a firm that goes viral, and not in a good way. HR professionals are purveyors of compliance, and a rigorous process for decision-making prevents subjectivity, which may otherwise make the firm vulnerable to litigious actions (Brown, 2017). Decision-making theory drives one of the assumptions in the research model that business expectations of job performance require a rationale-based and systematic decision-making process. Subjective Expected Utility (SEU) theory for decision-making is a mechanical process of weighing the set of alternative solutions and selecting the option with the highest probable outcome (Cozier, Ranyard, & Svenson, 1997). The decision-making process consists of three stages: 1) information search, 2) definition of alternatives, criteria, and individual preferences, and 3) selection (Hudson, 2015). Alternatively, Image Theory suggests decision-making is not analytic and radically opposes the predominant SEU model (Beach, 1990). In the opposing camp to SEU theory is the concept of Affect Heuristics. Zaojonc (1980) is quoted for his explanation of Affect Heuristics (Finucane et al., 2000):

We sometimes delude ourselves that we proceed in a rational manner and weigh all the pros and cons of the various alternatives. But this is probably seldom the case. Quite often "I decided in favor of X" is no more than "I liked X." Most of the time, information collected about alternatives serves us less for making a decision than for justifying it afterwards (p. 155).

Although the expectation is that SEU theory is the driver of accurate decision-making in business, given the demand in HR literature to take a data- and evidence-based decision-making approach to improve HR outcomes, suggests otherwise (Rousseau & Barends, 2011; Roberts, 2007). The alternative models are recognized with Rasmussen and Ulrich's (2015) suggestion that HR professionals may be subject to a psychological theory of cognitive dissonance; they have justified gut decision-making in their own minds versus evidence- or data-based decision-making approach.

Other research on decision-making influence includes the organizational environment factors, notably culture. Nouri et al. (2017) utilized the Hofstede cultural dimensions to assess the impact on decision-making, the findings contributing to our understanding of regionalized differences and implications for simulation performance. Related, Van Der Westhuizen et al. (2012) found that cultural dimensions impacted participatory behavior in decision-making.

Outside of HR, decision-making in the firm is discussed extensively. In Hudson's (2015) text, which aggregates seminal research articles in business decision-making, business decision-making methods are derived from the rational decision-making model and are customary. The methodologies include Aggregation and Ranking Alternative nearby the Multi-Attribute Ideal Situation (ARAMIS) for individual decision-making and Aggregated of Individual Ranking/Complex Aggregation of Individual Ranking (AIR/CAIR) for group decision-making. Both approaches systematically weigh alternatives such that the individual or group utilizes the information available to derive the optimal solution. Hierarchical models were assessed in situations where limited information was available and proved beneficial in business internationalization decision-making, and subsequently, the mode of internationalization. Compartmentalizing the decisions reduces the complexity and allows one to assess the decision with fewer factors, making the decision-making process more manageable. In summary, the business decision-making models support SEU theory.

Technology-Aided Decision-Making. Given the fast advancing technological capabilities to support decision-making, this research assessed the need for human decision-making and possible obsolescence. Although technology-aided decision-making is helpful, the literature does not indicate that technology wholly manages decision-making or will in the near future due to the complexity and compliance needs (Leicht-Deobald et al., 2019). However, HR teams are currently benefiting from some technology-aided decision-making. For example, Oracle has developed in their HR software COVID-19 resources to help return employees to work, track testing and vaccination requirements, and help the HR professional decide on an employee's return to work (Mena Report, 2021). However, as foreshadowed with analytics and technology, decision-making aided by technology is also subject to technological limitations. Leicht-Deobald et al. (2019) preface the argument with seemingly positive examples of assisted decision-making – Xerox Services recruitment algorithm that scores an applicant based on job fit; JP Morgan's algorithm identifies potentially fraudulent behavior of employees. Although there are benefits to aided decision-making, compliance problems also exist, including accountability, transparency, power, and social control (Leicht-Deobald et al., 2019).

Interestingly, some HRIS and AI-based software/cloudware companies tout their decision enabling features for HR, including IBM's Talent Watson and SAS. However, according to Leight-Deobald et al. (2019), a dark side exists, where such decisions dehumanize employees and dismiss other features in recruiting a candidate, such as personal integrity. In addition, Leight-Deobald et al. (2019) argue an adverse effect of monitoring and social control from such technology through Zuboff's (1988) concept of anticipatory conformity. In anticipatory conformity, the saturation of measurements and pressure of visibility results in a conformity behavior, lacking discovery and creativity. Further, the opacity of the more complex algorithms may hide inherent flaws in the program's learning. Leight-Deobald et al. (2019) exemplify how a recruiting advertisement algorithm may learn its target audience from current talent. If gender, racial, or other bias exists in the existing talent profile, that issue will imprint on the algorithm perpetuating the problem in advertising, selection, and decisions.

2.5.1 Decision-Making Self-Efficacy

Vargas et al.'s (2018) results on HR analytic tool adoption find self-efficacy and gender contributing variables to a technology acceptance decision. The results beg the question, does the behavior approach alone provide a robust framework for understanding all the HR decision-making variables? Ajzen and Madden (1986) would argue no, and guide future researchers to include self-efficacy in rational decision-making models to increase explanatory and predictive power.

Self-efficacy is rooted in social cognitive theory to explain motivation and actions (Bandura & Locke, 2003). Self-efficacy is the belief in one's ability to succeed in a given task (Bandura, 1997). The importance of self-efficacy in decision-making due to the regulating effect is significant (Bandura, 1997; Tabernero & Wood, 2009). However, Judge et al. (2007) specifically addressed work-related and task performance and found that self-efficacy contributions were minimal, whereas cognitive and personality factors were more substantial. Self-efficacy, a distal characteristic, contributed more to simple task performance but receded as the tasks became more complex, and proximal characteristics were the prominent predictors of success (Judge et al., 2007). Bandura (1997) explains that self-efficacy is not the sole predictor of decision-making, rather a mediating cognitive factor that should be inclusive in decision-making models to ensure a holistic understanding of behavior.

2.5.2 Decision-Making and Job Performance

Despite the discussion overlap, the literature on job performance and decision-making are two separate streams. Dalal et al. (2010) considered the divide a problem and identified a lack of cross-fertilization. Dalal et al.'s (2010) panelist, Mohammed, states that "effective decision-making is often a precursor to achieving effective team-performance outcomes" but recognized the "decision-making component is often not directly modeled" (p. 397). Seong and Hong (2018) reiterate Dalal et al.'s (2010) concerns and attempt to bridge the gap between their group performance and decision-making study. However, Seong and Hong (2018) research stopped short of addressing effective decision-making; instead, they measured the participation of group members in decision-making, finding a positive relationship between performance and participation. SHRM results for Situational Judgement Tests (SJT's) and performance suggest we should see the relationship (SHRM, 2015) and that the work done in the professional streams could contribute more to this academic gap.

2.6 Literature Gap

Competency modeling has reared its head in the HR AC debate and stirred a gap in and of itself. In modeling for a future state, SMEs are in a great debate over who and where AC exists. The competency modeling process does not help us answer the call because of the lagging nature. The lack of mobility and process focus in modeling limits the ability to adapt competency models to rapidly changing jobs. Further current modeling lacks a holistic structural assessment and cross-reference, which allows for gaps in modeling and variability in taxonomy.

Prior literature in AC, decision making, and job performance has yielded several gaps. First, there is no single accepted competency model for the AC cluster, rather a presentation of the needed skill set co-mingled in other competencies, arguments for specialty occupations with their own competency models (albeit not complete), and/or not comprehensively tested for decision-making and performance. Although much of the research agrees to specific components, there are variations in nomenclature (notably logic and numeracy features), the positionality of the skills, and how the skills contribute to decision-making and performance. Further, despite competencies being an individual-based mechanism for job performance, the researcher found the theoretical underpinnings were incorrectly aligned to organizational capability theory (e.g., Shippmann et al., 2000; Kryscynski et al., 2017; Boudreau & Jesuthasan, 2011; Boudreau and Ramstad, 2007). Consequently, much of the current literature has formed a gap in theory to individual construct alignment. AC formation is still in its infancy and conceptual. A competency cluster is needed to ensure efficacy, identify development solutions for HR professionals, and increase confidence in the competency attributions to job performance and adaptability to changing needs.

The omission of an evidence-based approach to analytic competence, ironically espoused as the rationale for AC utilization, is a worthy gap to address, if not for rigor and credibility among the professional field. Although multiple calls to action in the literature for a formidable assessment of AC, no one has taken up the call (Margherita, 2021; Marler & Boudreau, 2017; Rousseau & Barends, 2011; Maurer, 2018). Addressing the gap with both an evidence-based approach to competency model development and testing the model for contribution to job performance will provide: 1) HR professionals an understanding of the value analytics may or may not bring to their job performance, 2) increase confidence in which KSAOs contribute to their performance, and 3) contribute to academic competency modeling theory with the testing of the attributes of the competency framework.

Fitz-Enz and Mattox (2014) indicated a "recipe" exists to AC, yet no one has empirically tested it. Other scholars make similar observations that AC enhances HR professional abilities to perform in their roles, but no distinction as to the composition of those KSAOs (Soundararajan & Singh, 2017; Kryscynski et al., 2017; Waters et al., 2019), and some of those assertions are from generalized observations, not a measured analysis. How do we know which skills to "upskill," and how much of each skill we need if we do not have the recipe? Further, without evidence, why would HR professionals believe that analytic KSAOs are beneficial to the job? After all, HR professionals are being taught to be evidence-driven.

Related, the gap in the research on AC composition has caused a rift in the literature. Subsequently, the debate between the data and evidence camps needs an empirical assessment. It is truly a chicken or the egg question that remains unsettled in AC, which begets which, evidence-driven or data-driven. In 2017, Ulrich et al. suggested an advanced data analysis, step-wise approach to becoming an analytic designer and interpreter, urging HR professionals to obtain numeracy skills. However, Ulrich et al.'s (2021) revised model shifted to a critical thinking approach, succumbing to environmental pressure to focus on critical thinking, high-level strategic skills, and soft skills. The shift is perplexing because of acknowledged evidence from both study series that data skills and analysis were more significantly related to job demands for business decisions than the other skills championed in the model (Ulrich et al., 2021).

Competency models also do not have a consistent approach to the organization and functionality of AC. For example, Waters et al. (2018) wrote most of their analytics process guide applying a myriad of SHRM model competencies, disjointing the KSAOs for the specific action of accurate decision-making in the business examples across larger competency domains. The Waters et al. (2018)/SHRM method for AC does not align with the behavioral approach such that the competency leads to effective and specific actions, the guiding principles of competency models (Boyatzis, 1982). The SHRM approach is also not systematic and opens the door for missed or under/over-stated competency needs. The mixed use of terminology could confuse HR professionals and academics alike, leading to misinterpretation and lack of validity[2].

An underlining assumption in decision science and I/O literature is the link between job performance and accurate decision-making. I/O literature has theoretical underpinnings in decision-science but assumes that performance is an adequate proxy for decision-making. Likewise, decision-science suggests the practical value of decision-making in business is to increase job performance. The assumptions from both fields create a gap in our knowledge of the relationship between decision-making and performance (Dalal et al., 2010). Breaking out the performance and decision-making variables provides a more robust model, meeting an expressed desire in the literature to close the gap (Dalal et al., 2010). Job demands and, subsequently, performance in HR consists of a multitude of activities to include more social competencies than other business disciplines. The contributions decision-making makes to performance is of especial interest given HR is not considered a typical business function. The lack of knowledge regarding the relationship of decision-making to performance could be of unique interest given the HR discipline's label for gut decision-making and social functionality. Further, as will be evident in the final model, not all AC skills best align with

[2] As a point of clarity the SHRM competency model has a robust validity measure, the argument is specific to the suggestion of piecemeal SHRM competency associations with their analytic process steps. Waters et al. (2018) does not provide evidence of a competency assessment as applied in the guide, disjointed from the SHRM competency model domains.

individual decision-making, given how social competency functions to support job performance.

2.7 Research Questions

As described, the current literature wants for a more refined dive into AC's composition, relationship, and power in HR professional decision-making capabilities and performance. This leads to the following research questions:

1. *What* analytic competencies drive higher job performance for HR professionals?
2. *How* do these analytic competencies drive decision-making for higher job performance?

2.8 HR Analytic Competency Cluster

The researcher baselined the competencies present in the literature to a theoretically grounded framework to fill the competency model gap, a novel approach for future state competency modeling. Modeling on a competency framework aligns the methodology correctly to the individual level of analysis. The competencies are coded based on the primary dimensions – cognitive, functional, social, and meta-competence – from the LeDeist and Winterton (2005) framework. This method is unique and advantageous because it will identify the competency gaps and adequately fill them. Further, this research advances competency modeling by identifying typologies and defining the skill set that espouses the typology, not done by former researchers using the holistic framework (e.g., Persaud. 2020). Campion et al. (2011) best practices were consulted and utilized where appropriate to this general AC cluster for HR professionals. The depth of the competency framework, vernacular selection, research-driven approach to building the model, and granularity align with the best practices (Campion et al., 2011). Campion et al.'s (2011) guide is intended for firm-based competency development. As such, some features were modified for a generalized HR professional model (e.g., instead of firm-based objectives and alignment analysis of needs, a broader analysis across the HR discipline was used). Boyatzis (1982) states that many conceptual models often fall too deep into specific occupational skills or are too broad. With these words of wisdom, the model strives to balance constructive skills and abilities, driven by the current conceptual and qualitative input from the field and research. In improving the modeling process for future-state competencies, the literature review specifically calls out process modeling literature to ensure an accurate and actionable skill set that is not too vague; a problem called out in HR literature for analytics (Margherita, 2021).

Process modeling literature makes inferences and specific statements to KSAOs, and the more detailed dive bridges subject matter expert and job analysis like rigor as prescribed by Lievens et al. (2004). Further, as inspired by O*Net, a proper review of the presented competencies in tangent literature was completed to ensure consistent taxonomy as applied across occupations versus creating an orthogonal competency model. The research methodology will allow for more generalizability of KSAOs and insights for similar competency clusters and job demands (Peterson et al., 2001).

The literature review included a review of professional publications on HR professional sites such as SHRM, Psychology databases such as PsychInfo, and Business databases such as Business Source Complete. Explicit and implicit competency references in analytic process guides (e.g., Waters et al., 2018; Boudreau & Ramstad, 2007; Falletta & Comb, 2020) were incorporated. Figure 6 is the finalized HR AC Cluster and output of the modeling process. The KSAOs presented in the model were then reviewed on their own merits in competency domain literature – industrial psychology via PsychInfo database and decision science literature, which enriched the competency model with empirical findings and construct formation.

Cognitive Competence. Cognitive competence if formalized as the Logic competency that consists of KSAOs of effective inquiry, research design, and ability to gain insights from the results of that inquiry (Soundararajan & Singh, 2017; Falletta & Combs, 2020; Boudreau & Ramstad, 2007; Fitz-Enz & Mattox, 2014; Waters et al., 2018; Patre, 2016). Logic is theoretically grounded in evidence-based HR decision-making. Evidence-based decision-making is the "demonstration of HR practices that have a positive influence on the company's bottom line or key stakeholder (employees, customers, community, shareholders)" (Noe et al., 2017, p. 11). Rousseau and Barends (2011) provide an HR professional model that focuses on critical thinking, a questioning mindset, and then acting on the evidence. Boudreau and Jesuthasan (2011) define logic-driven analytics as a fundamental principle to evidence-based decision-making. Fitz-Enz and Mattox (2014) considered the mental framework to create a logical research design the "art" of analytics. Logic is a conceptual competency that is hard to formulate into explicit notions and, based on Le Deist and Winterton's (2005) argument, may explain why there is a lack of empirical measurement in previous research.

Functional Competence. Functional competency is comprised of two sub-competencies, numeracy and software literacy, which encompass the ability to manage data and conduct statistical analysis. Numeracy and data analytics are utilized nearly synonymously in HR literature. Waters et al. (2018), Soundararajan and Singh (2017), Edwards and Edwards (2019) prescribe statistical and quantitative methods to obtain desired predictive and prescriptive solutions for decision-making. The term numeracy is used in this dissertation because of the functional alignment to the larger body of competence research (Cokely et al., 2012). Qualitative research in digitally transformed organizations supports numeracy demand; the ability to design, extract, understand, analyze, and interpret data was a main thematic finding (van den Berg, Stander, & van der Vaart, 2020; McCartney et al., 2021). In the case of numeracy and software literacy, the extensive literature review suggests two distinct skill sets (Cokely et al., 2012; Lunsford & Phillips, 2018), unlike HR models that intertwine or omit the specific contributions of each (Ulrich et al., 2021a). McCartney et al. (2021) support the distinction in their HR analyst competency analysis. The lack of clarity of how to use numeracy may contribute to ambiguity for HR professionals, and software use and implications have their own unique pitfalls (Cheng, 2017).

Software literacy is essential for future business analysts (Cegielski & Jones-Farmer, 2016). Vargas et al.'s (2018) research demonstrated that HR professionals must first overcome proficiency challenges if HR organizations want to utilize the tools to advance analytic capabilities. Software competency may prove to amplify numeracy skills since some software can perform advanced mathematical functions (Eubanks, 2019). Technology proficiency is embedded differently across various competency models in HR (e.g., a separate competency domain versus a supporting skill within a competency domain) and suggested for the HR profession as a whole (Ulrich et al., 2012; SHRM, 2016).

Social Competence. Social competency consists of Persuasion, a competency that comprises previously separated notions of Environment and Process Management and Communicating Findings. During the review and analysis of these separate constructs, a more formidable competency of persuasion effectively encompassed both (Plouffe et al., 2016). The novel methodology, in this case, allows for more consensus across the occupational domains and the ability to relate common competencies across disciplines and occupational titles (Scott & Reynolds, 2010).

Communicating Findings research points to specific skills to obtain influence, sell the solution or obtain buy-in (Fitz-Enz & Mattox, 2014; Soundararajan & Singh, 2017; Waters et al., 2018). Most notably, the literature points to storytelling and visualization ability to weave the data and insights together as essential skills (Fitz-Enz & Mattox, 2014; Soundararajan & Singh, 2017; McCartney et al., 2021). Researchers and studies have concluded that storytelling positively impacts multiple business functions (Denning, 2006; Spear & Roper, 2013; Klein, Connell, & Meyer, 2007; Boldosova, 2020). Also referred to as a narrative, storytelling is considered a sense-making instrument (Boldosova, 2020). Vora (2019) describes data storytelling as novel because one applies the ancient practice of storytelling to data, a new concept. Vora (2019) describes data storytelling as beneficial for organizational decision-making. Storytelling reduces the mass of data to what is relevant and links that information, creating efficiency and understanding of the presentation material and the decision output. Vora's (2019) interpretation aligns with the 2020 HRCS cycle results, where HR professionals simplify the complexity of information. The sense-making aspect of storytelling enhances the HR professional's ability to link decisions to data (Ulrich et al., 2021b). Brown et al. (2005) define storytelling as a knowledge medium and provides a conduit for necessary knowledge flow between people in organizations. However, the research does not directly link narrative capability and job performance in an empirical investigation. Persuasion's constructs of rational and inspirational appeal are conjoined in HR literature. The use of logical arguments and facts with the visual appeal and vision (Plouffe et al., 2016) are symbiotic with the demonstrated use of data visualization to build logical arguments and stories as a sensing instrument (Conger, 1998; Boldosova, 2020).

Environment and Process Management is the other element of persuasion not directly linked, but the tactics are embedded in the HR literature. Environment and Process Management account for values, culture, influence, and stakeholdering to obtain buy-in. Fitz-Enz and Mattox (2014) “recipe for analytic success” includes what they refer to as *stakeholdering*, where one allows the executive to make a hypothesis that commiserates with consultation in persuasion, where one engages the target in providing advice or suggestions for the project for which buy-in is the objective (Plouffe et al., 2016). Further, HR analytic process and competence literature are sprinkled with the term persuasion to describe the act of gaining buy-in (e.g., Waters et al., 2018; Lucia & Lepsinger, 1999). Boudreau and Ramstad (2007) underpin their *Process* construct by incorporating value, cultures, and organizational influence into the talent decision-making process. Research regarding the lack of management understanding of the connection between HRM decisions and strategic performance drove the importance of audience knowledge, interest, and perceptions for tailoring the presentation of solutions or recommendations in the LAMP model (Boudreau & Ramstad, 2007). Kryscynski et al. (2017) glean limited insight into the social typology that incorporates values, culture, and influences. One question was mapped high in Process from the LAMP framework – Does the HR professional uses data to influence decision-making in [Organization Name]. Again, not an independently measured construct, but the analytic construct as a whole was positively related to HR performance (Kryscynski et al., 2017). Similarly, Fitz-Enz and Mattox (2014) prescribe identifying stakeholders and influencers; however, basing these recommendations on their expertise. According to Graham (2014), in practice, identifying the right stakeholders can be a "nightmare" and not a given in the business application and such selection requires balancing individual objectives and the business outcome desired.

Culture and values influence on decision-making have their own body of literature. They are often not described in terms of competency; instead, they are the social construct that shapes our cognitive processing and interactions. In the work environment, the values and cultural social constructs create one's sense of the reality of which decisions are influenced (Mumley, 2019). Schnebel (2000) defines ethics as the link between values-orientation, rationale, and person or group causality. Values then are the soft rules in the decision-making process for business leaders (Schnebel, 2000). In ethical dilemmas, the strife between keeping group consensus and one's psyche can be quite confounding (Mumley, 2019). Schnebel (2000) prescribes communication theories to reconcile differences across different cultural frameworks, knowing when and where implicit and explicit modalities permeate best in informing the decision. Schnebel's (2000) communication mechanism may explain why HR literature on communication and social competency are interlinked.

The ability to account for cultural influences is no less important. Nouri et al. (2017) utilize game theory and Hofstede cultural dimension indices to explain the implications of culture on decisions in an AI environment. The resulting multi-attribute relational value model of decision-making includes weights for rational factors and cultural factors such as individualism versus collectivism, power distance, and uncertainty avoidance (Nouri et al., 2017). Although Nouri et al.'s (2017) study explains what drives decisions (versus how), the study emphasizes that the decision's environmental factors of culture and values are relative to successful implementation.

Plouffe et al. (2016) work bridge I/O psychology and persuasion, considering environmental factors. The internal business team is subjective to a highly formal coupling with an established business hierarchy, the expectation of compliance to current organizational policies, and subject to multiple forms of coercion. The persuasion construct adequately addresses all the components of social competency typology within the AC literature. In addition to addressing influence, soft tactics include appeals to the value and ideals of the audience. Persuasion is also relative to selling and gaining buy-in. Persuasion literature segues well given the direct construct similarity to the current HR literature and is more empirically driven. Again, the proper competence assessment in tangent literature has proven valuable because persuasion is a more researched and comprehensive competency construct. Plouffe et al. (2016) described and validated the value of persuasion internal to the firm. The nine common tactics include: rational persuasion, inspirational appeal, consultation, ingratiation, personal appeals, exchange, coalition tactics, pressure, and legitimating tactics (Plouffe et al., 2016). Conger (1998) finds that executives align good persuasion to higher performance. Further, Conger (1998) defines persuasion as inclusive of vivid language and stories, not just numbers. Thacker and Wayne (1995) also find that influence tactics with reasoning positively relate to promote-ability. The positive associations with performance variables provide a reason to test these constructs against HR performance, although conflicting sales profession research suggests the specific persuasion sub-dimensions – rational persuasion and consultation – may be more dream than reality (Plouffe et al., 2016). Plouffe et al. (2016) discovered that rational persuasion and consultation were associated with lower performance in the sales discipline, opposite of their hypothesis. Alternatively, hard tactics, not considered in HR literature, were related to high sales performance (Plouffe et al., 2016).

Meta-Competence. Finally, nearly omitted from the research, meta-competence is informed by Waters et al.'s (2018) analytic process guide. Waters et al.'s (2018) use of critical evaluation, a SHRM competency construct, includes assessing the analytical process for opportunities and improvements. Therefore, the HR AC Cluster includes the ability to critically evaluate and learn from your previous actions. The lack of meta-competency in models is an interesting phenomenon in light of the importance of learning functionality in artificial intelligence and how the brain functions in decision-making (Paul & Fehr, 2014). For example, Reinforcement-Learning (RL) is where previous trial and error results and subsequent reward and punishment stimuli drive future decision-making in artificial intelligence algorithms. RL is analogous to the research on dopaminergic neurons of the midbrain (Paul & Fehr, 2014). Outside of the HR literature, Tannenbaum and Cerasoli's (2013) study on after-action review capabilities, or debriefs as a form of learning from experience, validates the active exercise of post-process evaluation or critical evaluation.

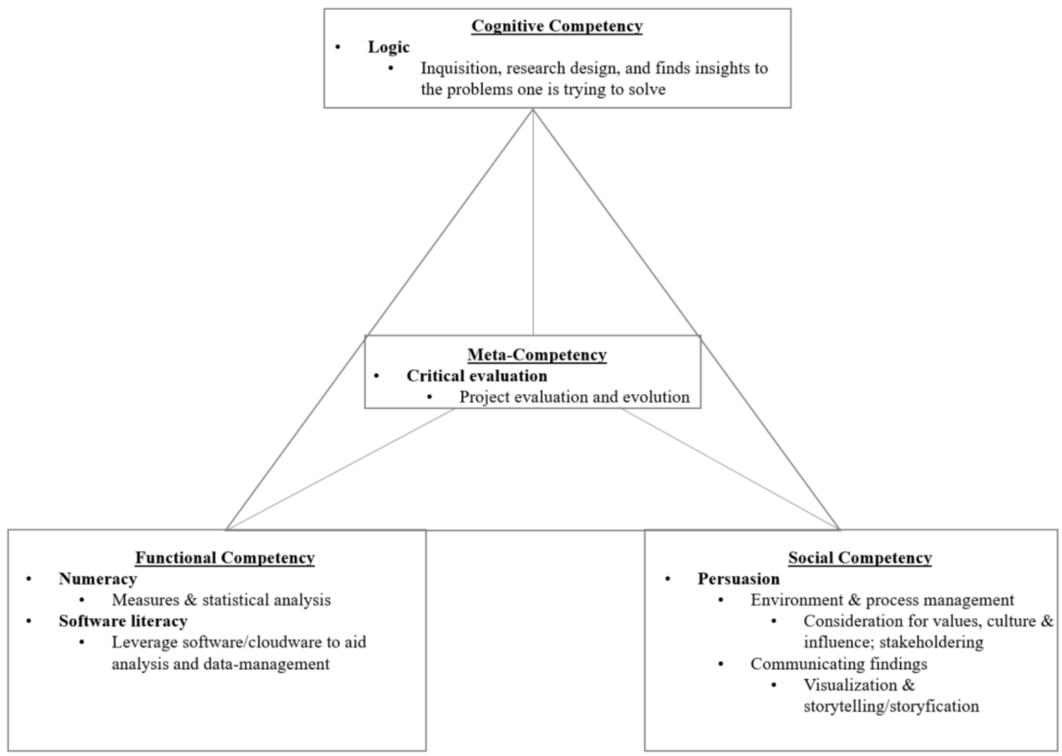
SHRM's (2016) competency model suggests critical evaluation is a larger body of sub-competencies such as critical thinking, problem-solving, and decision-making. However, some defined behaviors offer applied learning, such as "transfers knowledge and best practices from one situation to the next" (p. 41). Inconsistent with the literature, the SHRM model mixes Le Deist and Winterton's (2005) competency typologies of cognitive and meta-competency. The SHRM model also blends actions and performance outputs that are separate from competencies in the Boyatzis (1982) model. Ulrich et al. (2015), opposing the SHRM method, housed analytics in its own domain and placed components of

SHRM's communication and critical evaluation competency within the analytics domain. Therefore, consistent with the LeDeist and Winterton (2005) competency framework, the critical evaluation meta-competency will be specifically defined as the ability to self-evaluate and effectively assess one's intervention. This definition aligns with the meta-competency and HR literature on applied analytics. This research also demonstrates evidence of lack of competency model rigor in the HR domain has resulted in models that incorrectly mix competencies and behaviors, a problem highlighted in Stone et al. (2013).

Figure 6 summarizes the HR AC cluster developed by the author to meet the intent of having an individual-level theoretical driven framework that is holistic. The model is built on the LeDeist and Winterton (2005) framework.

Figure 6

HR AC Cluster



Now that the competency model is formalized, Table 3 then visualizes the presence of the competencies in the literature. Process models, informal annotations, and the HR analyst model are provided to create a complete illustration of where the competencies were identified in previous literature. The table illustrates that not one guide or model fully implements all the competencies indicated in the research or needs a holistic model. The guides were often more comprehensive but are not empirically tested for each construct, as advised in

Boyatzis (1982). Therefore, given the holistic and extensive nature of the HR AC Cluster presented, the research model will be built on the author's analysis.

Table 3

Competency and Process Matrix

Competency or Skill Summaries	Fitz-Enz & Mattox (2014) "Recipe"	Soundararajan & Singh (2017) Skills for Analytics	Fitz-Enz & Mattox (2014) "Art & Science"	McCartney et al. (2021) HR Analyst AC
Logic		+	+	+
Numeracy	+	+	+	+
Software Literacy				+
Communicating Findings	+	+		+
Environment & Process Management	+			+
Critical evaluation				

Process Guides	Falletta & Comb (2020) "Analytic Process Cycle"	Boudreau & Ramstad (2007) "LAMP"	Waters et al. (2018) "Guide to Analytics"	Patre (2016)"6 Hats"
Logic	+	+	+	+
Numeracy	+, o	o	+	+
Software Literacy	+, o			
Communicating Findings	+	+	+	
Environment & Process Management	+	+	+	+
Critical evaluation			+	

Key	
HR Skill- Explicit for an HR professional	**+**
Outside HR- needed but can be done outside the HR discipline	**o**

Chapter 3

Methodology

The methods section starts with building the research model and subsequent hypotheses. After the model development, the instrumentation for each construct is summarized. The methods section concludes with the study process, including data collection, preparation, and analyses to inform the findings. The ethical considerations and philosophical views that support this methodological approach are provided in Appendices K and L.

3.1 Research Model Development

The AC Cluster built and comprised of logic, numeracy, software literacy, persuasion, and critical evaluation, must now be tested on job performance. AC is presented with the dependent variable of job performance first, and the model is worked back through the decision-making and the competency variables. In defense of the model, each variable relationship is provided in detail along with hypotheses development. The control variables are also included and the rationale behind their selection.

3.1.1 Decision-Making Accuracy and Job Performance

High job performance is expected when professionals perform their tasks above a defined standard (Noe et al., 2017). HR tasks include making people decisions regarding policies, processes, and practices within the firm. Thus high job performance should mean that an HR professional makes the best possible decisions regarding policies, processes, and practices. The dissertation hypothesis follows this logic and contends that decision accuracy will increase HR professional job performance. HR decision in talent hiring is positively related to the new hire's job performance (Roth & Bobko, 1997; Boudreau, 1991; Boudreau & Ramstad, 2007); evidence of the positive relationship with evidence-based decision-making and HR job performance (e.g., talent selection made with evidence-based approach resulted in a higher quality of hires with increased performance).

As noted in the literature review, accurate decision-making is often an assumption in the industrial psychology literature as a forgone requirement for positive job performance; however not always modeled even though it should be (Dalal et al., 2010). Likewise, decision-science literature often assumes improved job performance is a consequence of accurate decision making (Dalal et al., 2010). Therefore in this dissertation, decision-making is distinctly called out in the research model to align with the behavioral approach and address the assumption that decision-making and performance are positively linked.

It is with this review that the first hypothesis is established:

H1: Decision-making accuracy will be positively related to job performance.

3.1.2 Logic and Decision-Making Accuracy

Decision-making accuracy is predicated on how one arrives at a decision. Does one use their mental skills and abilities to parse facts and evidence or rely on their gut? Logic competency is the ability of the person to look at a problem for which a decision is to be made, ask the right questions, design a method of approach, and then utilize the facts and evidence to come to a sound conclusion; a rational approach. Decision science literature suggests a methodical approach that weighs all options, uses facts and evidence, and improves decisions by reducing risk (Cozier, Ranyard, & Svenson, 1997). HR-based research also indicates that such methodical approaches (utilizing facts and evidence to weigh options) to arrive at a decision will increase job performance (Roth & Bobko, 1997). Subsequently, the HR professional utilizing a non-rational approach, which omits the Logic competency, should have an adversarial and negative relationship to decision-making accuracy. The literature supports the deduction that the HR discipline is not a reliable source for strategic decision-making because HR professionals rely on their gut or instinct (Chen, 2015; Rasmussen & Ulrich, 2015). Therefore, the utilization of Logic competency should enhance decision-making accuracy.

The ability to utilize logic competency to increase decision-making accuracy is further supported with HR evidence-based research. In a firm-level case study, HR professionals were given tools to help derive decisions with facts and evidence, resulting in measurably improved results of a retail firm's performance (Severson, 2019). The results indicate the professional made better decisions using evidence-based methods instead of the previous approach based on instinct. Likewise, an HR professional positively impacted a medical industry firm by implementing an evidence-based HR practice in another case study. The case study firm increased organizational performance and attributed this improvement to evidence-based methods (Severson, 2019). Individual-level analysis, although limited, also indicates a positive association with the presentation of logic competency and job performance. Kryscynski et al.'s (2017) study does not have a unique construct for logic, but generalized AC and HR professional performance results were also positively related. Kryscynski attributes the positive relationship between AC and performance to the professional's enhanced value with improved empirical-based decision-making. Given that this research finds only positive evidence of Logic competency utilization to decision-making and performance variables, it is reasonable to assume a positive relationship between logic competency and accurate decision-making. Therefore, the hypothesis is that logic will positively impact decision-making accuracy.

H2: Logic will have a direct positive impact on decision-making accuracy.

3.1.3 Numeracy and Decision-Making Accuracy

Numeracy has strong relationships in the literature to decision-making accuracy (Cokely et al., 2012; van den Berg, Stander, & van der Vaart, 2020), despite critiques suggesting it is an outsourceable skill (Boudreau & Ramstad, 2007). This dissertation hypothesizes that numeracy skills will increase decision-making accuracy. The quantitative skills to retrieve, organize, and analyze data (to include statistical calculations), or simply numeracy, are fundamental requirements in the analytic process of decision-making (Waters et al., 2018). Numeracy is the critical function that turns data into useful information to derive decisions (Shron, 2014). Without numeracy, one only has generalized facts and research to inform decisions. Whereas with numeracy, one has firm-specific data to create a custom and targeted decision and response to a problem (Roberts, 2007). Holsapple et al. (2014) explain that one can use rationale skills in a Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis. However, one cannot obtain predictions, interpretations, or decisions with such an analysis, as one could from analytic effort (referenced as the data analysis process). Moreover, numeracy has an error-reducing function by creating more reliable and valid estimates (Cokely et al., 2012; Galesic et al., 2009).

Molefe’s (2013) and van der Togt and Rasmussen's (2017) work suggest numeracy skills in HR professionals will be essential: recognizing what data is available and the implications; how to structure the analysis to obtain a valuable output; and then the ability to interpret those results for HR decision-making. Further, only the HR professional is intimately aware of the available data and the context of the people problem from which a decision is to be made (Bassi, 2015). In decision-making and judgment literature, Cokely et al. (2012) study determined a direct and positive effect of numeracy on lottery decision-making, which is relative since HR decisions often deal with probabilities for risk reduction in decision-making (Edwards & Edwards, 2019). Further, the data-driven models that allow a professional to derive prescriptive solutions to problems require progressive quantitative methods (e.g., HR metrics to advance statistical techniques such as regression, process control, and SEM), and with those methods, the appropriate numeracy skills (Soundararajan & Singh, 2017). Therefore, this dissertation follows the camp of Bassi (2015), Kapoor and Kabra (2014), Edwards & Edwards (2019), Waters et al. (2019) that the skills must be housed within the HR professional. Proponents for external purveyors of numeracy acknowledge limitations in obtaining HR professional buy-in and, subsequently, firm buy-in because the HR professional did not achieve the same level of insight as the statistician (Simón and Ferreiro, 2018).

H3: Numeracy will be positively related to decision-making accuracy.

3.1.4 Software Literacy and Numeracy

The ability to mobilize data is enhanced by the HR professional's ability to master the application tools that house, manage, and facilitate numeracy (Alletta & Comb, 2020; Ulrich et al., 2012; Lunsford & Phillips, 2018). The utilization of software tools strengthens the relationship to decision-making accuracy by aiding, and in some cases, performing the numeracy process on behalf of the HR professional. Some programs go as far as to recommend solutions (Holsapple et al., 2014; Eubanks, 2019). Such tools for the HR professional take the form of software/cloudware that performs basic data management functions, advanced functions performing statistical analysis, and other compelling features such as creating visualizations to support the data-analysis output. The ability of software to perform numeracy processes, develop visual aids, and simplify data in the hands of the HR professional, means they now have a crutch to lean on for the formidable numeracy competency (Lunsford & Phillips, 2018; Eubanks, 2019). The software automates many numeric functions and performs complex analysis, reducing human error and easing the cognitive burden. Further, the visualization function aids the professional's ability to digest data and make sense of the information (Alverson & Yamamoto, 2016).

However, the software requires its own literacy in return. Even with user-friendly graphical user interfaces, the professional may need to understand the data hierarchy to produce the desired software output (Lunsford & Phillips, 2018). Some emergent and boutique programs have predictive and prescriptive outcomes but require a minimum of the user to understand what is being sought in the data (Eubanks, 2019). However, more common programs that will perform an analysis require the professional to identify the statistical tool for proper analysis and understand the statistical output. HR adoption of analytic software tools has proven challenging and not universal (Vargas et al., 2017). Therefore, this research incorporates software literacy related to increased numeracy competence in the specific context of AC (Lunsford & Phillips, 2018; Eubanks, 2019).

H4: Software literacy will positively moderate the relationship between numeracy and decision-making accuracy.

3.1.5 Critical Evaluation and Decision-Making Accuracy

A holistic model is not complete without consideration for meta-competence. The HR AC Cluster incorporates critical evaluation competency as an ability to evaluate one's problem-solving process and evolve in their practice. Literature informs us that we learn from the consequences of our decisions through observation and behavior and increase our decision-making accuracy with this learning process (Paul & Fehr, 2014). This dissertation proposes that the AC needs a learning mechanism to flourish. Data-process models suggest analytics is a buildable skill that grows in maturity. Critical evaluation is an ability to mature skills, an internal mechanism where one understands what they need to work on, learn from their experiences, and improve future tasks and decisions. Limited literature about HR AC regarding critical evaluation is available, which was not a well-established dimension before this research.

Consequently, additional evidence is provided from the decision science literature to support the relationships and function of this competency in decision-making. After-action reviews are a tool for aiding a person in processing a decision in retrospect, understanding the efficacy, and brainstorming better alternatives in the future (Tannebaum & Cerasoli, 2013). The research on after-action reviews, like critical evaluation, requires earnestly assessing their process, actions, and results and determining improvement opportunities. The after-action review expects the individual to implement what was learned from the review or evaluation. Tannebaum and Cerasoli (2013) demonstrated that those who effectively utilized after-action reviews increased decision-making performance. Therefore, it is reasonable to find that those who demonstrate the meta-competency of critical evaluation will also improve decision-making accuracy.

H5: Critical evaluation will have a direct positive relationship with decision-making accuracy.

3.1.6 Persuasion and Job Performance

Persuasion. In analytic process models, persuasion skills are utilized after the HR professional has come to a decision or recommendation. That decision or recommendation has to be presented to other stakeholders for buy-in to ensure the firm supports the action the HR professional plans to pursue. This competency is distinctive from the other competencies that are a priori to decision-making but is considered a vital part of the analytic process and professional performance. Therefore, the persuasion construct is uniquely related to performance, not decision-making.

In addition to the relationship, this dissertation also contends that specific faucets of persuasion are expected to increase performance. HR literature suggests that rational, consultation, coalition, and the inspirational appeal of Persuasion are expected to enhance job performance. Persuasion emulates desired skills in selling

HR solutions to the broader organization: bring an evidence-based approach in the presentation; utilizing stakeholder hypothesis to build the argument; storytelling and visualization for both aesthetic and sensing appeal; and utilizing one's knowledge of the audience and culture to tailor the recommendation and gain buy-in. Although Plouffe et al. (2016) found evidence for different persuasion features for increased job performance, their research was conducted on sales professionals; a profession with an external customer target audience versus HR's internal organizational leadership audience. Further, HR professionals are known for their social and empathetic skills and contributions (Welch & Welch, 2012). The descriptors of persuasion significant in sales performance (e.g., hard tactics such as the pressure) oppose HR professional appealing characteristics. Such hard tactics could create a cacophony in the audience's view and dissonance with the HR professional's constitution. Whereas the rational, consultation, coalition, and inspirational appeal characteristics will be expected to support HR performance. Therefore, the relative hypothesis-

H6: Persuasion will have a direct positive impact on job performance.

Self-Efficacy as a Mediator between Competencies and Accuracy. Self-efficacy or confidence in decisions is derived from one's belief that one can succeed at a given task. Competencies provide the HR professional the means to perform the job or successfully achieve the tasks. Concurrently, the psyche's role in self-regulating the decision process should also be considered (Bandura, 1997).

Bandura (1997; 1977) defends this self-regulated function of self-efficacy impacts all variables on task performance. Those with low self-efficacy possess negative thoughts about their ability to perform the task and achieve personal development (Srinivasan & Jomon, 2018). Meanwhile, those with high self-efficacy pursue higher-order goals and embrace highly challenging tasks (Srinivasan & Jomon, 2018; Bandura, 1997). Higher confidence means the professional will not second guess and waiver on their decisions. When professionals lack confidence in making decisions, the decision-making accuracy is expected to diminish partly. When a professional is confident, decision-making accuracy is expected to increase partially (Bandura, 1997). Admittedly, previous generalized research has demonstrated the limited impact of self-efficacy in complex decisions (Judge et al., 2007). However, focused study in HR and analytics indicates self-efficacy is an influential factor; the self-regulating function of the individual psyche significantly impacts HR analytic software adoption (Vargas et al., 2018). Further, self-efficacy inclusion is supported in the literature that defends the impact of critical psychological states on job performance, meaning how we feel about ourselves, the work, and our environment impact our job performance (Hackman & Oldham, 1976; Siengthai & Pila-Ngarm, 2016). The hypotheses follow proponents for self-efficacy in job performance modeling and recommended mediating paths from the competency variables to job performance, in this case, accurate decision-making (Bandura, 1997; Vargas et al., 2018; Srinivasan & Jomon, 2018). In the research model, three variables directly impact decision-making - Logic, Numeracy, and Critical evaluation. In support of the Bandura (1997) modeling guidance, these three competencies associated with job performance should have a mediating relationship.

H7: Self-efficacy mediates the relationship between logic and decision-making accuracy.

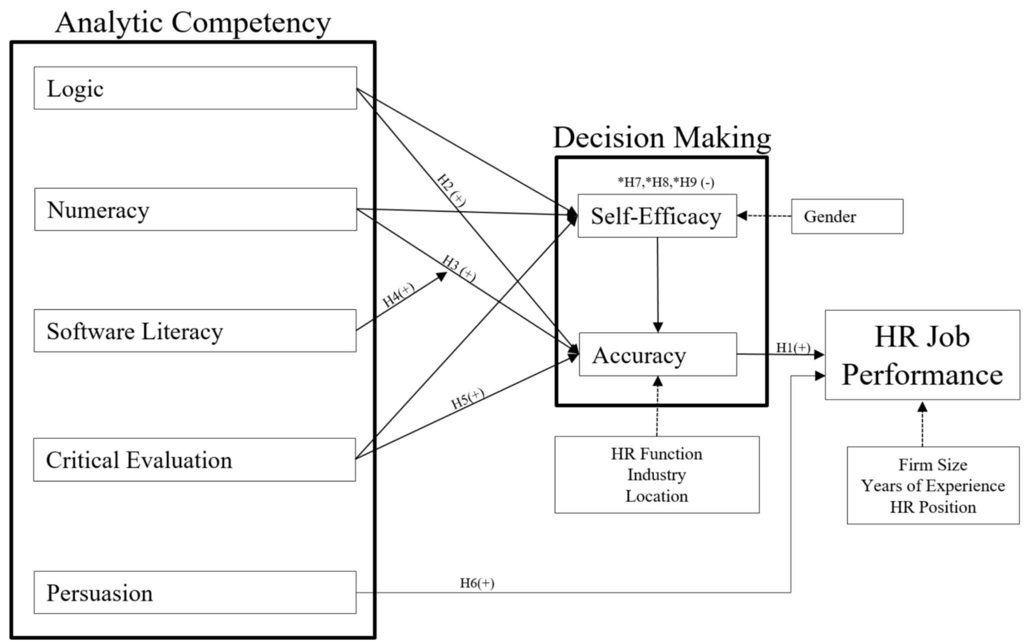
H8: Self-efficacy mediates the relationship between numeracy and decision-making accuracy.

H9: Self-efficacy mediates the relationship between critical evaluation and decision-making accuracy.

The hypotheses are depicted in the research model in Figure 7.

Figure 7

Research Hypothesis Model



Note: * denotes a partial mediating relationship between competencies and decision-making accuracy

3.1.7 AC Composition

The analytics literature consistently points to logic and numeracy as driving constructs in analytics (Fitz-enz, 2010). The other constructs of software literacy, critical evaluation, and persuasion were not as inclusive in the research or always present among the KSAO demands. The expectation is that logic and numeracy will have a more considerable impact on the decision-making, contrary to Fitz-Enz and Mattox (2014) estimates. The analytic processes are built on solid problem-solving methods and computational data analysis to develop data-driven solutions.

In Fitz-Enz's own words, these two competencies are the "art and science" that is analytics. The other competencies providing supportive abilities to drive the decision and desired outcomes. The expectation in this hypothesis is no different; the prominent competencies or main ingredients in analytics literature - logic and numeracy - should expect higher composition when utilized in the context of decision-making.

H10: Logic and numeracy competencies will be stronger predictors of decision-making than software literacy, persuasion, and critical evaluation competencies.

3.1.8 Control Variables

The model also includes control variables identified throughout the literature as influential to decision-making self-efficacy, decision-making accuracy, and job performance. For decision-making self-efficacy, the control of gender was determined based on the results of Vargas et al. (2017), Bandura (1977), Bandura, 1982, and Talukder and Quazi (2011); in these studies, females were limited by their own beliefs they could master skills such as data analysis and subsequently lower scores on research variables.

Decision-making accuracy research includes several control variables. First, a defense of a variable not included – Business Acumen. Although Coetzer and Sitlington (2013) suggest the inclusion of Business Acumen in future competency modeling studies with analytics, Kryscynski et al. (2017) assessment in HR-specific competency analysis proved otherwise. Kryscynski et al.'s (2017) assessment of business acumen was inefficient for additional modeling; the EFA cutoff score had to be reduced below standard cutoffs to have a measurable result and was negligible in the contribution to the performance assessment. This study will not incorporate business acumen because of the limited effects in the literature on the AC cluster.

This research then assessed other variables and found them applicable for inclusion. Whether the HR professional is a talent recruiter, HRBP, compensation analyst, etc., impacts the complexity of problems the professional is exposed to and expected to solve within the organization. Kryscynski et al. (2017) found a significant difference between HR function and performance, exemplifying compensation roles as having higher analytic presentation, evidence that the HR function is an important control. The HR function control is modeled onto decision-making, the variable expected to be influenced by the presentation of AC (Kryscynski et al., 2018). Further, the functional title of Information Systems, Technology, & Analytics will be of interest given the debate on the specificity of this cluster in this emergent HR function. In addition to function, the organization's culture and values are social constructs that influence decision-making accuracy (Van Der Westhuizen et al., 2012). Given that culture and value influences are both geographic and business-specific (Nori et al., 2017), the firm location and industry are proxy controls.

At last, the controls on HR performance are included to ensure a robust model. (Ulrich et al., 2015; Han et al., 2006; Voermans & van Veldhoven, 2007). First, this research must address other non-analytic competencies. Kryscynski et al. (2017) and Boyatzis (1982) address the robust nature of competencies by identifying only those that may overlap and confound the results of the specific competency of interest in assessing a focused competency group. Research contending soft skills, notably change agency, are a significant competency to HR performance, and more so in some international environments and certain HR functions (e.g., HR Business Partners need more change management skills than HRIS specialists). However, given the opposing nature of these competencies, they are not expected to bias the results and work as confounding variables to the outcome of this research (Kryscynski et al., 2017; Creswell, 2014). Therefore, this research continues with the focused competency set on HR analytics. Control variables include individual demographic factors such as years of experience and role level (Gerhart & Rynes, 2003). Firm size is an influential factor of compensation (Gerhart & Rynes, 2003), and because compensation data will measure HR job performance, firm size is also included.

3.2 Instrumentation

This research method closes a gap in competency modeling behavior by assessing the identified competencies on decision-making and job performance dependent variables. Based on suggestions by Soundararajan and Singh (2017), the following research questions drove this research methodology:

1. *What* analytic competencies drive higher job performance for HR professionals?
2. *How* do these analytic competencies drive higher job performance for HR professionals?

The competency constructs had to be identified either from previous research or developed. Given a novel AC model, most had to be developed. The process for each construct is summarized along with robustness checks. This research utilized SEM to measure and assess the competencies since they are latent constructs. Likewise, the pilot and main study rollout and the data collection process are detailed. The analysis process is summarized- organized first on the measurement model and then the structural model where the path estimates are formed. Finally, the research on the mediation and moderation processes are outlined. Appendices A through I provide the survey instruments utilized for each construct.

3.2.1 Competency Instruments

Logic. A complete cognitive measure aligned with the competency was not prevalent in the literature review. However, Kryscynski et al. (2017) identified two items loaded high onto logic from the LAMP framework. These two questions did not encompass the importance of generating insights as informed by the literature and fall short of the minimal items for latent construct measurement (Ulrich et al., 2021a, 2021b; Soundararajan & Singh, 2017; El-Den et al., 2020). Additional items added to encapsulate the ability to generate insights were edited through an expert panel review, pilot processing, and subsequent loading. The final instrument is a 3-item, 7-point Likert Scale.

Numeracy. A validated test that assesses probability had already been developed by (Cokely et al., 2012). The Berlin numeracy test for competence (BNT-C) provided numeracy from a statistical dimension not previously available (Cokely et al., 2012). However, the Berlin numeracy instrument does not follow the same reflective approach El-Den et al. (2010) recommended. El-Den et al.'s (2010) recommendation is consistent with the other identified measurements. Further, the construct should encompass the progressive nature of numeracy as defined in data-driven models. Therefore, items were developed informed by the literature and subject to Almanasreh et al.'s (2006) content validity process. One of the items was found insignificant of the four developed through the pilot process and was dropped. The final instrument is a 3-item, 7-point Likert scale.

Critical evaluation. The research lacks inclusivity of meta-competence, so the fact that critical evaluation had not been previously assessed was no surprise. In addition, research outside of HR often utilized AI simulation, which would not help understand HR professional utilization. Therefore, items were developed as informed by the literature (El-Den et al., 2020). Again, similar to logic and numeracy, the expert panel and pilot process were utilized to refine and select the final instrument construct, a 3-item, 7-point Likert Scale.

Software literacy. Lunsford and Phillips (2018) had performed a preparatory study for future researchers on HR software uses and functionality. The resulting software categories and types were incorporated into a proficiency scale. Given the similar question construction to self-efficacy items and the most precise response measure, the Bandura (2006) 0–100 point sliding scale was utilized in place of a Likert scale. Due to the work of Lunsford and Phillip (2018) to define the types of HR software and proficiencies no reliability and validity tests were conducted.

Persuasion. Plouffe et al. (2016) described and validated the value of persuasion internal to the firm, establishing nine common tactics. Of those tactics, only rational persuasion, inspirational appeals, consultations, and coalition tactics are implicated in HR literature and included in the AC competency instrument pilot.

Additionally, the inspirational appeal construct was modified to emphasize language from the literature review regarding storytelling (Falletta & Combs, 2020; Soundararajan & Singh, 2017; Fitz-Enz & Mattox, 2014). The introductory summary was also modified for HR context (e.g., instead of a sales setting, the introduction asks respondents to answer the questions from the perspective of an HR work environment). The only sufficiently loaded items were from the inspirational appeal tactic during the pilot study. The final instrument in the main study was a 4-item, 5-point Likert scale for persuasion based on the inspirational appeal tactics or behaviors used within an organization.

3.2.2 Decision-Making

Decision-Making Accuracy. Following Boyatzis' (1982) model for effective specific actions or, in this case, the decisions for action, the organizational environment, and the job demands needed to be simulated. The ideal measurement is an SJT because they are decision accuracy assessments, are tailored for work-related scenarios, and require utilizing the KSAOs desired by an applicant. SJTs have been a prominent source of decision judgment in industrial and organizational psychology because they exhibit strong criterion-related validities and smaller racial and sex subgroup differences (Ployhart & MacKenzie, 2011). SJTs are utilized extensively in SHRM competency testing (SHRM, 2015).

Further, SJTs measure several different constructs, making them multidimensional measurement methods (Ployhart & MacKenzie, 2011). Christian et al.'s (2010) meta-analysis of SJTs for criterion-related validity demonstrated high validity. SJTs are typically developed through a three-part process: 1) situation generation, 2) response option generation, and 3) scoring. The process is completed with subject matter experts, job experts, and supervisors to create an accurate occupational test. As of 2021, SHRM utilizes SJTs for its certification program because of their validity to demonstrate professional performance (SHRM, n.d.). The certification programs are growing in demand, and certification is positively related to salary, experience, education level, and job title (Bayer & Lyons, 2020). Per Ployhart and MacKenzie's (2011) guidelines, the SJTs for this study were made with HR managers and executive leaders in the HR field. The use of SMEs to develop the criterion for job requirements was validated with Weekley et al. (2019), and the accuracy of such SME judgments were high. To ensure validity, the SMEs identified for the SJT review are managers in the field who know the job extremely well and significant moderators of SME accuracy (Weekley et al., 2019). The instrument consists of three situational summaries and eight multiple-choice answer questions. The questions were derived from prepared SHRM certification practice tests and HR practice problems in Waters et al. (2019) and Edwards and Edwards (2019).

Decision-Making Self-Efficacy. Bandura (2006) states that self-efficacy measurements should be specific to the construct the individual's confidence is being assessed. Bandura (2006) is a strong proponent of responding to confidence on a 100-point scale. This research follows Bandura (2006) prescriptively, modifying a self-efficacy instrument for problem-solving provided as an example in the text. Instead, the respondents were asked about their confidence in solving HR problems. The confidence scale items reflect the number of SJTs the respondent appraises they can answer correctly. Eight items were generated, corresponding to the number of SJT questions.

3.2.3 Job Performance

Job performance has been measured in several different ways in the literature. HRCS utilized 360 reviews to assess individual job performance (Ulrich et al., 2012; Kryscynski et al., 2017). The 360 review is complex to administer because the review process needs the dyad of the individual and the supervisor, peers, and subordinates (Ulrich et al., 2012). The alternative is another subjective measure: the employees' perceived performance and efficacy (Vargas et al., 2018). However, the industrial researcher takes a more simplistic approach to gather and analyzing performance and compensation data. Commonly known as salary surveys, these industrial tools are utilized to inform compensation and merit programs (Willis, n.d.). The performance data is based on company-initiated performance reviews. Professional affiliations and research departments use salary surveys trend practices and find consistency across industrial research agencies and results regarding merit increases, performance, and the relationship between pay and performance (SHRM, 2020).

Performance Reviews. An overwhelming majority of US workers receive performance reviews (Cappeli & Conyon, 2016). Although subjective as the 360 review, the functional and informative performance review is positively related to merit pay and bonuses, promotions, demotions, dismissals, and quits (Fisk, 2016). Organizations are interested in moving away from the annual reviews and are transitioning to frequent informal feedback. The staying power of yearly performance appraisals can be attributed to organizational concerns for manager capabilities: the ability to commit the time for more frequent feedback; the desire to avoid tough performance conversations if not formally required; ability to provide effective frequent feedback; and concerns for lack of commitment and seriousness to the alternative (Lake & Luong, 2016). Salary surveys assess annual performance reviews based on a generic scale with the following ratings: below average, average, above average, and highest possible (SHRM, 2020), consistent with standard industrial performance scales. The instrument will include 2-items on performance based on the generalized SHRM scale (2020). SHRM has also utilized supervisor performance data to support competency assessment (SHRM, 2015).

Merit Compensation. Merit- or performance-based systems were designed to recognize competency-based performance (Spencer & Spencer, 1993). This dissertation assessed an alternative variable, merit increases, to measure performance (Helm et al., 2007). Merit increases prove to be an adequate proxy because of the solid and consistent relationship with employee performance (Helm et al., 2007; Panjaitan et al., 2020; Rodjam et al., 2020). The use of merit increases aligns with the logic that the firm has a system that measures the performance and a compensation system that rewards the performance (Fisher et al., 2005). Subsequently, the merit plan is usually based on individual performance appraisal (Rynes et al., 2005; Schwab & Olson, 1990). SHRM's (2020) annual compensation reporting provides a snapshot of the current merit behavior and relationship to performance. Industrial research organizations agree that merit increase behavior has been consistent in recent years. The mean employee increase for 2020 was 2.7% and is expected to be the same for 2021. The budgeted increase per person for 2020 was a mean of 2.9% and median of 3.0%. The merit increases for 2020 are slightly lower than anticipated, and industrial analysis contributes this dip due to the COVID-19 pandemic. The budgeted merit forecast for 2021 is 3.0% for the median quartile, 2.5% for the lower quartile, and 3.0% for the 75th quartile. Merit increases are significantly related to performance, and on average, high performers in 2020 received an increase of 3.6%, middle performers of 2.5%, and low performers of 0.6% increase (SHRM, 2020; Park & Sturman, 2016). The SHRM (2020) analysis suggests that company size is influential and should be controlled when utilizing compensation data.

Given the applicable HR professional data on performance and measures, this dissertation includes perceived performance and merit reporting to measure job performance. The language for the questions are based on salary survey standards, which are especially familiar to HR professionals. In addition to the two performance questions, respondents will be asked a third item, their 2020 merit increase. The final study results did not utilize this response because not enough participants completed the question. The rationale for this response behavior is discussed in Chapter 5.

3.3 Data Collection

3.3.1 Pilot Testing

The first step was to conduct a preliminary evaluation of the original constructs by an expert panel for content validity analysis. Content validity methods followed Almanasreh et al.'s (2006) guidance, developed based on the current research and theory. Next, the researcher conducted the judgment and quantifying step, making revisions based on feedback. The content validity index (CVI) is one of the most widely utilized methods to validate original constructs. The results of the panel review were assessed against the CVI threshold of .78 based on the Polit et al. (2007) approach. The researcher utilized an expert panel of five HR executives and high-level managers. The panel represented varying areas of HR: organization development, compensation, business partners, HR systems, and talent acquisition. All the panelists held bachelor's degrees or higher, and two held doctoral-level degrees. Four of the panelists were female, and one was male. The original logic construct had a CVI of .80, and numeracy and critical evaluation had a perfect index of 1.0. Therefore, the original constructs met the threshold for further pilot processing. During the multi-tiered piloting process, the panel was reconvened to assess necessary edits due to low factor loading. CVI scores remained unchanged in the second review.

Creswell (2014) explained that pilot testing is vital for obtaining content validity and improving the instrument. The pilot participants needed to resemble the sample population such that the feedback would reflect the population's experience. This research intends to understand HR professional AC on decision-making and performance. The participants had to be intentionally sought to represent the population of interest, the HR professional actively working in an HR role within a firm. The researcher deliberately sought out all types of HR professionals from all levels within the organization (e.g., entry-level up to executive professional). This broad approach is due to the mixed research results about who performs decision-making as a significant part of functional HR job tasks. An HR professional is a person currently working at an organization conducting human resource management for most of their work responsibilities.

The researcher sought pilot participants through South Florida regional businesses, SHRM chapter outreach, LinkedIn network, and the researcher's employer for availability for post-pilot interviews. The researcher did not request the participation of her direct reporting employees to prevent any conflict of interest, since the researcher assesses the employees' performance. Post-pilot qualitative questions and interviews with respondents were utilized to ensure the survey instrument was clear. Any ambiguity was addressed during the pilot process to ensure the administration of the instrument was without variability in response interpretation (Creswell, 2014). During the pilot, improvements were identified, and revisions were made and incorporated into the final instrument rollout. Participant feedback was predominately positive with minimal changes, except the requests for larger charts in the SJTs to make them easier to read.

Sample power is an essential consideration because adequate power contributes to the accuracy of the relationship output in the analysis (Wolf et al., 2013). The minimal statistical power for achieving an accurate result is 80% (Cohen, 1988). SEM approach is considered a large sample demand process (Kline, 2016). If the sample is too small, issues can occur, such as estimation convergence failure, and inaccurate parameter estimates and model fit statistics (Wang & Wang, 2012). Determining the main sample size is more complex with latent variables because of the desire to prevent both type I and II errors. The number of variables in the model are the basis for the guidelines (Tanaka, 1987). The Soper (2021) a priori calculation was used to achieve a minimum 80% statistical power with SEM. The a priori calculation incorporated six latent variables, 26 observed variables, a medium effect size of .3, and a significance level of .05 with an output minimum sample of 161. An RMSEA power analysis with the final model degrees of freedom of 96, N=161, and a significance threshold of .05, resulted in a power of 88%, meeting the desired threshold of 80% (Jak et al., 2020; Kline, 2016). The researcher obtained exactly 161 completed surveys, an acceptable threshold for CFA and SEM analysis. According to Baker (1994), the appropriate pilot sample is 10–20% of the main sample size. However, a minimum recommendation of 50 for EFA ensures adequate power (Jackson et al., 2013;

Baker, 1994). The first pilot was short of the desired number, with 30 participants. However, valuable feedback was incorporated into the instrument constructs, and the latent constructs were re-piloted to ensure the viability of the instrument. The second pilot utilized a purchased convenience sample of HR professionals, like the process for the main study and further described in main study methods. Fifty-five total respondents were obtained for the final pilot review, meeting the power threshold.

Pilot Analysis. An exploratory factor analysis (EFA) was performed to ensure the fitness of the constructs, assess common method bias, and validate construction alignment for the newly developed instruments (Podaskoff et al., 2003). The analysis was conducted in SPSS v. 27. The initial results indicated the critical evaluation competency instrument had an item more associated with numeracy, likely due to the inclusion of the word "measures" in the item, based on the review with pilot participants. The critical evaluation item was revised to focus on the evaluation aspect of the competency. The logic competency did not present the desired loading, and questions were refined in more specific and direct terms of inquiry and insight. Likewise, the critical evaluation construct did not meet the minimum requirements for a latent construct, 3-items with a loading of 0.70 or higher. The items that did not load were removed, and new items were generated based on the literature. The second pilot phase EFA results supported construct utilization; the factor loads for each construct were more significant than 0.70 with a range of 0.744 – 0.916. Supportive of the new constructs, no common-method bias was identified. The pilot unrotated had no single factor loading greater than 50%, the highest single factor accounting for 45.47% of the variance (Podaskoff et al., 2003). However, the second pilot introduced a new finding, the Eigenvalue threshold of one (Kaiser, 1960), which resulted in only two constructs and not three as was produced in the first pilot; logic and numeracy items loaded together while critical evaluation loaded separately. Waldeck et al. (2021) addressed overlapping constructs and when they should be maintained, suggesting that the constructs have unique contributions to the study to sustain separate constructs despite Eigenvalue loading. Like Waldeck et al.'s (2021) argument, the latent items in this study bring unique value, in this case, functional and cognitive dimensions of competence. As a result, this study continued with separate latent constructs in the model assessments. However, the final model analysis includes both convergent and individual construct model results for a robustness check.

The persuasion construct was also included in the EFA analysis during the pilot, even though it was previously validated. The robustness check ensured that the variation in participant occupation did not impact the construct reliability. Two of the construct items did not load as expected during the assessment. One item in the Coalition construct had an inadequate factor loading (.161) for the Coalition construct. Upon reviewing the Coalition item with pilot participants, the word *influence* or *influencer,* which was included in the item, is the likely source of the change in loading. Since the Plouffe et al. (2016) publishing influencer has rapidly become a term for narrative- and entertainment-based persuasion in social media (Breves et al., 2019), and consequently conflated the constructs in the initial pilot, the word *influence* was changed to *convince* to prevent a mis-association with other persuasion methods.

Finally, the item "Describe how my solution could serve as an opportunity to accomplish exciting and worthwhile objectives" did not load adequately (.157). Pilot participants were interviewed to understand their interpretation of the construct. The item was revised to elicit a more illustrative interpretation versus factual, as was interpreted from HR professional perspective. The revised wording is "Create a depiction of how my solution serves as an opportunity to accomplish exciting and worthwhile objectives."

3.3.2 Main Study Collection

Sampling Methods. This research seeks a population with particular characteristics: HR professionals who currently work in the discipline. Other HR competency studies have used non-probable convenience sampling and snowball techniques to capture this specific population (Ulrich et al., 2012; Ulrich et al., 2021a; Kryscynski et al., 2017). Bornstein et al. (2013) discussed the limitations of convenience sampling, including lack of generalizability and ability to detect subpopulations beyond the study sample but also recognized convenience sampling as the most common form due to the participant availability and prohibitive nature of probability sampling as is in this study case. To reduce sample bias, quotas were required in the purchased response for geographic distribution across the US, and the respondents were of homogeneous occupation (Jager et al., 2017). Non-response bias was assessed by comparing early to late respondents in an ANOVA (Linder et al., 2001; Miller & Smith, 1983). There was no significant difference in response behavior ($p = 1.0$). Further, two bogus questions were included as a screening tool to prevent careless responses. Those who did not respond or did so with the incorrect response were screened out (Meade & Craig, 2012). The sample population was compared to research on HR work distribution to assess any differences in panel response. The panel results are less experienced than the McLean and Co (2021) trend report. However, distribution across occupational roles was consistent with demographic reporting (Ulrich et al., 2021).

The instrument was digitized on the Qualtrics platform for Internet administration (Oztimurlenk, 2021). Several advantages exist for online surveys: convenience, rapid data collection, cost-effectiveness, ample time for respondents, easy follow-up, confidentiality, security, availability of specialized populations, support complexity, and visual aids (Rea & Parker, 2014). Disadvantages include a limited response base, self-selection, and lack of interview involvement (Rea & Parker, 2014). Qualtrics' digital administration provides mechanisms to prevent data loss and transcription issues. Qualtrics exports into Excel and CSV files, which are helpful for immediate processing. The purchase responses from

Qualtrics pre-recruited HR panel are a viable option to incorporate a quasi-probability sampling in an open population (Sue & Ritter, 2012). Online surveys allow for a broader geographic distribution (Sue & Ritter, 2012). The Qualtrics panel is considered a prolific tool for business research (Spencer, 2019). Lowry et al. (2016) made the case that such tools as online purchases panels (to include Qualtrics) have substantive value to support research outreach and present similar risks as traditional paper and pen methods. Similarly, Smith et al. (2015) found that such commercial tools are helpful when researching hard-to-reach populations.

The research was partially funded through scholarships from Phi Kappa Phi and Delta Mu Delta honor society scholars totaling $1,000. The rest of the purchase cost was paid for by the researcher.

COVID-19 Implications. The COVID-19 pandemic caused global economic and labor shifts. The implications for this study focus on the potential impact of merit compensation, given the economic influence on the variable. Although expected to be lower, the merit compensation was still expected to be an indicator of performance. To ensure consistency and avoid convoluting merit responses between years, respondents were asked to speak specifically to their 2020 merit increase rather than their most recent yearly increase to control for COVID influences on compensation. This method kept all responses directed to the same year, such that a respondent did not include alternative years that may have had higher compensation adjustments. Performance rating data, to date, does not indicate any divergence from non-COVID periods (SHRM, 2020). However, to ensure consistency, participants were asked to respond based on their 2020 performance cycle to ensure perceived performance responses were based on the same time frame as the merit response.

As a result of the pandemic for HR professionals, another issue also reported by the Qualtrics administrator was survey fatigue and increased stress (McLean & Company, 2021). During the pandemic, an increase in survey demand for HR professionals regarding practices and policies diminished their desire to participate in additional research. They also endured greater workloads and stress in responding to changes in talent demands and policy requirements (McLean & Company, 2021).

3.3.3 Data Preparation

Upon completing the survey administration period for the main study, the data was gathered and cleaned for further analysis. The data was assessed in SPSS v. 27 for any missing data utilizing the frequency function. The results were ideal with <1% missing data, less than the 10% threshold of missing data to prevent bias (Gaskin, 2021) on all questions except about merit (10.5%). Compensation disclosure can break a social norm (Rosenfeld, 2017). The alternative measure, the annual performance review, was used in lieu of the merit question to prevent a response bias. The secondary measure was included due to concern for response behavior. In all other cases, responses with missing data were omitted to avoid bias. Outliers are not feasible for the instruments since they are predominantly Likert scales (Gaskin, 2021). The desired N = 161 for statistical power was met with precisely 161 complete responses. The only survey item that posed a concern regarded merit compensation, and due to response omission, the item was not utilized in the final analysis. Normality checks included performance item skewness and kurtosis checks for normal distribution. Skewness between -1 and 1 is considered adequate (Gaskin, 2021). The kurtosis threshold, less than three times the standard error, was set for outlier impact on distribution (Sposito et al., 1983). The skewness was within an adequate range at .158. At .232, the kurtosis was less than three times the standard error of .381.

Chapter 4

Findings

The analysis starts with data collection, followed by an assessment of the measurement model, and concludes with the structural model assessment. Each step builds into an acceptance review of each hypothesis. Post-hoc hypotheses and model development are included as a result of the structural model assessment. A summary chart of method, findings, and rationale can be found in Appendix N.

4.1 Preliminary Analyses

The research methods included parameters to obtain the optimal sample feasible given the difficulty in measuring the population and getting a representative sample. The sample demographics follow the same trends as the available workforce; the largest representation of available employees was ages 25–35 (Census Bureau, 2020), which corresponds to the years of experience for early-career HR professionals as a higher representation in the sample. Albeit, late-career respondent representation was anticipated to be higher, the decline is likely due to respondent age and the online format being least favorable for the older demographic (Brosnan et al., 2019).

Table 4

Sample Demographics

Variable	**Category**	**Frequency**
Gender	Male	72
	Female	89
Position	Support, nonexempt	7
	Entry-Level Professional, exempt	10
	Intermediate or Experienced Professional, exempt	35
	Advanced or Expert Professional, exempt	37
	Supervisor or Low-Level Management	14
	Middle Management	32
	Executive or Senior Level Management	26
HR Function	Generalist	59
	HR Business Partner	12
	HR Strategic Partner	31
	Talent Acquisition	19
	Organizational and Employee Development	23
	Total Rewards (Benefits and/or Compensation	4
	Inclusion, Diversity, & Engagement	4
	Labor Relations	6
	Information Systems, Technology, and Analytics	3
Years of Experience	0 – 5 years	59
	6 – 10 years	60
	11 – 15 years	21
	16 – 20 years	8
	21 – 25 years	5
	> 25 years	8

As a comparison point, the most recent HRCS roles and tenure results are compared to the sample population. HRCS uses convenience and snowball sampling; however, its sample is large, with 3,549 assessed HR professionals (Wright et al., 2021). The HRCS 360 methodology includes reviews of subordinates, resulting in over sampling of managerial roles, which may explain some of the difference in population representation, HRCS having a more extensive senior management and later tenured distribution.

In the study sample, the high representation of early career, 74% of the population between 0-10 years of service, aligns with a high representation of entry-level individual contributors and decreased representation of high-level positions in senior and executive management, 16%. The lower representation of senior positions was expected as senior-level positions are associated with higher tenure. The representation in the dissertation sample better aligns with organizational structure frequency than the HRCS study (i.e., the average HR leader is responsible for four individual contributors resulting in a higher demand for lower-level and consequently lower tenured individuals) (OrgVue, 2019). Conversely, HRCS representation of those in 0-10 years of service is 29% of the sample. The study sample's generalizability on tenure was assessed against the snap-shot data from the Bureau of Labor Statistics (BLS). The BLS Beta Labs (2021) provides information on the worker's characteristic experience in days of prior work experience by percentiles. The average work experience for an HR-exempt individual is just 4.3 years[3] and is a more prominent representation of the population with BLS reporting 674,800 jobs (71% of the BLS HR population[4]). HR manager (generalized title for HR managerial roles at all levels) average tenure is 10.5 years of experience, and HR leadership roles account for 161,700 jobs (17% of the BLS HR population) (BLS, 2021). Although the sample for the dissertation study does not align well with HRCS, the representation more closely represents the HR population, yet still over samples management and higher experienced individuals, as presented in Figure 8. Therefore, the researcher argues that the sample resembles the population more closely than previously accepted HR competency research and has more external validity.

[3] Calculated year equivalence of days based on the 2050 hours work year and a standard 8-hour work day.
[4] Population is consistent of the BLS occupations for human resource specialist, manager, and assistant.

Table 5

Population Position and Experience Comparisons

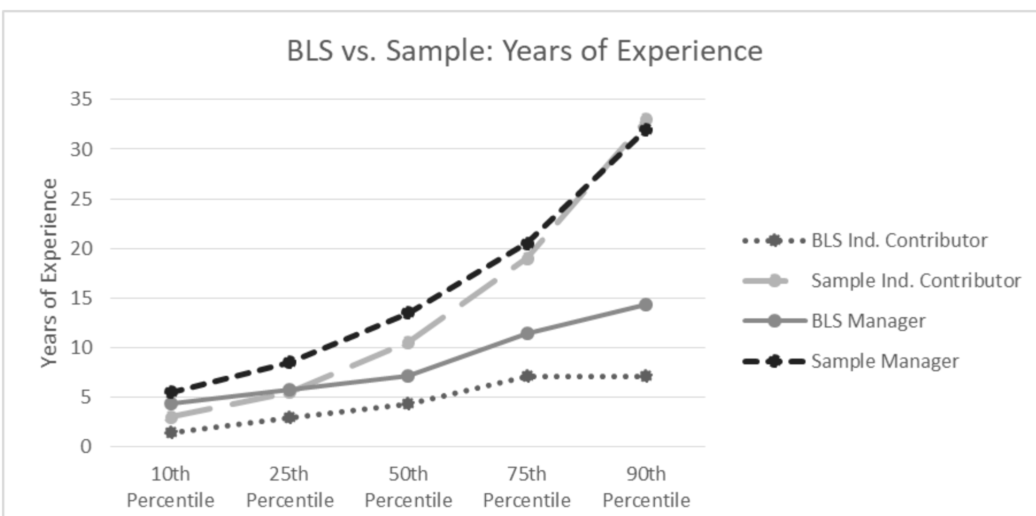
HRCS Position and Experience Comparison

Experience	Sample Percent	HRCS Percent
0–5 years	37	11
6–10 years	37	18
11–15 years	13	23
16–20 years	5	20
21–25 years	3	14
>25 years	5	14

Position	Sample Percent	HRCS Percent
Executive or Senior Level Management	16	37
Manager or Senior Technical Professional	52	33
Professional or Individual Contributor	28	25
Other	4	5

Figure 8

BLS Years of Experience Comparison



4.2 Measurement Model Assessment

Measures were implemented for each latent construct of competency, decision-making accuracy, decision-making self-efficacy, and HR job performance. Construct development summaries are provided in the instrumentation section, and the instruments are provided in Appendices A–I. El Den et al.'s (2020) guidance on using reflective indicators, a research and theory-driven development process when a new construct was needed, and methodical item generation were consulted and utilized when new items were needed. The software literacy, self-efficacy, and dependent variables decision-making and job performance were also informed by earlier literature and previously developed constructs.

Assumptions. Structural Equation Modeling combines confirmatory factor analysis and structural regression analysis of latent and observed variables. The assumptions of SEM were assessed as part of the data preparation and measurement model assessment. The first assumption is that SEM requires a large sample size. There are several rules of thumb about sample size including ratio of sample size to number of parameters (20:1, 10:1 and 5:1), a target sample size of 200 for SEM research, and power analysis (Kline, 2016). The researcher used a more specific quantitative method in conducting a power analysis to determine the sample size for this study, as recommended by emergent literature (Kline, 2016; Soper, 2021; Jak et al., 2020). As noted in the pilot testing, the a priori power analysis and an RMSEA analysis were conducted to ensure the sample size was adequate. The minimum samples size for the power analysis of 161 was met.

Second, SEM assumes no missing data, which was addressed in the data-preparation process. Third, SEM assumes that three or more observed variables are used to measure each latent variable. Each of the latent variables used in this study were measured using three or more observed variables.

The main statistical assumption for SEM- is multivariate normality of the variables. Mardia's coefficients was utilized to assess multivariate normality and the results did not violate normality assessments (p values > .05). Additionally, each variable was assessed for normality using measures of skewness and kurtosis. As summarized in the data-preparation section skewness and kurtosis checks were performed and met normality thresholds.

The researcher did not check for outliers because Likert scale measurements are bounded. Finally, regression analysis assumes linearity in the parameters. There is no theoretical justification or applied research on this topic that suggests non-linear parameter relationships.

Validity and Reliability Checks. Upon completion of data cleaning, the research followed guidelines for assessing the validity and reliability of the scale measures. Table 6 summarizes content validity and discriminant validity measures for the second pilot study. The measure of internal reliability was for the responses from the main study. The CVI is only performed for newly developed constructs and thus just present for numeracy, logic, and critical evaluation. Cronbach's Alpha, AVE, and CR were not performed or required for dependent variables. Likewise, self-efficacy and software literacy construct were not assessed for CR or AVE because they were based on previous well-defined research.

Table 6

Validity and Reliability Statistics

Construct	Number of Items	Mean	SD	CR	AVE	Cronbach's Alpha	CVI
Logic	3	13.813	1.520	.874	.301	.822	.80
Numeracy	3	17.956	2.641	.894	.263	.785	1.0
Software literacy	4	291.725	61.900	N/A	N/A	.780	N/A
Critical evaluation	3	14.106	1.179	.883	.284	.801	1.0
Persuasion	3	3.940	.981	.894	.294	.786	N/A
Self-Efficacy	8	578.763	147.152	N/A	N/A	.937	N/A
Decision-making accuracy	3	1.43	.846	N/A	N/A	N/A	N/A
Job performance	1	2.013	.614	N/A	N/A	N/A	N/A

First, to verify the newly minted scales the expert panel assessed the relevance of the items. The new instruments' subsequent score was assessed via a content validity index (CVI) score. The logic, numeracy, and critical evaluation CVI scores were adequate for implementation, ranging between .80 and 1.0, above the .78 threshold (Polit et al., 2007).

Construct validity was then assessed using the recommended guideline for convergent validity, average variance extracted (AVE) metric of 0.50 or greater and discriminant validity, HTMT < 0.90 (Hamid et al., 2017; Van Doorn et al., 2019).

The AVE scores were not desirable, falling below the 0.50 threshold. The HTMT between constructs was below the 0.90 (ranging from .536 to .844) threshold except for between numeracy and logic, which was above the desired threshold at 1.03. Although the thresholds were not fully met, the AVE and HTMT output was considered acceptable for further analysis. The SEM model can account for complex behaviors that exhibit relationships to multiple constructs, and the researcher expected the analytic constructs to have convergence since they are utilized in conjunction.

Presser et al.'s (2004) guidelines were followed regarding feedback mechanisms from pilot respondents for any needed revisions or adjustments to the survey. Pilot respondents were interviewed to assess if questions were unclear or interpreted differently than that of the expert panel. Internal reliability was analyzed with Cronbach's Alpha, the desired technique for Likert instrument surveys. The logic scale measured at .824, numeracy at .882, and critical evaluation at .860 Cronbach's Alpha, all acceptable as they met the 0.70 threshold (Whitley, 2002). Additionally, a composite reliability (CR) or sometimes referenced as construct reliability was performed and the internal consistency of the latent constructs (Gaskin, 2021). The CR measure also met the desired threshold 0.70, ranging from .874 to .894.

The researcher is utilizing a single instrument to assess both the independent and dependent variables. The variance is assessed for common method bias (CMB) to ensure the single source response is not an inflated factor of dependence (Podsakoff & Organ, 1986). Harmon's single factor test was conducted in SPSS v. 27 as prescribed in Podsakoff et al. (2003) to assess common method variance (CMV). In SPSS, the EFA, principal axis factoring with a fixed factor of 1, un-rotated, was utilized to conduct Harmon's test. If less than 50% of the variance was explained by one factor, the results would suggest no CMB. Harmon's test of the final measurement model had 38.52% of the variance explained by one factor, less than the 50% threshold; thus, no CMB was identified (Podsakoff & Organ, 1986). Therefore, the researcher defends that utilizing a single source did not influence the dependency assessment erroneously.

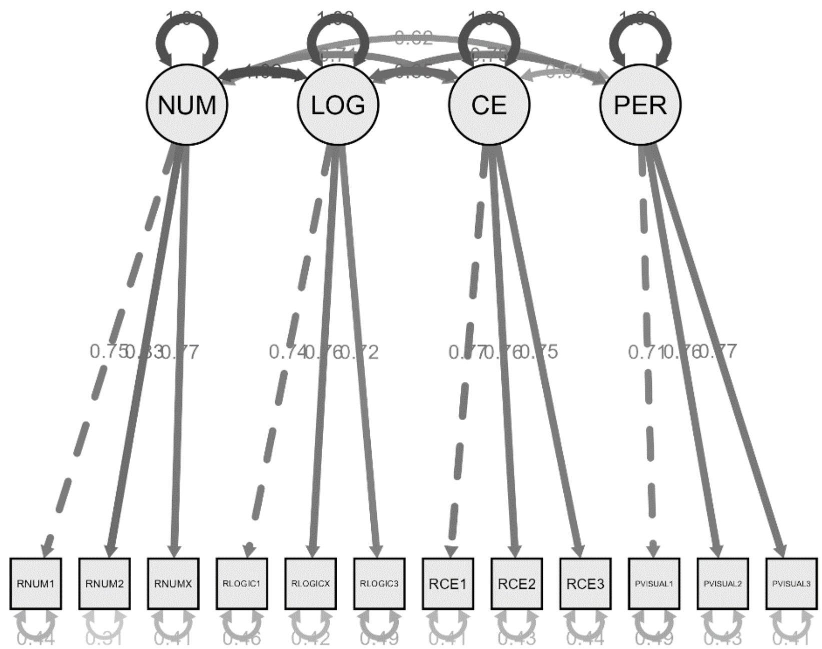
Confirmatory Factor Analysis. Confirmatory factor analysis (CFA) is utilized to ensure the latent constructs align with the instruments used in the study. CFA and SEM recommendations for fitness include:

- Exact fitness should be assessed utilizing the Chi Square (χ^2), and recommended the p-value to be insignificant (Van Doorn et al., 2019; Kline, 2016; Hooper et al., 2008),
- Incremental fit indices of comparative fit index (CFI) and Tucker-Lewis index (TLI) > .95 are ideal (Van Doorn et al., 2019; Kline, 2016; Hooper et al., 2008), with acceptable ranges to .90 (Hu & Bentler, 2009),
- Root mean square error of approximation (RMSEA) of <.06 (Van Doorn et al., 2019) to < .07 (Hooper et al., 2008) with no significance, and
- Standardized root mean square residual (SRMR) < .08 (Hooper et al., 2008; Hu & Bentler, 2009).

The CFA analysis suggests a moderate fit: $\chi^2 = p < .001$ (not desirable), CFI = .953 (good fit), TLI =.931 (moderate fit), RMSEA = .077 (low fit), SRMR = .048 (good fit). The instrument items loading for logic, numeracy, critical evaluation, and persuasion met the threshold of greater than 0.70 for instrument utilization (Whitley, 2002). The CFA model is provided in Figure 9. Again, this model was considered acceptable due to the expected co-utilization of the skills to perform analytic processes.

Figure 9

CFA Model of Latent Competencies



Finally, the eigenvalues were evaluated for the logic, numeracy, and critical evaluation factors. Eigenvalues measure the amount of variance explained by the latent construct and is the sum of the squares of the factor loading. The standard threshold is 1 (Kaiser, 1960); however, in the case of fewer than 30 variables, the threshold of 0.70 is acceptable (Stevens, 2009). The output suggests a one-factor model to meet the Eigenvalue threshold. Considering the expected construct overlap due to how the competencies work together in a holistic model, the 3-factor model was deemed adequate for further analysis. Additional configuration analyses were completed in the final SEM model to assess model fit (one factor or three).

Finally, a construct correlation analysis, Table 7, was completed. This matrix is provided as a best practice for getting an initial understanding of the relations present in the final SEM model (Kline, 2016).

Table 7

Construct Correlation Matrix

Construct	1	2	3	4	5	6	7	8
1. Logic	-							
2. Numeracy	.588**	-						
3. Software Literacy	.562**	.589**	-					
4. Critical Evaulation	.309**	.294**	.282**	-				
5. Perusaions	.462**	.477**	.525**	.251**	-			
6. Self-Efficacy	.483**	.469**	.532**	.175*	.436**	-		
7. Decision-Making Accuracy	-.093	-.106	-.142	-.008	-.151	-.015	-	
8. Job Performance	.193*	.197*	.220*	.184*	.198*	.289**	.007	-

The correlation table provided initial insights supportive of the hypotheses development regarding performance and the AC constructs; however, the table foreshadowed that the value of the decision-making instrument is not as substantive as desired.

4.3 Structural Model Assessment

This study utilized SEM, a method suitable for a behavior approach for latent variables (Lowry & Gaskin, 2014; Tenenhaus et al., 2005). SEM is a measurable multivariate technique generally used to break down the structural connections by utilizing multiple statistical tools simultaneously to derive construct contributions to each other and the dependent variables (Van Doorn et al., 2019; Tenenhaus et al., 2005). The researcher utilized JASP 0.16.1, an open-sourced statistical program for conducting the confirmatory factor analysis (CFA), mediation with SEM, and SEM analysis. The final path loading and significance for each hypothesized path were utilized to determine support/not support of the hypothesized pathways. Subsequently, the results were used to determine if the competency model predicts decision-making and job performance.

The mediating relationships were also analyzed in JASP by utilizing the SEM functions. Instead of the two-step process to obtain the indirect path prescribed by Baron and Kenny (1986), a one-step analysis of the indirect path with bootstrapping was utilized (Sarstedt et al., 2020). Cheung and Lau (2008) and Sarstedt et al. (2020) considered a within SEM tool mediation approach superior to tandem analysis in tools such as PROCESS in SPSS because of the ability to process latent variables.

Model Fit. An SEM analysis was conducted using JASP with bootstrapping of 1,000 resamples as prescribed in Chin et al (2003). According to

Kline (2016), Goss-Sampson (2018), Hooper et al. (2008) guidance, assessing the model itself consists of several fit measures, summarized during the CFA. The results suggest a moderate, but adequate fit model RMSEA = .054 (good fit), SRMR = .068 (good fit), CFI = .933 (moderate fit), TLI = .919 (moderate fit), and a significant χ^2 with $p = < .001$ (poor fit). Ideally, the fitness scores would have been higher. The OJT was considered a contributing factor in assessing the loading and insignificance of the decision-making scores.

The fit indices, considered acceptable for further analysis, the hypothesis testing was then assessed. To determine hypothesis acceptance the path significance value was utilized. Hypothesis acceptance was set at a $p \leq .05$. For reference, the research hypotheses model is reproduced in Figure 10. Figure 11 depicts the research model's path diagram, coefficient estimates, and path significance. The results of the hypothesis are organized in Table 8.

Figure 10

Research Hypothesis Model

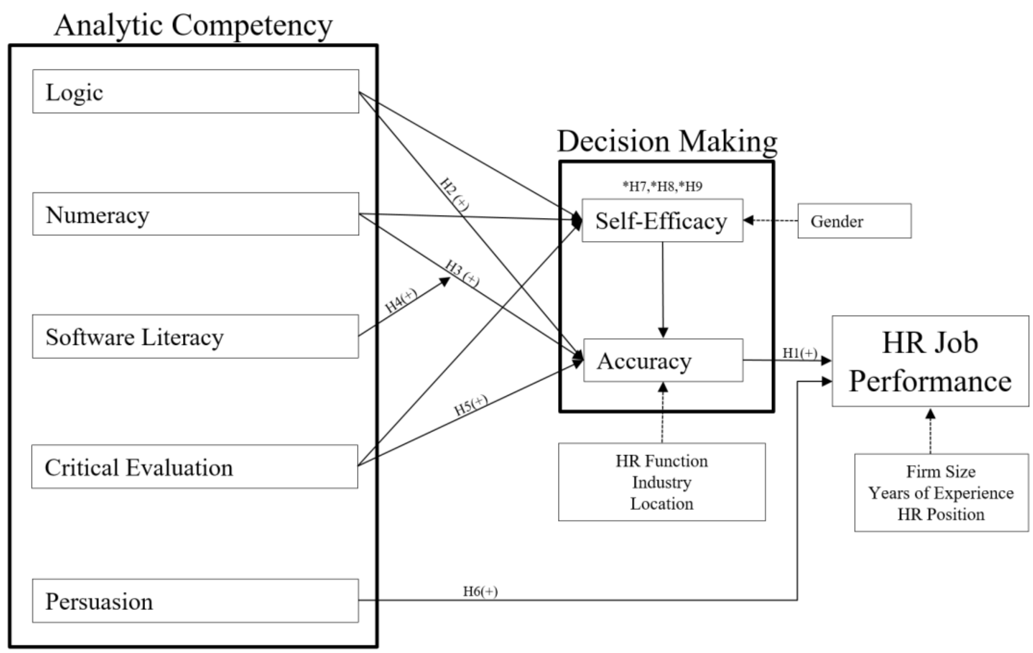


Figure 11

SEM Model Plot

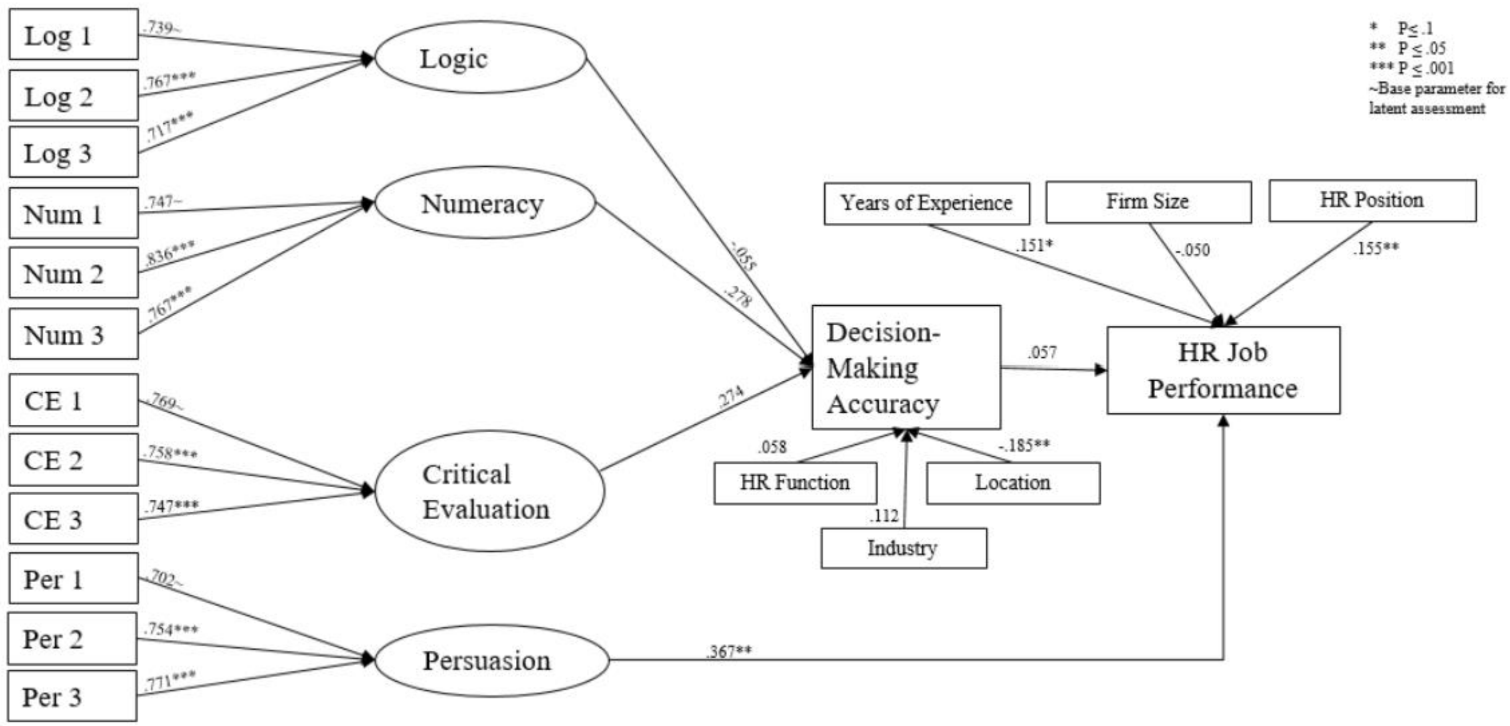


Table 8

SEM Hypothesis Summary

	Hypothesis	*Path Coefficient*	*Critical Ratio*	*P-Value*	*Outcome*
H1 (+)	D-M Accuracy → Job Performance	0.057	0.755	0.450	Rejected
H2 (+)	Logic → D–M Accuracy	-0.055	-1.213	0.225	Rejected
H3 (+)	Numeracy → D–M Accuracy	0.278	0.716	0.474	Rejected
H5 (+)	Critical evaluation → D–M Accuracy	0.274	1.398	0.162	Rejected
H6 (+)	Persuasion → Job Performance	0.254	2.952	0.003	Accepted

Control Paths

From	*To*	*Path Coefficient*	*Critical Ratio*	*P-Value*	*Outcome*
HR Function	D–M Accuracy	0.058	0.755	0.450	Rejected
Industry		0.112	1.453	0.146	Rejected
Location		-0.185	-2.414	0.016	Accepted
Experience	Performance	0.151	1.915	0.056	Accepted
Firm Size		-0.050	-0.611	0.541	Rejected
HR Position		0.155	1.956	0.050	Accepted

As presented in Table 8, nearly all the hypotheses were rejected, meaning the p-value thresholds were not met. No hypotheses of competencies (H2, H3, H5) on decision-making accuracy were supported. Likewise, in H1, the hypothesis of decision-making accuracy on performance was not supported. Interestingly, H5, the hypothesis that persuasion would positively increase performance was supported. The p-value thresholds used to assess the control variables were conservatively set to 10%. The conservative threshold ensures that important control variables were not inadvertently deleted from the model (to protect against Type II errors). Experience and position on job performance and location on decision-making accuracy were significant at the 10% level.

4.3.1 Moderation Results

Due to the lack of significance of direct relationship to SJTs, the moderation analysis is moot and not supported. Therefore, in the current model configuration, H4 is not supported.

4.3.2 Mediation Results

Due to the lack of significance of direct relationship to situation judgment tests, the mediations analysis is also moot. Accordingly, H7, H8, and H9 are not supported in the current model configuration.

The final hypothesis H10 (which is not depicted in the hypothesis summary) states logic and numeracy will be stronger predictors of decision-making than the other constructs. H10 could not be assessed because of the lack of significance in the relationship between the cluster variables and the SJTs.

4.3.3 Result Assessment

This study predicted that logic, numeracy, software literacy (in-directly), and critical evaluation influence decision-making accuracy. The HR professionals' decision-making self-efficacy was expected to partially mediate logic, numeracy, and critical evaluation. Further, the persuasion AC construct had a direct positive impact on job performance. Finally, decision-making accuracy was expected to predict job performance. The results were not supportive of this model summary. The moderate fit is partially attributed to the situational judgment test results. The raw scores were substantially lower than those from the pilot study; the highest score was 75% versus the pilot, which had two respondents with perfect scores and a normal distribution. The test scores were analyzed with an adjusted score based on SHRM's scoring of the certification test during the certification launch (Sparacino, 2017). Although the results slightly improved, they were not sensitive enough to pick up significance between decision-making and competency evaluations and did not increase model viability. Additional analysis was completed in light of these results.

4.4 Revised Model Development

The model was rerun with a revised hypothesis set assuming a direct relationship to performance from the competencies because of the value of the questions that drive this study, evidence from the correlated data, and research on performance and competencies (Sanchez & Levine, 2016; Wright et al., 2021). The following sections provide the rationale for a revised model with new hypotheses and results that support the decision to move forward with a revised model.

4.4.1 Rationale for the Revised Model

The foundation of this research and essential to the decision to develop a revised model, the research questions are provided as a starting point:

1. *What* analytic competencies are needed from HR professionals to drive higher job performance?
2. *How* do these analytic competencies drive higher job performance?

Before this study, the assumption between performance and decision-making was an acceptable practice (Kryscynski et al., 2019). Although operationalizing the process of AC through decision-making is valuable, understanding the competency aspect of *how* is more desirable. The combination and functionality of the competencies are no less part of *how* that can be assessed if the research takes the same assumptions from previous competency research (e.g., Kryscynski et al., 2019; Ulrich et al., 2021a). Practical knowledge about how the competencies work together (or not) can still be derived to drive higher performance in assessing the direct relationship.

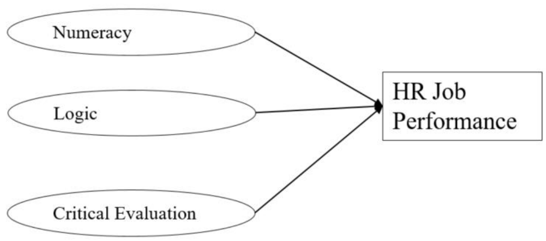
Kline (2016) reminds us that we shouldn't be wed to our original assumptions and model configurations. After assessing the results, the literature was revisited; more consideration was needed for the latent construct configuration of logic, numeracy, and critical evaluation. The LeDeist and Winterton (2005) holistic model is a pyramid where the competencies are used in coordination, similar to individual gears linking together to create a working machine. The original hypothesis model was proposed such that the individual competencies demonstrate a unique positive relationship. However, as prescribed in process models, the skills are utilized in conjunction to derive increased performance except for persuasion, which is used separately to obtain buy-in (e.g., Waters et al., 2019). If the configuration were analogous to the gears of a machine, such an arrangement would be like placing each gear in the machine without the cogs engaged. The previous model may have underestimated the interwoven nature of the competencies. Further, the conflation of the competencies in the CFA provides more evidence of the interwoven nature of logic, numeracy, and critical evaluation. Therefore, the revised model includes a larger latent construct, the new AC construct, consisting of the three sub-latent constructs logic, numeracy, and critical evaluation. Taking a sub-dimensional approach is consistent with previous practices in entrepreneurial competency assessments (Tehseen et al., 2020).

An analysis was run for each model configurations- illustrated in Figure 12. The purpose is to test the hypothesis that a larger latent construct is the ideal model for how the three analytic competencies are configured. Williams et al. (2018) took a similar approach to seek an ideal model configuration. For simplicity, Figure 12 only shows the part of the models that change. The first model illustrates the configuration for the original hypothesis. The second model was to assess the significance of the dimensionality. The researcher created a consolidated analytic competency construct using logic, numeracy, and critical evaluation items with factor scores of 0.70 or higher. The analytic competencies (logic, numeracy, and critical evaluation) are distinct in the literature, in contrast to the statistical results and lack of divergence, suggesting a consolidated assessment is warranted. Model 3 addresses the constructs' as coupling and reflects a dimensional presentation with a larger latent construct comprised of sub-constructs working together, like gears in a machine, to create a higher performance output. The expectation is that Model 3 will have the best overall model fit.

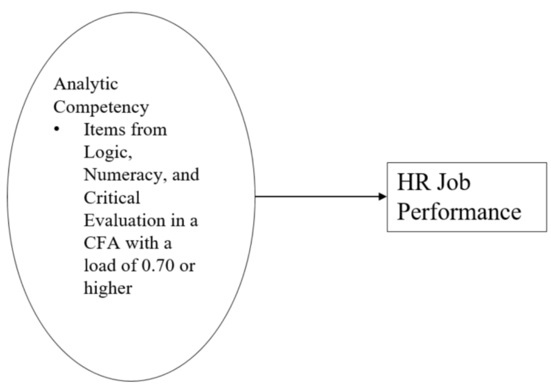
Figure 12

Model Testing Configurations

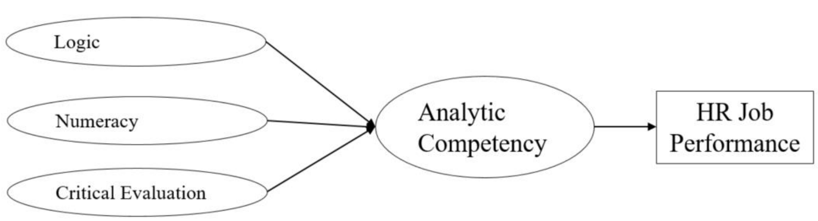
Model 1: Original Hypothesis



Model 2: Consolidated construct



Model 3: Revised sub-latent model



The revised model must also reconsider the retention of the remaining variables. In reviewing the other original model competencies, software literacy was identified as an indirect competency expected to impact numeracy. However, in the revised model, numeracy does not work as an independent latent variable on job performance. Consequently, software literacy was not assessed in the revised model. Persuasion, the only remaining competency derived from analytic process models, was supported in the original hypothesis as significant for job performance and is retained in the revised model as a separate latent construct.

The last construct for consideration is self-efficacy. The literature is consistent that self-efficacy mediates work performance, sustaining the relevance of the construct in the model (Bandura, 1997; Bandura & Locke, 2003). Originally, self-efficacy was hypothesized to mediate decision-making. Although the self-efficacy questions were directed toward confidence in the decision-making instrument, the questions were delivered as representative of the participant's self-appraisal of their ability to solve HR problems. Hence, the original self-efficacy instrument is a viable self-efficacy assessment for mediation analysis on generalized HR job performance, not just decision-making accuracy.

The controls for job performance with the significance of $p \leq .10$ or better were retained in the revised model structure, including experience and HR position. Due to lack of significance, the other control variables were removed for a more parsimonious structure. The revised hypotheses are provided below:

R-H1: A model with a latent analytic construct composed of sub-latent constructs numeracy, logic, and critical evaluation (henceforth AC) will produce a higher model fit than alternative models.

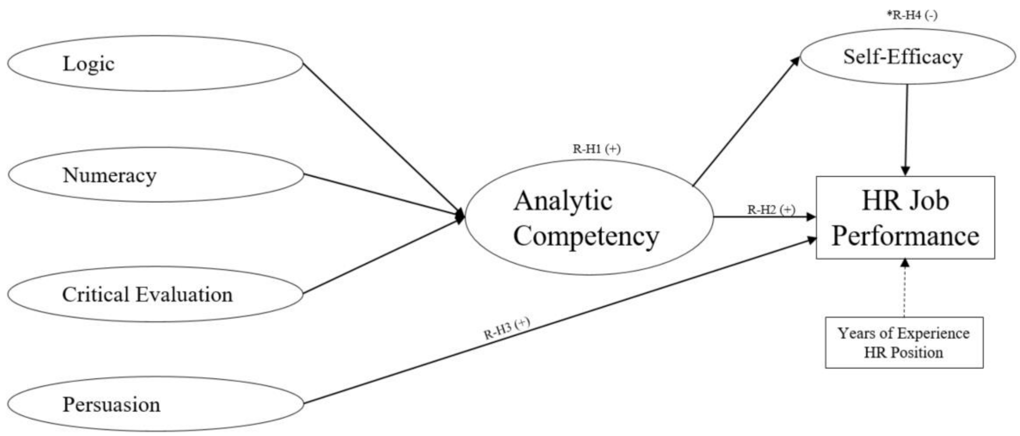
R-H2: AC will have a direct positive relationship on job performance.

R-H3: Persuasion will have a direct positive relationship on Job Performance.

R-H4: Self-Efficacy partially mediates the relationship between Analytics and Job Performance.

Figure 13

Revised Hypothesis Model



Note. * denotes partial mediating relationship between AC and Job Performance.

4.4.2 Revised Structural Model Assessment

The model was again run in JASP with bootstrapping of 1,000 resamples as prescribed in Chin et al. (2003).

Model Fit. The same fit indices and metrics were used to assess the revised model. Table 9 reports the fit indices and shows that Model 3 marginally outperforms Model 1 and significantly outperforms Model 2 confirming hypothesis R-H1. The results from Model 3 suggest a moderate to good fit: RMSEA = .057 (good fit), SRMR = .069 (good fit), CFI = .950 (good fit), TLI = .939 (moderate fit), albeit still not a desirable χ^2 retaining significance, p = < .001.

Table 9

Fit Indices Comparison

	RMSEA	*SRMR*	*CFI*	*TLI*	χ^2
Model 1	0.062	0.069	0.950	0.936	$p < .001$
Model 2	0.099	0.181	0.859	0.825	$p < .001$
Model 3	0.057	0.068	0.950	0.939	$p < .001$

Figure 14 depicts the path diagram and coefficient estimates of Model 3. The results of the hypothesis are organized in Table 10. With the exception of R-H3, the hypotheses for the revised model are confirmed.

Figure 14

Revised SEM Plot Model

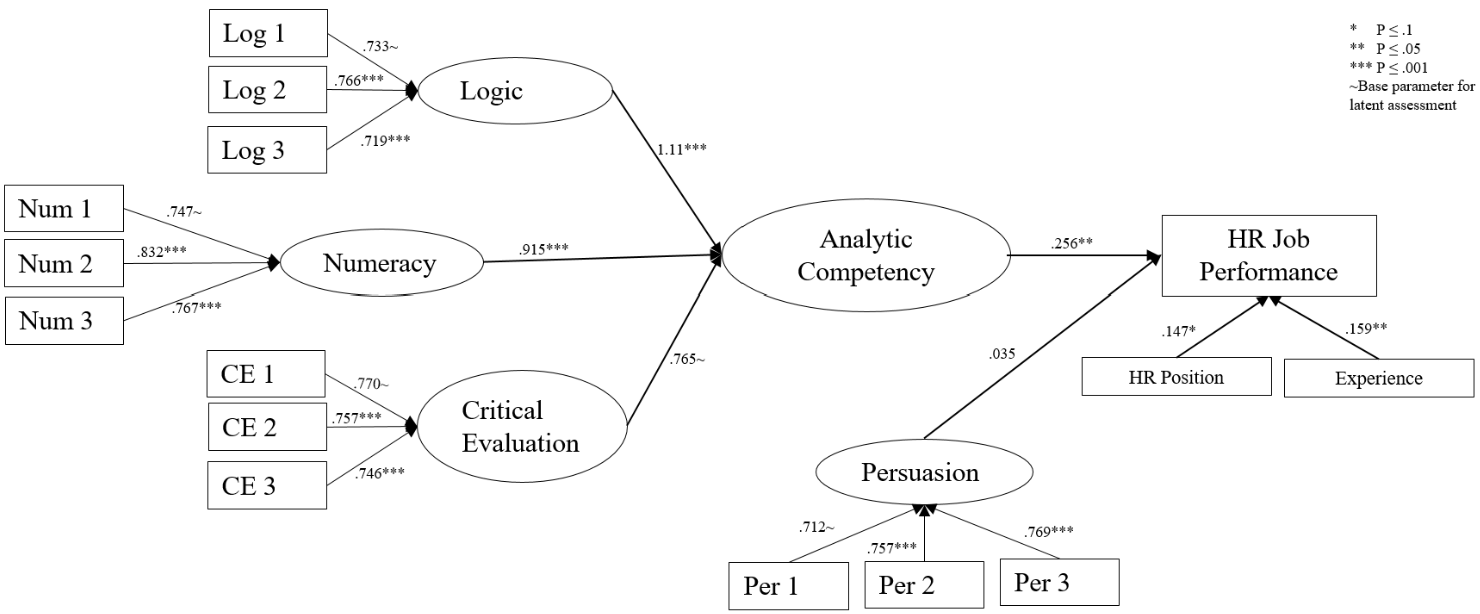


Table 10

Revised SEM Hypothesis Summary

	Hypothesis	*Path Coefficient*	*Critical Ratio*	*P-Value*	*Outcome*
R-H2 (+)	Analytics → Job Performance	.256	2.170	0.030	Accepted
R-H3 (+)	Persuasion→ Job Performance	.035	.282	0.778	Rejected

Control Paths

From	*To*	*Path Coefficient*	*Critical Ratio*	*P-Value*	*Outcome*
Experience	Performance	.147	2.034	0.042	Accepted
HR Position		.159	1.884	0.060	Accepted

4.4.3 Mediation Results

Lowry and Gaskin (2014) recommended utilizing SEM software with bootstrapping to create and test the interaction, given the latent variables. The Self-Efficacy mediation was analyzed in JASP using the SEM function. The Lavaan syntax for Sobel's (1982) test was inputted in JASP to assess mediation significance. As show in Table 10, the Sobel (1982) test result for the partial mediation was significant, supporting the R-H4 in which Self-Efficacy partially mediates the relationship between Analytics and Performance.

Table 11

Mediation Analysis of Self-Efficacy on Analytics

Variables			*Direct Effect*	*Indirect Effect*	*Total Effect*	*p-value*	*Outcome*
IV	Med.	DV	*(Estimate, SE)*	*(Estimate, SE)*	*(Estimate, SE)*		
R-H4 - Analytics	S-E	Job Performance	0.173, .082	0.090, .045	0.263, .072	.044	Accept

4.4.4 Revised Result Assessment

The revised model was expected to predict performance through the latent analytic construct consisting of sub-constructs numeracy, logic, and critical evaluation (the skill set utilized to inform decision-making). Persuasion was expected to increase performance independent of these competencies due to how the skills are employed separately in process guides for applied analytics in HR. Self-efficacy was expected to perform as a mediator on the latent analytic construct. The results were supported, except for persuasion. Running the model without decision-making produced a better model fit and a more accurate understanding of how the AC constructs impact performance.

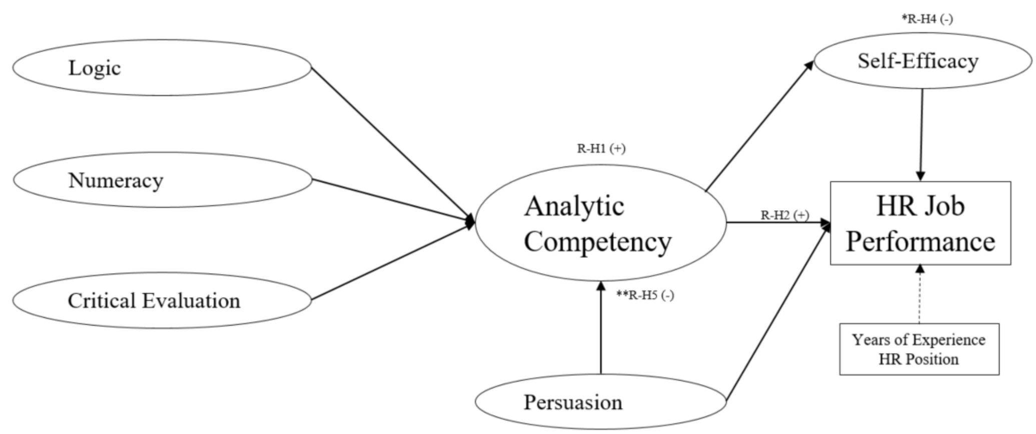
4.4.5 Revised Model Post-Hoc Assessment

The null result associated with persuasion suggests that additional post hoc analysis is warranted. Why was persuasion regressed on performance significant in the original model but no longer significant with the introduction of the other analytic competencies directly to performance? The findings on persuasion were related to broader social and scientific competencies in a literature search to unearth the rationale behind the outcome of the null result. Goodell (1977) suggested that those who are trained in research skills are socialized not to engage in public communication. Goodell (1977) championed the progress of social competence, promoted effective communication skills for layman understanding, and suggested promoting education to engage the scientific community. Goodell's campaign was over 40 years ago, yet a new generation continues to campaign for scientists and researchers to overcome social competency inadequacies (Olson, 2018). A similar phenomenon in competence coordination is described; social competence inadequacies emerge when a higher presentation of functional and cognitive dimensions of competence occurs. Given the inability to increase social competence adequately in the scientific fields, and functional and cognitive skills in the HR profession, the competency development problem may be more profound. The holistic model may need to be considered a tool to understand capacity constraints; with higher utilization of some competency dimensions, other dimensions are reduced. In the case of HR performance, the profession has a proclivity for social competence skills (Huong Vu, 2017; Ulrich, 2021b; Ulrich et al. 2017; SHRM, 2016). A consequence of a capacity constraint could be a suppressed value of more common competency dimensions when high valued and rare dimensions (e.g., AC in HR professionals) are present. The subsequent hypothesis is that the social construct, persuasion, is mediated with increased utilization of AC. Because the significance of the singular regression of persuasion on job performance is significant (.240, 0.077, p=.002), and the lack of significance of persuasion in the revised model with the inclusion of the AC cluster, complete mediation is expected, illustrated in Figure 15.

R-H5: AC will fully mediate persuasion on job performance.

Figure 15

Full Model 3 with Persuasion Mediation



Note. * denotes a partial mediating relationship between AC and Job Performance. ** denotes a full mediating relationship between Persuasion and Job Performance.

The mediation analysis for persuasion and AC, like self-efficacy mediation, was run in JASP. The results are provided in Table 12. Modeling with sub-dimensions supports a parsimonious mediation analysis of persuasion on the analytic competencies. The results of the analysis were significant; the analytics construct mediated persuasion on job performance. Further, given that the direct effect was not significant, full mediation was confirmed (p = .616).

Table 12

Mediation Analysis of Analytics on Persuasion

Variables			*Direct Effect*	*Indirect Effect*	*Total Effect*	*p-value*	*Outcome*
IV	Med.	DV	*(Estimate, SE)*	*(Estimate, SE)*	*(Estimate, SE)*		
R-H5 - Persuasion	Analytics	Job Performance	0.055, 0.111	.147, 0.072	0.203, 0.077	.042	Accept

4.4.6 Revised Results Summary

The results of the revised model output supported the new hypotheses that the AC construct, comprised of sub-latent constructs numeracy, logic, and critical evaluation working together, significantly improves performance. Also, the hypothesis that self-efficacy would mediate the impact of the AC on performance was supported. The hypothesis that persuasion improves performance was not supported. However, upon post-hoc analysis, the AC construct fully mediated the persuasion competency. The mediation output introduced some insights into grander competency problems in professions with demands in multiple competency dimensions.

Chapter 5

Discussion, Implications, Recommendations

This study aimed to define, develop, and assess the AC for HR professionals. The practical problem was rooted in a broader issue of effective modeling for new and emergent skill demands in an occupation. A study of 161 HR professionals assessed analytic competencies, decision-making, and job performance to answer the research questions. The modeling, methods, and development contributions are addressed first with discussion and implications. Then the modeling results are discussed in the context of the research questions, and recommendations are provided. The dissertation concludes with a final summary and reflection.

5.1 Competency Modeling

Before discussing the model itself, the method to obtain the model needs to be addressed. The methodology was instrumental to this study's purpose and in answering the first research question, *what* are the competencies. Before this study, the stagnation of competency modeling was a noted problem (Stone et al., 2013). This study utilized the HR analytics competency problem to illuminate why the modeling literature must evolve to meet the needs of actual demands in occupational settings. This study helps advance human resource development by providing a competency modeling tool intended to increase learning and development capabilities versus memorializing embedded job knowledge and capabilities.

Additionally, this study demonstrates how current competency modeling could create silos in competency literature, limiting understanding of how competencies impact performance. Cross-profession and construct-focused research, often not included in modeling processes, provides invaluable insights in further enabling competency implementation. For example, the use of after-action review process tools may prove a helpful mechanism in increasing meta-competence or critical evaluation in HR problem-solving. Without expanding the research outside the HR domain or traditional expert review, this connection would not have been feasible. Similarly, the standardization of the persuasion construct in place of micro-trending terminology (aka "Storyfication") expands our capability to discuss and discern which dimension of this social construct enhances a profession and provides an additional source for personal development.

From this dissertation, the practical implications for organizations surpass the HR discipline, as the revised competency modeling methodology could be applied to other occupations where gaps or deficits in job performance or future work needs are being defined. When organizational development professionals seek to create a competitive advantage through their workforce, the revised method gives them a tool to think beyond the job of today and plan for the future. Further, the cross-professional and competency-based literature review increases the evidence base in the competency model's capability to improve relative performance.

Finally, the holistic framework requires the modeling team to think through all aspects of KSAOs needed to accomplish work tasks, expanding the analysis beyond what is merely observed. Without this intentional framework in assessing the competency cluster, one may overlook critical competencies that drive task performance, especially in new and emergent competency demands. This novel methodology removes potential blinders in those evaluating the job. The practical implication for talent development is this intentional mechanism; explicitly examining each competency dimension in the job analysis helps the assessor move past their own expectations for KSAOs in the job performance. With this dive into the HR AC problem, the competency modeling problem becomes more salient and the value of a revised methodology more palpable. Hopefully, the applied research re-energizes the topic of competency modeling in a time when occupations are not only changing rapidly in the exemplified discipline of HR but in a broad range of occupations.

5.2 Methods and Instrument Review

The method for this research was an online survey format with purchased panel responses. Several controls and assessments were implemented to increase generalizability, including geographic stratification and sample representation comparisons. However, some limitations are present because of the sampling method. First, the sample size was a limitation. Although the sample met the power threshold, it may not have been large enough for the sensitivity desired, given the complexity of the model. Second, the respondents were paid participants. Although such a method does increase the risk of concern for external validity of study findings, such methods are considered acceptable practice and increase participant willingness without increased ethical concerns (Bentley & Thacker, 2003). Third, the demographics of the HR population are not fully known to make an exact comparison; the data available and presented for comparison was from other convenience sampled research. The comparisons do demonstrate some variance between early- and late-career representations. However, the researcher finds some benefits to the sample demographics because the sample is more closely aligned with generalized BLS HR experience data. Further, the dissertation study dataset is not exclusive to HR professional organization networks, which is a limitation of previous studies. The professional organization-affiliated HR population may behave and perform differently from the generalized population. A case in point further discussed is the SJT.

The Situational Judgement Tests were based on certification and professional HR textbook problems. However, the output of the main study demonstrated low scores; the highest raw correct score was 75%, and the sensitivity needed to assess decision-making was inadequate. However, the pilot scores were unremarkable with a normal distribution. In retrospect, the participant outreach for the pilot included professionals more fluent in SJT question format, given that many participants were recruited through SHRM chapter leadership outreach. SHRM members, and more so SHRM leaders, are more likely to have studied, prepared for, and completed SHRM certification programs and consequently have more exposure to SJTs. The main study obtained participants through a purchased response on the Qualtrics platform and reached a broader audience who may or may not have been familiar with this type of testing format. The SJT scores suggest that more research is needed as the value of these certification programs may increase the ability of HR professionals to conduct decision-making. Lengnick-Hall and Aguinis (2012) proposed additional research on the value of HR certification programs on job performance (still left unanswered). Future research on SJT and certification programs may be even more valuable than proposed if the certification program increases the ability to solve problems and not merely increases knowledge of relevant material. Likewise, as these certification programs evolve, the weight of the items on the certification test in the SJT format versus knowledge testing (e.g. reciting compliance regulation) should also be analyzed for purported contribution to increased performance. The SJT result limitation in this dissertation provides evidence supporting Lengnick-Hall and Aguinis (2012) propositions. As such, value still remains for future research to assess the certification programs' performance contributions. Further, it would be valuable for future HR competency research to understand if the certification programs that provide more robust applied SJTs as part of the testing protocol if that testing format increases performance. As a result of the growth and demand for certification, the testing format research might be a great avenue for increasing analytic skill development (Bayer & Lyons, 2020). In conclusion, although the results of the SJT score proved a limitation in the study, they also provided additional insight for future research on decision-making and suggest additional research is warranted in the field of SJTs and HR certification programs.

The other pre-defined instruments are also notable topics of discussion. The value of cross-profession research is emphasized as having increased value for competency development. Cross-professional study also provides a source for instrument sourcing, and in this case, a persuasion instrument was identified from the sales discipline. This research demonstrated the value of testing competency tools utilized in other professions. However, the cross-profession instrument use was taken with appropriate caution, and robust assessments were utilized because of the importance of P-E fit (Mumford et al., 2017; Raffiee & Byun, 2020). The Plouffe et al. (2016) persuasion construct was multi-dimensional and well calibrated for the sales field, where such competency needs are likely more robust and nuanced. Whereas in HR, the multi-dimensional loading was not supported. The lack of persuasion dimensional loading is likely due to less intense demand, and hence the sensitivity of the dimensions was not met. At the same time, the persuasion instrument created efficiencies in the development and assessment process. Although HR utilization of persuasion was expected to be less robust a priori, more of the dimensions of persuasion were anticipated to be viable. The viable persuasion dimension in the CFA was also the most prevalent in HR literature and still proved insightful to the study results.

The other pre-defined construct was self-efficacy. Self-efficacy is a more long-established instrument that has stood by more rigorous scale standards for scale accuracy (Bandura, 2006) utilizing a 100-point scale, unlike the more common 7-point Likert scale (Preston & Colman, 2000). The implementation of scales in the digital platform was user-friendly in pilot feedback, with a sliding mechanism. Given the proliferation of digital platform research (Oztimurlenk, 2021) and the accuracy of higher point scales (Alwin & Krosnick, 1991), future research should assess the implementation of 100-point scales in digital formats. The digital format provides ease of use, not available in a written form where such scales can be unwieldy.

The logic, numeracy, and critical evaluation instruments were new and developed for this study. The development process was iterative and took two pilot phases to obtain well conforming latent constructs. Developing the competency structures also foreshadowed how the competencies would overlap. In retrospect, this further supports the holistic model because of how the competencies are utilized in conjunction to complete job tasks. Ideally, these item sets would be utilized in future research on HR competency or outside the discipline for similar competency assessments and further validation. These item sets could also be utilized in applied settings for professional development assessments. However, one concern is the self-evaluative scores and the inflation of perceived capability compared to the participants' abilities to perform on the SJTs. The high perceived analytic competence combined with low SJT scores and the manager performance evaluation scores suggest low analytical competence expectations. Although one can expect self-assessments to be more optimistic than actual performance (Lindeman et al., 1995), the raters' perceptions were also high. A recommendation from this outcome is a more detailed and inclusive assessment of analytic competence in performance evaluations, such that decision-making outcomes are an integral part of the evaluation.

The dependent variable also warrants discussion. Ideally, the merit compensation response would have been a more sensitive measure. However, a limitation of this study was the incomplete response rate on the merit question. The study included the performance appraisal as a backup item for the dependent response variable in preparation for the likelihood of this response behavior. The complete response rate on the performance review items supports that the performance review is still alive and well. Further, the complete response rate, as opposed to the compensation item response rate, suggests that participants are less concerned about sharing their performance outcomes. Also, response behavior by some, despite piloting with no issue, indicates either lack of understanding or nontraditional compensation measures. Five respondents indicated they had a merit increase between 25 - 60% of their salary, which would be extreme outliers of standard increases reported between 0 - 5% percent (SHRM, 2020). The suggestion for future research is to utilize performance reviews to support the respondents' increased response behavior, reliable interpretation, and participant comfort.

For the most part, controls were interesting because of their lack of relevance. The lack of significance for controls may also be attributed to the small sample size. No controls identified in the literature were significant at a $p \leq .05$. Two controls were partially significant ($p \leq .1$), years of experience and HR position, and were retained for vigor. HR position refers to role level, ranging from non-exempt individual contributors up to executive leadership roles. HR position and responsibility growth usually commiserate with experience and an expected outcome to be significant concurrently and positively predict performance within this research. However, of more interest was the outcome of the HR function, which was not significant at all. HR Function in the literature has a debated role in analytic processes. However, this study suggests no difference in performance outcomes based on competency self-assessment. As a result, a recommendation is that future studies take a generalized approach to AC in HR and not narrow assessment based on function until more discernable evidence proves otherwise.

5.3 Results Discussion

5.3.1 Answering the Research Questions

The research aimed to answer two questions-

1. *What* analytic competencies drive higher job performance for HR professionals?
2. *How* do these analytic competencies drive decision-making for higher job performance?

The research utilized novel and improved competency modeling techniques to answer the first question. The competency structure was tested to answer the second question. Unfortunately, the *how* may not be fully answered due to the limitations of the SJT results. However, the results provided some context for *how* analytic competencies work together. First, the results suggest the combination of all three – logic, numeracy, and critical evaluation working in coordination support improved performance. Second, AC is not engaged with the persuasion construct for optimal performance, conflicting with previous research. The contrary result for persuasion suggests a need for additional research regarding how competencies interact and may delimit or enhance proficiencies. The holistic model becomes an exciting platform on a theoretical level because our human capacity to develop and grow has limitations. More research is needed to understand if the holistic model also houses boundary conditions in that large portions of one competency dimension leave less room for another competency dimension. Organizations should assess the human limitations to embolden all desired competencies in formulating their localized competence structures and job design.

Further, modeling with a holistic framework might provide insight into the intersection of intelligence and competence and find complementary outcomes versus opposing views when intelligence too was just one-dimensional. Future research could utilize social, cognitive, and functional competence dimensions and compare performance outcomes to Baczynska and Thornton's (2017) emotional, analytic, and practical intelligence typologies. We may be better positioned to predict who would best perform in jobs with high competence demands and who demonstrate similar intelligence proclivities.

With the study results in mind, this discussion addresses the HR problem: Where do we house HR’s AC in-house or utilize external resources? The researcher would have defended internalized competence more broadly for HR professionals beforehand. The answer may require HR leaders to think more strategically about their internal professional team and analogous to a sports team. In football, there are players whose dominant competence is their physical mass, power, and brute strength, while others whose valuable competence is agility and speed. And then there is the quarterback who can orchestrate the field, call the plays, and calculate their opponent’s abilities such that the output of the team’s action results in the most distance toward the goal post. HR leaders, for now, may be best poised to have a combination of talent in-house – some team members whose strength is in the dimensions of social competence, others who have high analytic prowess. The precipice of success will likely be the leaders within their organization who help bridge these two resources, the quarterbacks of the HR team. Future research is primed to now seek an answer to the ideal HR organizational competence composition. Answering HR organizational AC composition is a complex question because HR professionals have different functional roles and objectives, meaning different goalposts. Recall the McLagan (1989) HR wheel where some HR functions have goals of resource development whereas others have goals to manage resources and information. The analytic HR players must be able to support decision-making for each functional demand. The literature debate prior to this study is too polarized on HR AC ownership when in actuality, HR organizations need to be dynamic in their internal competency structure, at least until we further research how to optimize all dimensions of competence. However, job descriptions and assessments may need to be more breathing doctrine within the occupation, and management will need to hire based on competency gaps within their team. Joinson (2001) discussed how job descriptions were changing to be more adept to a competency-based structure versus specific tasks. However, today even the broader competency job description may need to be amenable to the organization's needs at the time of hire and individuals assessed on those specific dimensions for which they were hired versus all the competencies required within the occupation.

The literature and this research result suggest knowledge of analytics, use of the competencies, and job performance assessment of AC is limited. As HR considers its internal resource development, the order of competence acquisition and organizational level of presentation is also an important area of future research. If the HR leaders are not fluent in the skills and effective utilization, they will be ill-equipped to assess the performance of subordinates'. Further, the lack of AC at higher levels in the organization could perpetuate HR organizational support for non-SEU decision-making. Defining the perfect quotient of AC competence development and placement to meet HR functional objectives should be the next generation of research.

Relative to this discussion, the research has debated internalized logic and numeracy skills versus outsourced. This study suggests that increased performance occurs when these skills are utilized together. Therefore, HR professionals are best positioned to collectively possess numeracy, logic, and critical evaluation versus just segmented dimensions to enhance performance. The value of the “art” or logic of analytics to the beholder is inadequate without the technical skills or “science” to produce a performance output valued by HR management.

In addition to competence modeling, the study result has implications for process models that inform HR professionals to utilize the analytic cluster. First, process models should be explicit of the people resources implicated in the process. Second, research on process model efficacy is warranted, given the AC (comprised of numeracy, logic, and critical evaluation) value to performance and the mediation of persuasion. Notably, the value-add of enhanced presentation skills and storytelling to support business decisions and buy-in may be overstated for HR professionals. Considering the audience is often informed internal business leaders, the value-add may be more so in well-defined and evidence-driven argument than in the ability to use the analysis in a story or to visualize recommendations. If process research supports persuasion, HR development programs will not only need to build analytic skills but also how to connect persuasion and AC to enhance performance.

5.3.2 The Roadmap

The intent of this dissertation included identifying a path to desired performance through effective decision-making. On the academic side of the house, additional research is needed to ferment expectations. However, enough evidence is presented in this dissertation to inform what the HR discipline should do next from the professional side. HR leaders must push to integrate competency development into secondary education programs, hire for competency gaps given the potential capacity limitations of current staff, and reform performance management expectations to incorporate SEU decision-making.

When the practical problem was introduced, signs in the literature indicated we were not preparing professionals with the skills (Scanlan, 2007). The support for the collective skillset of logic, numeracy, and critical evaluation, along with poor SJT scores, indicates that the secondary education programs are not adequately training early career professionals in the skills of the future, especially considering higher participation of early-career individuals in the survey. Meeting the competency gap will require business and HR undergraduate programs to include analytics in the curriculum as a standard for basic requirements, not just in graduate programs. For roadmap purposes, this dissertation discussion dips into HR analytics andragogy since the literature and results give us clues on how to improve practices. The curriculum should start building numeracy skills and utilizing the continuum of data as the building blocks to enhance the ability to use data to solve problems. Then the curriculum should build on the numeracy skill with applied pragmatic exercises resulting in HR decision-making responses. The practical exercises build logic because the student must develop a method to solve the problem. The practicums should have a debrief phase where students assess their interventions, such that the curriculum actively incorporates the complete AC cluster to include meta-competence. Several HR development programs currently promote a storytelling component (e.g., Bersin). However, the dissertation results indicate that professional development time is better spent building the AC cluster.

The HR analytic capacity concerns were introduced at the onset of HR's transformation into a more formidable strategic business function. Recall, Roberts' (2007) prediction that despite the information at HR's fingertips, it is unlikely the current practitioners would be able to master data-driven decision-making. Fast-forward 25 years and the discipline is still a dearth of analytic skills. However, building a skill requires onboarding mastery that can then be shared. The highly functional and cognitive-based skillset will be best developed by hiring strategically into HR functions, individuals with high AC and demonstrate an aptitude for teaching and modeling the AC cluster. These individuals will be a focal to support the department and help bridge the competency gap. Further, individual development plans should have the principles of analytics at a minimum. This strategy will be a seed for knowledge sharing, establishing best practices, and awareness of the value-add of data-driven decision-making.

The last road-map recommendation is to increase positive accountability through the performance review process. HR leaders are not immune to the discomfort and avoidance of the tough conversations that can accompany performance reviews. The inflated rater performance scores compared to SJT scores indicate the profession is not yet challenging itself to meet the expectations of the discipline. However, evasion becomes less feasible if the structured review incorporates a competence dialog around decision-making. Performance reviews in HR should embed decision-making outcomes as part of competency assessments.

Specifically, assess if professionals took a methodical approach or resorted to gut decision-making and the results of those decisions. The elevation of the performance review as a tool of accountability should be looked at as a means to increase meta-competence, create a dialog around SEU performance and become a tool to reflect and improve upon practices. Taking a positive accountability mindset will be less adversarial than traditional performance reviews and allow the discipline to lift itself to a higher functional capability. Further, starting the conversation around the decision-making process (logic) will be more welcoming to numeracy adverse professionals.

Finally, as an output of this dissertation, the researcher proposes a revision to Bassi's (2010) definition of HR analytics to - *The application of logic, numeracy, and critical evaluation competencies to improve the quality of people-related decisions for increased individual and organizational performance.* The revised definition gives an HR professional a less ambiguous and more actionable definition.

5.4 Conclusion and Reflection

This dissertation contributed to competency modeling and human resource development processes and addressed a specific occupational challenge for HR professionals. The study results further supported the need and value of analytics while providing more insight into how AC works to improve performance. The meta, cognitive, and functional dimensions of analytics work in coordination, whereas the social dimension is reduced when assessed on HR job performance. Although the research did not support the decision-making hypothesis set, the SJT results suggest the professional competency gap may be too large to capture with the test utilized for this dissertation. Future research will need a more moderate assessment to obtain adequate sensitivity. The OJT outcome, too, supports the need for professional development in this field and exemplifies the AC problem in the profession.

Reflection provides a means to apply critical evaluation and learn from the work of this study in an applied setting. Yes, this study supported an analytic competency championed for the profession. Still, it also helped the researcher realize that one cannot expect every HR professional to grasp all competencies equally as an HR leader. Further, HR as a profession is still strides and bounds away from being the idealized business function that derives people policies, procedures, and practices from data and evidence-based practices. This study emerged from frustration working with peers in HR who believed the anecdote and thoughts of leaders were facts generalizable to the whole organization. These professionals were not taking an objective view or taking the time to study the problem thoroughly. In reflection, these professionals are also compassionate and engaged professionals valued for how well they work to resolve interpersonal conflicts. We may be asking too much to take on both types of tasks if their competency bucket is full as they are caring for the social functions of the organization. This research occurred during a pandemic where the employees' values, health, and financial well-being were magnified and became a national topic. The "great resignation", livable wages, and employee job shopping put the power of business in the employee's hands, not the employer. Business leaders looked to HR professionals to understand employees' thoughts and feelings toward new policies and requirements. Suddenly, the qualitative information from employee conversations was essential to the business and retention. Not that AC is not of importance, but the power of social competence was pushed into the limelight as an essential business function of the HR profession. Therefore, HR leaders should desire to have diverse competencies in their employee base and assess performance on the competencies they were hired to utilize, not a one-size-fits-all strategy, even within an occupational function. Although there may be opportunities to increase HR capabilities with practice, tempering expectations for individual development is warranted for now.

In this final reflection, there is much to gain in reviving competency modeling and, in research, not binding ourselves to standard practices. In working through the competency modeling guidelines, it wasn't that they were not helpful; the guidelines lacked structure, which created frustration and internal consternation as to the actual value of the model. Therefore, the importance of recognizing frustration and utilizing those experiences to improve the process can create growth not only pragmatically but also improve our understanding of theory.

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Appendices

- **Appendix A.** Logic Instrument for Analytic Competency
- **Appendix B.** Numeracy Instrument for Analytic Competency
- **Appendix C.** HR Analytic Software Literacy Proficiency Instrument
- **Appendix D.** Critical Evaluation Instrument for Analytic Competency
- **Appendix E.** Plouffe et al. (2016) Persuasion Instrument
- **Appendix F.** Situation Judgement Tests for Decision-Making
- **Appendix G.** Decision-Making Self-Efficacy
- **Appendix H.** HR Performance Measures
- **Appendix I.** Controls
- **Appendix J.** Definition of Terms
- **Appendix K.** Ethical Considerations
- **Appendix L.** Philosophical View
- **Appendix M.** Informed Consent
- **Appendix N.** Methods and Results Summary

Appendix A. Logic Instrument for Analytic Competency

7-point Likert Agreement Scale

1. Identifies important questions about the organization that can be answered with thoughtful research design.
2. Identifies connections in the research and develops valuable insights.
3. Ability to make deductions from information provided to arrive at sound conclusions.

Appendix B. Numeracy Instrument for Analytic Competency

7-point Likert Agreement Scale

1. Collects, trends, and can chart historical HR data.

2. Analyzes data outputs or displays from dashboards, metrics, or people analytic tools.

3. Utilizes statistical methods to obtain predictive and prescriptive solutions to HR problems.

Appendix C. HR Analytic Software Literacy Proficiency Instrument

The programs exemplified are based on Lunsford & Phillips's (2018) HR analytic tools study.

Rate your proficiency to conduct analytics in the following programs. Examples of analytics include: reporting, metrics, prescriptive analysis, predictive models, and data visualization such as charts and graphs. Examples are given, however the list is not exhaustive, and consider all relative software you may have experience within your responses.

0 10 20 30 40 50 60 70 80 90 100

Not proficient at all Moderately proficient Extremely proficient

Spreadsheet based software such as Microsoft Excel _________________

Statistical software such as SPSS, SAS, or R _________________

HR Information System Tools or Business Intelligence Tools such as SAP SuccessFactors, Oracle PeopleSoft, Work Day, Oracle, OrgVue, Fusion

____

Visualization tools such as SAS, Visier, or Tableau _________________

Appendix D. Critical Evaluation Instrument for Analytics Competency

7-point Likert Agreement scale.

1. Applies lessons learned to new problems resulting in improved outcomes.
2. Reflects on current practices and identifies opportunities for improvement.
3. Identifies problems that can be solved and identify the means to solve them.

Appendix E. Modified Plouffe et al. (2016) Persuasion Instrument

The following is modified from Plouffe et al. (2016) to have instructions tailored for the HR practitioner context. Also, the visualization and storytelling language was tailored in the inspirational appeal construct to better align with the terminology found in the HR literature (Fitz-Enz & Mattox, 2014; Soundararajan & Singh, 2017; Waters et al., 2018). The final analysis only utilized the Inspirational Appeal item set because the results of the CFA were not adequate for Rational, Consultation, and Coalition to conduct further analysis in the SEM.

INSTRUCTIONS – The questions below pertain to how you work and perhaps try to influence others within your organization. For these questions, recall when you have provided a solution, proposal or recommendation for a problem within the organization. The people you may need to speak to maybe in various positions (e.g., your direct manager, your VP of Human Resources, executive leaders outside of HR, colleagues, etc.). With this in mind, for each statement you are presented with, select the response choice (below) which best matches how often you use that specific behavior or tactic on others inside your own organization.

1. I can't remember ever using this behavior or tactic on anyone in my organization.
2. I very seldom use this behavior or tactic on others in my organization.
3. I occasionally use this behavior or tactic on others in my organization.

4. I use this behavior or tactic moderately often on others in my organization.

5. I use this behavior or tactic very often on others in my organization.

<u>Rational</u>

1. Make a detailed explanation of the reasons for a request.
2. Use facts and logic to make a persuasive case for a request or proposal.
3. Explain clearly why a request or proposed change is necessary.

<u>Consultation</u>

1. Ask the person to suggest things he/she could do to help you achieve a task objective.
2. Ask the person to suggest ways to improve a plan or proposal that you want him/her to support.
3. Encourage the person to express any concerns about a proposed change that you want him/her to support or implement.

<u>Coalition</u>

1. Ask someone the person respects to help convince him/her to carry out a request or support a proposal.
2. Bring someone else along to support you when meeting with the person to make a request or proposal.
3. Get someone with higher authority to help influence the person to do something.

Inspirational Appeals

1. Will make an inspiring speech, tell a compelling story, or presentation to arouse their enthusiasm for a proposal that is currently under consideration.
2. Develop appealing visualizations that describe what my solution could accomplish for them.
3. Create a depiction of how my solution serves as an opportunity to accomplish exciting and worthwhile objectives.

Appendix F. Situation Judgement Test for Decision-Making

Developed based on example problems and scenarios in Waters et al. (2018) and Edwards and Edwards (2019), and SHRM certification practice questions from Russell (2021). Correct responses are identified in bold font.

You are the HR director for a major cruise line. The company is looking for ways to increase return customer business. The executive team is looking for solutions from the talent strategy. Your cruise line is known for its signature entertainment and nightlife. Your current talent strategy focuses on identifying, selecting, and training some of the industry's best performers, chefs, mixologists, and musicians. The strategy of your competitors is unique off-shore excursions and free inclusion options. These methods (off-shore excursions and free inclusion options) are not cost-affordable solutions to expand on for your cruise line and have shown through industry research not to have as strong returns. Yet, the other cruise lines are hyper-competitive. The competitors have similar amenities and talent pools to choose from for talent. The following chart is from your customer experience surveys. The scores are an average on a 10-point scale, where 10 is an excellent experience, and 1 is a poor experience. Your focused talent strategy is significantly related to high scores in customer experience for those operational areas (e.g., the selection and training of the best mixologists is positively associated with high customer experience scores) and return customers. Your cruise line currently has the highest experience scores in bars and entertainment than any other cruise line on the market. The only negative comments on experience surveys are regarding WIFI services, availability of deck chairs, and a language barrier for customers trying to communicate in English with room support staff.

Area of Operation	Experience Scores
Bars	9.2
Entertainment	9.8
Spa Experience	9.6
Pool Staff	8.3
Room Support Staff	7.6
Restaurants	9.7
Customer Service	8.3

What do you present to the executive team as a result of this research?

A. Make no changes to the talent strategy and demonstrate to the executive team how the talent strategy supports the current business objectives to have a signature entertainment and nightlife experience. Your strategy is working.

B. Demonstrate how your talent strategy is working and offer options to enhance the entertainment experience by providing more options - increasing the number of show offerings and opening more bars and lounges.

C. Determine the greatest impact you can make is to increase room support staff scores. You recommend adding a pilot training program *English as a Second Language* for support staff with incentive and certification for completion.

D. Suggest to the executive team they look at other amenities such as WIFI service and increasing the number of deck chairs to have a targeted approach based on customer feedback scores.

The leadership team decides to take a different route based on additional information from the marketing team. The company will be adding a folded origami towel on each bed for better room presentation. You've been asked to determine if it was successful or not from a talent strategy perspective. How will you assess if this plan was successful?

A. Obtain feedback scores from the room support staff on their training experience to determine if they found the origami towel training beneficial.

B. Utilize benchmark data on industry room presentation (with and without towel origami) and cruise liner performance to estimate the value-add of this project.

C. Determine the marketing team is in the best position to support this analysis since they have the data on visual appeal and customer feedback.

D. Conduct a return on investment analysis based on the cost of towel origami training, change management support costs, customer satisfaction scores, and return customer data.

The cruise line is not happy with the results of the origami towel project and decides they need focus groups with employees to brainstorm solutions. What do you do to ensure the focus groups successfully brainstorm potential ideas and solutions for improvement?

A) Select a facilitator from within the organization to lead the focus group discussion.

B) Have supervisors assign engaged employees as members of the focus group.

C) Confirm that participants in the focus groups are representative of the workplace.

D) Structure discussion topics and set specific outcomes for the focus group.

An engineering manager approaches you about a problem with turn-over and tells you there is a "talent emergency". The organization has a long-standing program that is stable with expected steady growth through the next five years. The company has a popular benefits program, competitive salaries, and an annual bonus. You have not heard from other managers about this "talent emergency", but the manager insists the issue exists. As the HR manager, you have the following data on your talent dashboard for the past four quarters for the entire business unit.

Metrics	Q1	Q2	Q3	Q4	2020 Average
Separations	98	98	101	109	101.75
Average Headcount	1227	1227	1219	1210	1212
Turnover Rate	7.99%	7.99%	8.29%	9.01%	8.40%

What conclusions do you make as the HR Manager?

A. The manager feedback and the increase in attrition in the 4th quarter indicates there is a problem emerging, so you implement an aggressive retention strategy to reduce attrition

B. Determine you do not yet have enough information and assess other internal and external factors to the organization to inform your decision.

C. Determine there is a problem, but you need feedback from exiting employees and initiate an exit survey.

D. Determine there is no problem and provide the data to the manager to demonstrate the negligible increase in attrition; it's only a one percent increase.

Which of the following methods do you utilize to help the manager see if the turnover is within a healthy range and manageable?

A. Utilize a process control chart to provide a more robust method with visual indicator of when turnover is not within an acceptable range and accounts for cycles in attrition.

B. Conduct focus-groups with the employees of the manager to understand what is causing his employees to leave.

C. Develop a presentation that shows the engagement scores from the last engagement survey and exit surveys to demonstrate the manager's perceptions are not validated and that employees are engaged.

D. Continue to monitor quarterly the turn-over in his group and re-assess if the turnover continues to rise.

The VP of Engineering is made aware of the turnover concerns. You must present your findings and recommendations to the executive and senior engineering management team. What steps do you take?

A. Ask another HR manager for their input on the attrition data and how they would interpret the problem and utilize your combined expertise to develop a recommendation.

B. Request a meeting with the VP to better understand her/his concerns regarding the turnover and what may be causing the "talent emergency".

C. Provide a report to the executive management on current HR talent program features and your recommendations to continue to leverage the program as planned, given the lack of substance in the claim.

D. Increase talent recruiting and provide a synopsis of this activity and how it is helping meet the increased demand as a result of higher attrition.

You are a new VP of HR in a high-end retail company. You were hired to help turn around the brick and mortar sales which are lower than anticipated, even with digital sales adjustments. Your HR business partner for sales provides a grim report. The turnover of your sales team continues to be above industry benchmarks, customer feedback scores are low, and the site managers provide anecdotal reports that morale is low. The company's marketing team is frustrated because they have great foot traffic rates in the stores but low sale conversion rates. The marketing team believes HR is not doing enough to bring in the right talent. Your talent acquisition team is frustrated because they bring in talent faster than the industry standards, with high-quality hire scores among the retail management team. You suspect the management team is not fostering a culture that engages employees adequately and provides them with the support and training needed to meet customer needs and expectations. You believe you need some way to measure engagement. The CEO supports your plan for a new survey, but you need to work quickly. Several years ago, the last engagement survey was by a small but reputable firm that is not currently taking clients.

What is the best next step to take?

A. Quickly develop a request for proposal and send it to at least five of the survey service providers you found through an internet search, allow for a three-week response time.

B. Utilize a ubiquitous, inexpensive, and reputable web-based survey tool that can easily be initiated

C. Delegate this task to the HR Business Partner of sales, setting expectations that this is a top priority and a new vendor must be selected as soon as possible.

D. Inform the CEO that the prior service provider is no longer an option and ask what to do next.

The survey vendor provides some statistical results and explains a statistical difference between retail regions in engagement. You immediately receive what the vendor finds insightful analysis, but a polished report will not be available for several weeks. The sales data was also provided by the finance team for the previous quarter. The finance team explains that the regions are drawn to be similar in volume, size, and forecasted sales for easy comparison. Reported data provided below.

Regions were designated as

C = Central Region

NE = North East Region

NW = North West Region

SE = South East Region

SW = South West Region

Descriptives

EngagScore

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
C	35	66.46	7.812	1.320	63.77	69.14	56	79
NE	64	66.91	7.493	.937	65.03	68.78	55	79
NW	30	87.93	4.441	.811	86.28	89.59	81	95
SE	24	67.92	8.000	1.633	64.54	71.29	56	79
SW	32	66.50	8.056	1.424	63.60	69.40	55	79
Total	185	70.29	10.645	.783	68.75	71.84	55	95

ANOVA

EngagScore

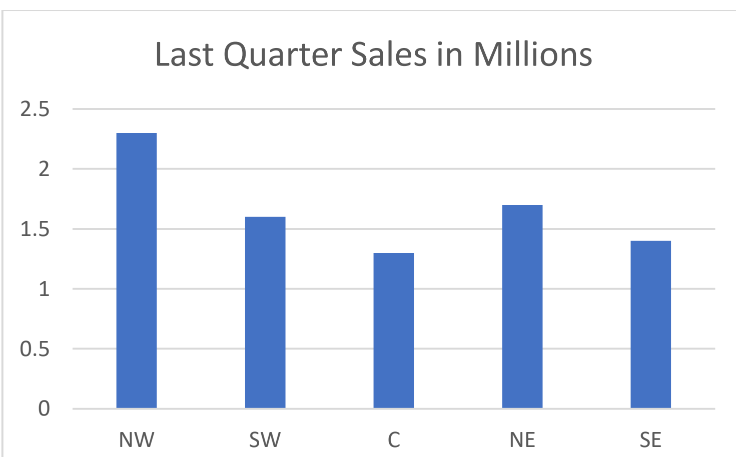
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	11180.415	4	2795.104	52.041	<.001
Within Groups	9667.823	180	53.710		
Total	20848.238	184			

Multiple Comparisons

Dependent Variable: EngagScore
Bonferroni

(I) RegionCoded	(J) RegionCoded	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
C	NE	-.449	1.541	1.000	-4.83	3.93
	NW	-21.476*	1.823	<.001	-26.66	-16.29
	SE	-1.460	1.942	1.000	-6.98	4.06
	SW	-.043	1.792	1.000	-5.14	5.05
NE	C	.449	1.541	1.000	-3.93	4.83
	NW	-21.027*	1.622	<.001	-25.64	-16.42
	SE	-1.010	1.754	1.000	-6.00	3.98
	SW	.406	1.587	1.000	-4.10	4.92
NW	C	21.476*	1.823	<.001	16.29	26.66
	NE	21.027*	1.622	<.001	16.42	25.64
	SE	20.017*	2.007	<.001	14.31	25.72
	SW	21.433*	1.862	<.001	16.14	26.73
SE	C	1.460	1.942	1.000	-4.06	6.98
	NE	1.010	1.754	1.000	-3.98	6.00
	NW	-20.017*	2.007	<.001	-25.72	-14.31
	SW	1.417	1.979	1.000	-4.21	7.04
SW	C	.043	1.792	1.000	-5.05	5.14
	NE	-.406	1.587	1.000	-4.92	4.10
	NW	-21.433*	1.862	<.001	-26.73	-16.14
	SE	-1.417	1.979	1.000	-7.04	4.21

*. The mean difference is significant at the 0.05 level.



The CEO wants a recommendation this week. Upon review of the data, which action do you take?

A. You do not have the final report to interpret the statistical results and ask for an extension from the CEO so that you can provide an accurate analysis.

B. The results do not give you enough information to suggest an action at this time.

C. Recommend conducting a focus group of central region sales staff to understand what is causing low morale since they have the lowest mean score of 66.46 on the engagement survey and low sales.

D. Recommend having the HR Business Partner of Sales start shadowing the North West region manager to identify best practices since that region has higher sales and significantly higher engagement scores.

Appendix G. Appraisal Inventory

Bandura (2006) based scale, modified from the scale building example on self-efficacy instrument for problem-solving. The Bandura (2006) guidelines are followed for construct terminology and scale to include scale title.

This survey is going to ask eight situational HR problems. Please rate how certain you are that you can solve the HR problems as of now.

Rate your degree of confidence by recording a number from 0 to 100 using the scale given below:

0	10	20	30	40	50	60	70	80	90	100
Cannot do at all					Moderately certain can do					Highly certain can do

	Confidence (0-100)
Can solve at least 1of the problems	________________
Can solve 2 of the problems	________________
Can solve 3 of the problems	________________
Can solve 4 of the problems	________________
Can solve 5 of the problems	________________
Can solve 6 of the problems	________________
Can solve 7 of the problems	________________
Can solve all 8 of the problems	________________

Appendix H. HR Job Performance

Performance scale based on Willis Towers Watson generalized scale for salary survey implementation in SHRM summary (Miller, 2021).

1. How would you classify your achievement on your 2020 performance review
    a. Highest Possible Rating
    b. Above-Average Rating
    c. Average Rating
    d. Below-Average Rating
2. How would your manager classify your achievement on your 2020 performance review?
    a. Highest Possible Rating
    b. Above-Average Rating
    c. Average Rating
    d. Below-Average Rating
3. If you received a merit-based increase for your 2020 performance, please provide the increase amount as a percent of your compensation.
    a. My work did not have a merit increase program during our last performance cycle
    b. [insert numeric value as a percent]

Appendix I. Controls

Gender

1. What is your gender?

a. Female

b. Male

c. Non-binary/third gender

d. Prefer not to say

Organization

What is the size of your organization?

a. 49 or less employees

b. 50-499 employees

c. 500-999 employees

d. 1000 or more employees

HR Position

Please select the level in HR that best aligns with your role in your current organization.

a. Support, non-exempt

b. Entry Level Professional, exempt

c. Intermediate or Experienced Professional, exempt

d. Advanced or Expert Professional, exempt

e. Supervisor or Low-Level Management

f. Middle Management

g. Executive or Senior Level Management

HR Function

How would you describe your role in HR? Please choose the option that represents the largest portion of your workload.

a. HR Generalist

b. HR Business Partner

c. HR Strategic Partner

d. Talent Acquisition

e. Organizational & Employee Development

f. Total Rewards (Benefits and/or Compensation)

g. Inclusion, Diversity, & Engagement

h. Labor Relations

i. Information Systems, Technology, & Analytics

Location

Where is your work location?

a. North America/Central America

b. South America

c. Europe

d. Africa

e. Asia

f. Australia

g. Caribbean Islands

h. Pacific Islands

i. Other: ______

j. Prefer not to say

[if North America/Central America response survey logic]

If you work in the USA what region do you work in?

a. New England - Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont

b. Middle Atlantic - New Jersey, New York, Pennsylvania

c. East North Central - Illinois, Indiana, Michigan, Ohio, Wisconsin

d. West North Central - Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota

e. South Atlantic - Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia

f. East South Central - Alabama, Kentucky, Mississippi, Tennessee

g. West South Central - Arkansas, Louisiana, Oklahoma, Texas

h. Mountain - Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming

j. I do not work in the USA

Industry

Which of the following best describes your current industry? (drop-down)

a. Accounting

b. Advertising

c. Aerospace / Aviation / Automotive

d. Agriculture / Forestry / Fishing

e. Biotechnology

f. Hospitality (Hotel, Lodging)

g. Computers (Hardware, Software)

h. Construction / Home Improvement

i. Consulting

j. Education

k. Engineering/ Architecture

l. Entertainment / Recreation

m. Finance / Banking / Insurance

n. Food Service

o. Government / Military

p. Healthcare / Medical

q. Internet / Web Services

r. Legal

s. Manufacturing

t. Marketing / Market Research / Public Relations

u. Media / Printing / Publishing

v. Mining

w. Non-profit

x. Pharmaceuticals / Chemical

y. Research / Science

z. Real Estate

aa. Telecommunications

bb. Utilities

cc. Transportation / Distribution

dd. Business / Professional Services

ee. Don’t work

ff. Other

Years of Experience

How many years of HR experience do you have? Please round to the nearest whole number.

[input number]

Appendix J. Definition of Terms

Human Resource Management

According to Noe et al. (2017), Human Resource Management (HRM) “refers to the policies, practices, and systems that influence employees’ behavior, attitudes, and performance” (p. 4). The definition has often encompassed additional adjectives, notably Strategic Human Resource Management (a.k.a. SHRM, henceforth Strategic HRM to avoid being confused with Society of Human Resource Management or SHRM). The strategic adjective further indicates an HRM that takes a future-looking perspective in planning and interest in the firm's long-term survival (Noe et al., 2017; SHRM, 2015; Jackson, Jiang, & Schuler, 2017). Scholarship has further prescribed HRM as having orientations of being hard, soft, vertical, and horizontal, all of which provide specific functionalities and advantages to managing human capital for the objective of firm success (Armstrong, 2000; Han et al., 2019).

HR Professional

An HR professional is one, who’s responsibilities within the firm, are primarily to conduct HRM. The responsibilities fall within several functions within the field – analysis and design of work, HR planning, recruiting and selection, training and development, compensation, performance management, and employee relations (Noe et al., 2017). The responsibilities are usually aligned in centers of expertise or excellence, depending on the organization's size and needs (Noe et al., 2017; Ulrich, Younger, Brockbank, 2008).

HR Business Partner

HR Business Partners (HRBP) are a specific type of professional, who’s responsibilities are centered around consultation. Popularized in the 1990s by Dave Ulrich, a seminal HR structure and competency author, the functional purpose for HRPB’s includes providing value-add solutions that help “turn strategy into action” (Kenton & Yarnall, 2010). Ulrich described four specific roles- Strategic Partners, Change Agents, Administrative Experts, and Employee Champions (Ulrich, 1997). The HRBP model is evolving and highly debated because of questionable success (Gerpott, 2015; LaFevor, 2018).

HR Specialist

An HR Specialist has a defined role typically within the shared services of Talent Acquisition, Training and Development, Compensation and Benefits, and HR Information (Noe et al., 2017; Scully & Levin, 2010; LaFevor, 2018). Unlike a business partner their role is centralized on specific functional skills such as recruiting, compensation analysis, and training course development.

HR Generalist

An HR generalist performs multiple functions and job responsibilities can span that of HRBP and specialist roles that are separated out in an HRBP shared service model. Unique from a specialist the generalist has a general knowledgebase that covers a wide range of areas, whereas a specialist has a deep level of knowledge in one area (Moss, 2018).

Competency

SHRM defines competency as "a cluster of knowledge, skills, abilities and other characteristics (KSAOs) needed for effective job performance" (SHRM, 2016, p. 4). LeDeist and Winterton (2005) define a complete competency framework as a holistic model consisting of cognitive, social, functional, and meta-competencies.

Skill

Skills are embedded within the competency definition and a building block. According to Merriam-Webster (n.d.), a skill is the ability to use one's knowledge effectively and readily in execution or performance. It is also considered a developed aptitude or ability.

Evidence-Based HR

Noe et al. (2017) describe the practice of evidence-based HR as a 'demonstration of HR practices that have a positive influence on the company's bottom line or key stakeholder (employees, customers, community, shareholders)' (p. 11).

Data-Driven HR

Data-driven decision-making derives an understanding of analytics from the levels of data analysis and through advancing stages, one can obtain insights and prescriptive solutions (Roberts, 2007; Soundararajan & Singh, 2017). The growth HR metrics, dashboards, and workforce analytics is derived from data-driven school of thought (Roberts, 2007).

HR Analytics

Defining analytics is an essential base for this dissertation. According to Bassi (2010) HR analytics is “the application of a methodology and integrated process for improving the quality of people related decisions for the purpose of improving individual and/or organizational performance” (p.11). Professional literature defines “HR analytics (also called people analytics or talent analytics) [is the] use measurement and analysis techniques to understand, improve, and optimize the people side of business” (Waters et al., p. 5). Margherita (2021) provides a synopsis of other terms used to describe HR analytics - workforce analytics, people analytics, human resource analytics, talent analytics, and human capital analytics. Of the terms used, people analytics is emerging as the most popular lexicon based on internet search results through 2018, followed by HR analytics, workforce analytics, talent analytics, lastly, human capital analytics (Paul Van der Laken, 2018). Fitz-enz (2014) describes analysis uniquely from reporting; instead, analytics provides answer versus data, what is needed versus what is asked, customized vs. standardized, involves the reader vs. not, and is flexible vs. inflexible.

LAMP framework

Defined by Boudreau and Ramstad (2007), the LAMP framework is an accepted model (Kryscynski et al., 2017) for defining AC within HR competency scholarship. The acronym LAMP represents the HR professional taking the right– Logic, Analytics, Measures, and Process – to solve problems and be a strategic force for change and competitive advantage.

Human Resource Information System

Like analytics, Human Resource Information Systems (HRIS) can have multiple terms synonymous in the literature to include Electronic Human Resource Management (E-HRM). An HRIS aims to gather information and process data required to enhance human resource management (Kavanaugh & Johnson, 2017). For comparison, Voerman and Veldhoven (2007) define E-HRM as the administrative support of organizations' HR functions using internet technologies. HR professionals have products available for a myriad of applications for the different HR functions, of which fall into an HRIS. In an example, HR organizations can run an Applicant Tracking Systems (ATS) for recruiting and talent acquisition; Learning Management Systems (LMS) for development, implementation, and recording of training programs; none-the-less more commonly known core HR functions, such as payroll, timekeeping, and benefits administration (Eubanks, 2019). Barišić et al. (2019) contends the difference between HRIS and E-HRM is the positionality of the technology; HRIS is used by HR professionals, whereas E-HRM functions as a tool for the company and external persons to the HR organization.

Appendix K. Ethical Considerations

Ethical considerations should be made throughout the research process, such that literature review, problem statements, purpose, design, and participant outcomes reach a high moral standard (Creswell, 2014). Creswell (2014) suggests actions to meet high ethical standards prior to conducting the study to include consulting relative code of ethics for professional associations, obtaining IRB approvals, identifying the appropriate gatekeepers or key personnel for help, selecting sites that will not raise power issues with the research and give proper credit for the work.

The most prominent professional association is SHRM. Their code of ethics includes a responsibility to add value to the organizations we serve and are responsibility to our own decisions and actions. We also must be advocates of the profession and engage in activities that enhance its credibility and value. Among other factors, the intent includes informing and educating current and future HR professionals, encouraging professional decision-making and responsibility, and building respect and credibility for the profession (SHRM, 2014). The nature of this research actively supports the code of ethics, giving HR professionals research that provides a mechanism for learning and growth, with the subsequent expectation to increase credibility and value. SHRM provides research-specific forums to support academic research and encourage utilization of these platforms for peer-to-peer outreach, not subject to power issues.

In addition to professional assessments, this research took appropriate academic ethical considerations to include IRB review and approval of the study before participant outreach. Further, this research was also conducted under academic scholars' advisement, who provide active tutelage and advisement throughout the research process.

Appendix L. Philosophical View

Creswell and Poth (2018) provide guidance on worldviews. This dissertation has taken appropriate information from industry, I/O to include behavioral and cognitive approaches, and the decision science fields to derive an effective model for HR professionals. This approach is quite pragmatic and is not tailored to one singular lens. Therefore, based on the definitions in Creswell and Poth (2018), the view of this research is pragmatism. HR professional, firm, and theoretical implications require the researcher to understand and gain support from a myriad of perspectives to be salient and create a valuable contribution to both practice and building knowledge. The relationship between academia and HR professional is noted as being discorded in HR but an area for opportunity to enhance research and the firm (Ulrich et al., 2015; Simón & Ferreiro, 2018; van der Togt & Rasmussen, 2017). Therefore, tailoring this work and weaving between both practical and academic pursuits is a logical deduction.

Ulrich, the seminal author on competencies, openly discusses who should be the purveyor of HR competencies – academics, HR professionals, or professional affiliations (Ulrich et al., 2015). In summation, Ulrich et al. (2015) determine that a triangulation of critical competencies from the industry, professional associations, and academia will move us forward and incorporate valuable input across critical stakeholders. Likewise, this dissertation will take from works directed toward the professional audience and academic literature to bind the knowledge, skills, and abilities that make up the HR AC in a more formidable model that meets the expressed need in both literature and professional realms (Margherita, 2021; Kryscynski, 2017).

Appendix M. Informed Consent

Informed Consent

Please read this consent document carefully before you decide to participate in this study. The researcher will answer any questions before you sign this form.

Study Title: Assessing the Analytic Competency Gap for HR Professionals: Providing HR a Roadmap to Data-Driven Decision-Making

Purpose of the Study: The purpose is to study the relationship between analytic competencies and decision-making and job performance for HR professionals

Procedures: This will be an approximate 20-30 minute survey of which the participant will answer questions regarding their own competencies. The participants will also be asked to provide their best judgment to problems presented in vignettes. The participant will also be asked demographic and job performance-related questions.

Potential Risks of Participating: The risks are no more than everyday life.

Potential Benefits of Participating: The participant may learn more about themselves and how they utilize analytic competencies in their job performance. Further, the results of this study may be used to enhance individual, HR department, and educational programs development, informing which analytic competencies may be most beneficial to job performance. The results of this study may also increase understanding of the role decision-making has on HR job performance.

Compensation: The compensation is as agreed upon by the survey implementation vendor.

Confidentiality: Your identity will be kept confidential to the extent provided by law. Instead of any personally identifying information, your information will be assigned a code number. The list connecting your name to this number will be kept in a locked file in an electronic hard storage device separate of the storage device the study will be housed, physically located in South Florida. When the study is completed and the data has been analyzed, the list will be destroyed. Your name will not be used in any report.

Voluntary participation:

Your participation in this study is completely voluntary. There is no penalty for not participating. You may also refuse to answer any of the questions we ask you.

Right to withdraw from the study:

You have the right to withdraw from the study at any time without consequence.

Whom to contact if you have questions about the study:

Chandra Talerico

8284 SE Woodmere St.

Hobe Sound, FL 33455

Email: ctalerico2018@my.fit.edu

240-818-1901

Whom to contact about your rights as a research participant in the study:

Dr. Jignya Patel, IRB Chairperson

150 West University Blvd.

Melbourne, FL 32901

Email: jpatel@fit.edu

321-674-7391

Agreement:

By clicking on the link below and completing and submitting this anonymous survey, I am consenting to participate in this research.

[SURVEY LINK]

Appendix N. Methods and Results Summary

	Study Metrics	Study Thresholds	Literature Recommended Metric	References	Researcher Rationale and Comments
Pilot Sample Size					
Expert Panel Size	5	5	5 - 10	Almanasreh et al. (2019)	Panel met desired criteria and threshold minimum of 5 participants.
Pilot, Phase 1, Size minimum	30	16	16-32 (10-20% of Study Sample)	Baker (2014)	Due to the length of time to acquire participants, the pilot was evaluated when Baker (2014) thresholds were met for assessing non-EFA factors and plans were made for a 2nd pilot to meet EFA sample power threshold.
Pilot, Phase 2, EFA power minimum	55	≥ 50	≥ 50	Jackson et al. (2013)	The final pilot threshold was higher to meet adequate power threshold for EFA
Main Study Sample Size					
SEM power minimum a priori calculation	161	≥ 161	≥ 161	Soper (2021)	Soper (2021) calculates a priori SEM minimums based on variables, desired minimum effect size, and significance. The minimum was based on output from Soper's (2021) calculator, assesed with the largest model variable arrangement in the study: 26 variables, .3 medium effect size, and significance level of .05.
Exploratory Factor Analysis					
Eigenvalue loading	3	1	3	Kaiser (1960); Waldeck et al. (2021)	Although the factor analysis did not meet the desired threshold for 3 factors, as prescribed in Waldeck et al. (2021) continuance may be and is warranted if the literatures supports separate dimenions. Model robustness checks are incorporated in the SEM and SEM modeling accounts for covariance.
Factor loading	0.744-0.916	≥ 0.70	≥ 0.70	Podaskoff et al. (2003)	The threshold for further analysis and main study continuance was met for the analytic cluster and one dimension of the persuasion instrument.
Preliminary Data Checks					
A non-statistical comparison of descriptives between the study and another sample was conducted. The study sample was determined to have a higher rate of early career participants. This was deemed acceptable because of the comparison to BLS data still demonstrated over sampling of higher career that presents in the HR population.					Position and years of experience are control variables in the structural model.
Skewness	0.158	-1 to 1	-1 to 1	Gaskin (2021)	Performance variables demonstrated a value within range and demonstrated limited skew, with a score near zero.
Kurtoisis	0.232	< .381	< .381	Sposito et al. (1983)	Kurtosis is less than three times standard error.
Data Integrity	< 1%	< 1%	< 10%	Gaskin (2021)	The completion rate of quality responses met the threshold. The one item that did not meet the completeness threshold, compensation (10.5%), was removed.
Correlation Matrix	variable	p < .05	p < .05	Kline (2015)	Descriptive tool for preliminary understanding of individual construct correlations and a best practice to include. The matrix provided context for continued model development.

	Study Metrics	**Study Thresholds**	**Literature Recommended Metric**	**References**	**Researcher Rationale and Comments**
Reliability					
Cronbach's Alpha	.824-.882	> 0.70	> 0.70	Whitley (2002)	Reliability threshold during the CFA for the new latent constructs were met.
Composite Reliability (CR)	.874-.894	> 0.70	> 0.70	Gaskin (2021)	The internal consistency of the latent constructs from the CFA are all above the threshold.
Validity					
Content Validity Index (CVI)	0.80-1.0	> 0.78	> 0.78	Polit et al. (2007)	The instruments met the threshold for content validity as assessed by the expert panel Likert results on relevance questionnaire.
Heterotrait-monotrait ratio of correlations (HTMT)	.536-1.03	< 0.90	< 0.90	Hamid et al. (2017)	The AVE and HTMTwas conducted during the CFA analysis. Similar to the Eigenvalue factor analysis the convergence was expected. The items are subsequently loaded onto a single larger latent construct in SEM, minimizing concerns for validity issues. Further, Gaskin (2021) notes the debate about AVE being a flawed measure. Finally, redundancy in subsequent SEM modeling and the ability of fitness indices to account for measurement models make the AVE measure somewhat moot (McNeish & Hancock, 2018).
Average Variance Extracted (AVE)	.263-.301	0.263	> 50	Gaskin (2021); McNeish et al. (2018)	
Response Bias					
Non-response bias assessment	p = 1.0	p ≥ .05	p ≥ .05	Linder et al. (2001)	Linder et al. (2001) provides a synposis of current best practices and recommends for assessing differences between early and late respondents with t-tests and ANOVA. In accordance with this practice no non-reponse bias were found- no significant difference between early and late respondents.
Common method bias - Harmon's Single Factor Test	45.47%, 38.52%	< 50%	< 50%	Podsakoff & Organ (1986)	One factor accounted for less than 50% of variance in both the pilot and main study suggestive of no common method bias.
Confirmatory Factor Analysis					
Root Mean Square Error of Approximation (RMSEA)	0.077	< .07	< .06 to < .07	Van Doorn et al. (2019); Kline (2016); Hooper et al. (2008); Hu & Bentler (2009)	Fit indices determine if the items adequately align with and measure the latent constructs. Although not all fitness measures were met, results were considered acceptable for further analysis.
Standardized root mean Square Residual (SRMR)	0.048	< .08	< .08		
Comparative Fit Index (CFI)	0.953	> 0.90	≥ 0.90 acceptable, ≥ 0.95 ideal		
Tucker-Lewis Indiex (TLI)	0.931	> 0.90	≥ 0.90 acceptable, ≥ 0.95 ideal		
χ^2 - Exact Fitness	p < .001	p ≥ .05	p ≥ .05		
Factor Loading	.71 - .83	≥ 0.70	≥ 0.70	Whitley (2002)	The loading value represents how much the item contributes to the latent construct. 0.70 loading represents an adequate contribution for item retention.

	Study Metrics	Study Thresholds	Literature Recommended Metric	References	Researcher Rationale and Comments
Structural Equation Modeling					
Original Model - Fit Indices					
RMSEA	0.054	< .07	< .06 to <.07	Van Doorn et al. (2019); Kline (2016); Hooper et al. (2008); Hu & Bentler (2009)	Fair model fit, but not strong model fit on all model fit indices, suggestive of additional model fit analysis was warranted. The exact fitness test looks to not reject the null, which was not feasible with significance of χ^2. Due to the tendency for χ^2 to be too conservative and reject acceptable models, additional indices are used. RMSEA and SRMR closer to zero is desired and met thresholds. The other indices are model fitness (hypothesis relationships are supported with the data) with ranges 0-1 with 1 being perfect. Neither met the ideal threshold, but met acceptability standards.
SRMR	0.068	< .08	< .08		
CFI	0.933	> 0.90	≥ 0.90 acceptable, ≥ 0.95 ideal		
TLI	0.919	> 0.90	≥ 0.90 acceptable, ≥ 0.95 ideal		
χ^2	p < .001	p ≥ .05	p ≥ .05		
Hypothesis acceptance testing	P > .05, except Persuasion	p ≥ .05	p ≥ .05		The significance values for all hypothesis suggested rejection, except for persuasion.
Revised Model - Fit Indices					
RMSEA	0.057	< .07	< .06 to <.07	Van Doorn et al. (2019); Kline (2016); Hooper et al. (2008); Hu & Bentler (2009)	Model fit increases compared to the original and alternative models assessment demonstrates improved fit.
SRMR	0.069	< .08	< .08		
CFI	0.95	> 0.90	≥ 0.90 acceptable, ≥ 0.95 ideal		
χ^2	p < .001	> 0.90	≥ 0.90 acceptable, ≥ 0.95 ideal		
TLI	0.939	p ≥ .05	p ≥ .05		
Hypothesis acceptance testing	p < .05, except Persuasion	p ≥ .05	p ≥ .05		The relationships between the hypothesized paths were significant for the AC cluster, supporting the AC hypotheses. However, persuasion in the new model becomes non-significant.
Mediation					
Hypothesis acceptance of partial mediation for Analytics - SE - Job Performance	0.044	p ≥ .05	p ≥ .05	Lowery & Gaskin (2014), Sobel (1982)	Mediation Sobel test was significant, confirming mediation. The assessment for partial mediation was confirmed as S-E did not fully mediate direct effects.
Hypothesis acceptance of full mediation for Persuasion - Analytics - Job Performance	0.042	p ≥ .05	p ≥ .05	Lowery & Gaskin (2014), Sobel (1982)	Mediation Sobel test was significant, confirming mediation. The assessment for full mediation was confirmed because the direct effect was completely nullified by the mediation.