ARTIFICIAL INTELLIGENCE (AI) IN EMPLOYEE SELECTION: HOW ALGORITHM-BASED DECISION AIDS INFLUENCE RECRUITERS' DECISION-MAKING IN RESUME SCREENING

By

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Abstract

Artificial Intelligence (AI) in Employee Selection: How Algorithm-based Decision Aids Influence Recruiters' Decision-Making in Resume Screening

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With the development of artificial intelligence (AI), algorithm-based decision aids have been adopted by more and more organizations to help recruiters and hiring managers screen and review job candidates. This dissertation assesses how HR recruiters integrate selection information produced by algorithms into assessments of job candidates' qualifications to make the hiring decisions. To assess how algorithm-based decision aids are used, I first investigate how individual characteristics of recruiters influence their perceived usefulness of algorithm selection information. I then examine how recruiters rate applicant employability when they are given different types of jobs (HR Assistant vs. Data Engineer) and algorithm-based selection information. Results showed that younger managers, managers with AI use experience and more recent hiring experience perceived algorithm-based decision aids useful. Recruiters were less likely to see algorithm-based information as useful if they reported algorithm aversion. Similar relationships were found when managers rated employability when presented with information from both resumes and algorithm-based decision aids. Finally, I found that applicant information from algorithm-based decision aids had more influence on manager ratings of employability when the job requires more technical skills than when the job requires more soft skills. Theoretical and empirical implications are discussed.

Keywords: AI, algorithm-based decision aids, resume screening, algorithm aversion, job type, policy-capturing.

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Dedication

I dedicate my dissertation work to my husband, Qixue Li, who has been a constant source of support and encouragement during the challenges of PhD program and life in the pandemic. I am truly thankful and grateful for having you in my life.

I dedicate this dissertation to my parents, who have always loved me unconditionally and whose good examples have taught me to work hard for things that I aspire to achieve.

I also want to dedicate my dissertation work to our sweet daughter, Mia Li, who has been a source of joy and energy in the past four years. Thank you for your love, kisses, and hugs. I am blessed to be your mom.

Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

The use of artificial intelligence (AI) in human resource (HR) management has increased significantly in recent years. A 2018 survey of 88,000 recruiting professionals worldwide conducted by LinkedIn found that 1/3rd reported that AI was the most important trend affecting how they hire and 56% reported that it was most helpful in selecting candidates (Das, 2018). Organizations around the world are embracing AI-based tools such as chatbots, predictive analytics, robotic process automation, and automated video interviewing.

In talent acquisition, onboarding, learning and training, and employee relations. For example, AI is used in the onboarding process to introduce new employees to information including company policies, task assignments, and team members (Singh, Bhavya, Singh, Ravesangar, & Saini, 2021). In training and development, AI is used to assess employees' skills and recommend learning programs by analyzing data and identifying employees who need training in a specific area (Sima, Gheorghe, Subic, & Nancu, 2020). For administrative tasks, AI-based software can automate repetitive and time-consuming administrative tasks, such as processing payrolls and benefits requests (Kurek, 2021).

One of the most common applications of AI in HRM is the talent acquisition process. Organizations are using AI technology to screen candidates, maintain databases, schedule interviews, and answer job applicants' queries (Mohan, 2019). These systems take two forms. The first is automating selection decisions using an algorithm or using the systems to narrow applicant pools by searching large pools of applications or resumes for specific types of skills or experience. The second is a decision-aid which creates some form of fit score for job applicants based on a set of desired characteristics or similarity to a set of existing employees. There are a number of AI-based systems and software now commercially available and widely used in new employee selection.

There is no common definition, and these systems have a wide range of features that vary in sophistication and application of artificial intelligence tools for selection. Most common is process automation and integrate with common applicant tracking systems (ATS) and widely used HR information systems (HRIS). This typically includes resume parsing using natural language processing (NLP) to process large numbers of resumes efficiently. There are also a set of resume screeners that use AI to develop and scoring algorithms to either screen in resumes for applicants that have specific qualifications or report a fit score to recruiters to use valuating candidates. To train the algorithms the software systems use a variety of methods. One technique is recruiters' choices that train the algorithm over time as recruiters select resumes. Recruiter choices train the algorithm to give higher scores to resumes that have similar characteristics. Second are selection tests for applicants that are then combined with resume information to develop predictive algorithms. For example, the technology company Xerox Service uses a recruitment algorithm to support HR managers in their hiring decisions by offering them a score of how well an applicant's qualifications fit a job (Peck, 2012). The algorithm behind this HR tool analyzes data from applicants via an online application pool and uses a series of tests and assessments to see how well the applicant would deal with challenges on the job. Finally, the most sophisticated systems use archival data on employee selection and performance to train algorithms to score applicants based on characteristics that are similar to employees selected in the past and current high performing employees.

The motivation to use these AI-based systems is the potential to improve employee selection by both automating tasks and improving selection decisions. Vendors sell these systems with the promise that they make selection processes more efficient, timely, and accurate. Especially in large organizations where recruiters spend significant time on repetitive and mundane tasks, such as reviewing applicants' resumes or going through the applicant tracking systems to gather information. These systems save time that can be better spent engaging potential candidates and improving the candidate experience in the hiring process. AI-based systems also hold the promise of making resume screening more comprehensive. When asking hiring and recruitment decisions, the existing belief among practitioners and researchers is that interviewers tend to make very quick judgments about applicants (e.g., Buckley & Eder, 1988; Heathfield, 2012; Judge, Higgins, & Cable, 2000). Scholars describe this as "snap decisions" (Buckley & Eder, 1988). When hiring managers make that "snap decision", do they really know what characteristics, experiences, education, and personality traits guarantee success in a specific job? Research suggests they do not (Chapman & Zweig, 2005). Meanwhile, technology companies and business consultants have praised the technological sophistication and usefulness of algorithm-based decision-making in selection to integrate applicant information in an efficient and predictive manner (Leicht-Deobald, Busch, Schank, Weibel, Schafheitle, Wildhaber, & Kasper, 2019).

AI is not yet ready to replace humans in this important process, but it is now considered by many HR professionals as a useful tool in the hiring process (Ahmad, 2015). Despite the ever-growing use of algorithm-based decision aids in employee selection, there has been very little research on how they are perceived by recruiters who are tasked with using them.

The purpose of this dissertation is to better understand how recruiters use the information produced by algorithm-based decision aids and integrate the recommendations with other resume details into perceptions of candidate qualifications. My focus in this research is an investigation of how perceptions of information from algorithm-based decision aids is influenced by the characteristics of the managers that use them, their algorithm preferences, and the type of job characteristics for which they are evaluating candidates. First, I seek to understand how individual differences including age, level of education, use of AI, data engineer experience, high-technology industry, hiring recency, and algorithm aversion contribute to recruiters' perceptions. Algorithm-based decision aids and how they use such information in assessing candidates. Second, I examine how perceptions of algorithm-based decision aids and assessments of candidate employability are influenced by managers experience with hiring, experience with algorithm-based decision aids and attitude towards algorithmic decision-making in general. Finally, I test the ways in which managers use algorithm-based job aids when they evaluate candidates for jobs that require different types of skills. Specifically, I examine how information from algorithm-based job aids used when evaluating candidates for jobs that require technical skills vs soft skills (Data Engineer vs. HR Assistant).

This dissertation makes a number of contributions to literature. First, I develop theory to predict that individual characteristics of recruiters will influence the ways in which they use information from algorithm-based decision aids in selection. I do this by applying theory from information systems research to management and HR. I use the technology acceptance model (TAM) to link age, level of education and technology background to managers' perceptions of algorithm-based job aids and their use of it in HR decision-making during the pre-screening process. I also apply the TAM to suggest that manager experience with algorithm-based job aids and experience with recent hiring should also influence perceptions and use of these systems. I also borrow the concept – algorithm aversion from the computer science field. I develop additional theory to explain how the use of information from algorithm-based decision aids is likely to depend in part on underlying individual preferences towards algorithms. This is algorithm independent of individual manager's background, should affect hiring managers' decision-making based on information from algorithm-based job aids. Finally, I develop theory to predict that the use of information from algorithm-based decision aids will differ across jobs that demand different skills and jobs that demand technical skills in particular. I argue that due to the nature of AI technology, hiring managers will have implicit beliefs about the ability to predict technical skills as opposed to soft skills from applicants.

The research offers a number of empirical contributions to research and practice. First, to my knowledge, no other empirical studies have explored how algorithm-based decision aids have been used by recruiters for their hiring decision-making. Practitioners have adopted the new technique and used it for a long time, research field is scarce and behind. This study used quantitative method to test how individual differences (i.e., age, level of education, recruiters' technology background, hiring experience with AI, and algorithm aversion) influence recruiters' decision-making for resume screening.

Second, attribution theory has been used in personnel employment selection in the research. Personnel employment selection involves predicting an applicant's future job performance from information about present and past performance. Previous research has used attribution theory in resume screening and included several categories of information, such as educational background, working experience, demographic information. Similarly, this dissertation successfully added one important and timely component (fit score) generated from algorithm-based decision aids or AI-related tools to investigate how the extra piece of information from the new technology would influence recruiters' decision-making. It completes the current personnel employment selection research.

Furthermore, the results of this study build a solid foundation for future research. As the use of AI systems to speed efficiency and provide additional information to recruiters to make the hiring decisions becomes more common in practice. It is critically important for organizations to understand the individual and situational characteristics that influence how recruiters understand and incorporate this information into their hiring decisions about job candidates. This dissertation strengthens our understanding of the effects that algorithm-based decision aids have on recruiters' judgement.

Chapter 2: Literature Review

Employee selection involves predicting an applicant's future job success from information about the present aptitudes and the past performance (Knouse, 1989). Research has examined a myriad of predictors from applicants' information gathered through resumes, applications, biographical inventories, interviews, and employment tests among others (Schmidt & Hunter, 1998).

The development of new technology has often brought new information for employers to assess candidates. For example, the advent of social media in recent years has provided more information from applicants that is added to the selection process and examine by researchers (Jeske & Shultz, 2016). AI (including algorithm-based decision aids) is another source of information about candidates, and there is little existing research on this influence selection decision-making. This dissertation addresses the question of what factors influence decision-making of hiring managers when presented with AI information in employee selection, more specifically, resume screening. To pursue the answers to this question, I first review the existing literature of employee selection, the different types of information used in selection decisions, and existing theoretical perspectives on decision-making in employee selection.

Employee Selection Information

During the selection process, hiring managers or recruiters use a vast array of different information to make hiring decisions. The most common selection predictors used are the category of biodata which has a long history in employee selection (Stokes, 1999). Biodata variables used to select employees include knowledge, skills, abilities, values, interests, goals, and job expectations (Breaugh, 2009). As far back as Goldsmith (1922) studies have shown that using a person's biodata would improve the hiring decisions. These biographical characteristics are measured using a wide array of selection tests including resumes, ability and proficiency tests, simulations, assessment centers, application forms, and interviews.

Applicants differ considerably in terms of their knowledge, skills, abilities, and other characteristics (e.g., *KSAO*s), and these differences affect their job performance (Stone, Stone-Romero, & Lukazewski, 2007). Because of this, companies use selection techniques to assess the KSAOs of applicants to predict their job performance. For example, organizations often measure KSAOs of applicants that are valid predictors of job performance such as training and experience. They also conduct a job analysis to establish job descriptions and job specifications for successful job performance. Finally, KSAOS are used to make selection decisions.

Another common group of selection predictors are *personality tests* (Rothstein & Goffin, 2006). A group of meta-analytic reviews demonstrates that personality traits predict different aspects of performance (Barrick & Mount, 1991; Mount & Barrick, 1995; Tett, Jackson, & Rothstein, 1991). Personality traits in research are measured as the "Big Five" dimensions of extraversion, emotional stability, agreeableness, conscientiousness, and openness to experience (Barrick & Mount, 1991). Barrick and Mount's (1991) meta-analysis investigated the relation of the "Big Five" personality traits and three job performance criteria (job proficiency, training proficiency, and personnel data) for five different occupational groups (professionals, police, managers, sales, and skilled/semi-skilled). Their results show that conscientiousness consistently predicts job performance criteria for all occupational groups. The estimated correlations for the other personality dimensions and job performance vary by performance criterion and occupational group. Extraversion is a valid predictor of performance for managers and sales employees. Openness to experience is a valid predictor of training proficiency, but not for job proficiency. The results for agreeableness suggest that agreeableness is not an important predict of job performance. Finally, Barrick and Mount (1991) found that most of correlations for emotional stability and job performance were relatively low.

Besides personality traits and biodata in employee selection, research has also investigated the effects of other less job-related categories of information. For instance, there is a large body of research on *physical attractiveness*. Most scholars have treated physical attractiveness as a characteristic as a single dimension that can be rated from low (unattractive) to high (attractive). Some researchers have restricted the definition of physical attractiveness to facial attractiveness (e.g., Cann, Siegfried, & Pearce, 1981; Jackson, 1983). Others have focused on other aspects of physical attractiveness, such as job applicants' dressing attire (Lambert, 1972), or weight (Larkin & Pines, 1979). Later, Morrow (1990) defined physical attractiveness as "the degree to which one's facial image elicits favorable reactions from others (P. 47)."

Research relevant to physical attractiveness has shown that highly attractive people are perceived as having positive traits (Gillen, 1981). Attractive applicants are perceived to be more qualified for employment than unattractive applicants (Cash, Gillen, & Burns, 1977; Dipboye, Fromkin, & Wilback, 1975; Raza & Carpenter, 1987), and attractive applicants are recommended to get higher starting salaries (Dipboye, Arvey, & Terpstra, 1977; Jackson, 1983). Research also combines sex and physical attractiveness to study employment decisions. Empirical studies of sex and physical attractiveness generally show that physical attractiveness is favorable to both women and men, but attractive males are preferred over attractive females in employment decisions (Cann et al., 1981; Cash & Kilcullen, 1985; Dipboye et al., 1975; Dipboye et al., 1977).

Finally, research has investigated the role of employee demographic characteristics in employee selection even though is it illegal under U.S. federal law to use these for selection decisions. These include factors such as gender, age, ethnicity, marital, and family status (Edgar & Geare, 2004). For example, studies have examined the effect of applicants' *gender* on the response to actual recruiters to hypothetical applicants. Older studies such as Shaw (1972) showed that males received more positive evaluations when gender difference was larger for management trainee versus engineering positions. Research has also shown that males received more positive evaluations for a semi-skilled position (Haefner, 1977); and for entry-level positions in accounting, electrical engineering, and sales (McIntyre, Moberg, & Posner, 1980). More recent research suggests that preferences for men in hiring and promotion decisions persist (Eagly & Karau, 2002; Nadler & Stockdale, 2012).

Prior research has also explored the impact of employee *age* (Pfeffer, 1985; Konrad & Hartmann, 2002). For instance, McKay (1998) found that 25% of employers regarded an applicant over 50 as too old to recruit. A field experiment from Lahey (2007) examined hiring conditions for older women in an entry -level job in two locations and reported that a younger worker is more than 40% more likely to have a further interview opportunity than does an older worker.

People from *ethnic minority groups* have experienced a history of discrimination in the U.S. (Kirton & Greene, 2000). Studies have shown that ethnic minority groups experience discrimination during the recruitment and selection process. For instance, Kirton and Greene (2000) have studies job offers for the minority group and the dominant group. Their results indicated that despite ethnic group members making more job applications, they received fewer job offers than the dominant group members. For example, Bertrand and Mullainathan (2004) manipulated race by assigning African American – or White-sounding names to help-wanted ads. Their results showed that white names receive 50 percent more callbacks for interviews. The racial gap is consistent across occupation, industry, and employer size. Lai and Babcock (2013) investigate how evaluators perceive an Asian American versus White job candidates in hiring and promotion. Their findings suggested that female evaluators were less likely to select Asian than White candidates to positions requiring social skills and were less likely to promote Asian than White candidates into those positions.

Finally, research has shown that *marital status* affects selection decisions. Even though it is illegal under many state laws to discriminate based on marital status (Unmarried America, 2012). Social role theory suggests that men occupy a social role associated with earning money and providing for their families financially, whereas women occupy a social role mainly responsible for children and family duties (Eagly, 1987). Based on social role theory, research in marital status discrimination has found that women are perceived to be less qualified for employment after marriage, whereas men are perceived as more suitable for employment after marriage (Hammer, 1993; Jordan, College, Zitek, 2012; Renwick & Tosi, 1978). By conducting an experiment that manipulated marital status, gender, and sexual orientation in interviews, Nadler and Kufahl (2014) examined participants' hiring decisions and found that single lesbian women received significantly higher ratings compared with married lesbian women, and married heterosexual women received higher ratings compared with single heterosexual women.

Employee Selection Decision Making

In addition to research on types of information used, scholars have also endeavored to understand how this information is used and integrated in selection decisions when managers have multiple indicators (Hollway, 1984; Iles & Salaman, 1995). To understand how people typically make selection decisions, we can consider the possible ways that people can use to make decisions adopted from Gatewood, Feild, and Barrick (2008) and Slaughter and Kausel (2013) presented the methods in their book "*Judgment and decision making at work*".

They classify selection information as generated through either mechanical or judgmental information. Mechanical includes selection information that is independent of the evaluator generated through empirical observation or testing such as biodata (e.g., ability testing). Judgmental information includes the subjective assessment of an evaluator (e.g., interviews). Furthermore, different selection indicators can be combined through either mechanical or judgmental process. Mechanical combinations of predictors are those decision-processes that either order selection information in a series of hurdles based on minimum qualifications or aggregate selection predictors using a formula or weighting scheme to rank candidates. Judgmental combinations are subjective determinations done by evaluators that take into account all selection information and either choosing a candidate or rank ordering candidates for final selection. Mechanical selection decisions are made with a predetermined formula whereas judgmental selection decisions allow decision-makers to decide how best to integrate the information to make final decisions. Adapted from Gatewood, Field, and Barrick (2008), Appendix A – table 1 shows a 2x2 which contrasts the type of information and the type of decision-process used.

This dissertation examines the judgmental process involved when recruiting decision-makers are presented with mechanically derived selection information from resumes and AI-based decision aids. This situation reflects how selection decisions are most commonly made in organizations when recruiters make judgments from standard employment applications (Goslar, Green, & Hughes, 1986; Boyd, Lankford, Loeb, Ronfeldt, & Wyckoff, 2011b), resumes (Cole, Rubin, Field, & Giles, 2007; Chen, Huang, & Lee, 2011; Tsai, Chine, Huang, & Hsu, 2011), standardized tests, such as cognitive ability (Chan, 1997; Chan, Schmitt, DeShon, Clause, & Delbridge, 1997; Chan, Schmitt, Sacco, & DeShon, 1998; Macan, Avedon, Paese, & Smith, 1994; Ployhart, Ziegert, & McFarland, 2003), personality (Holden, Kroner, Fekken, & Popham, 1992; Morgeson, Campion, Dipboye, Hollenbeck, Murphy, & Schmitt, 2007a, 2007b; Ones, Viswesvaran, & Reiss, 1996; Rose, Stecher, Miller, & Levin, 1998), or situational judgment tests (McDaniel, Morgeson, Finnegan, Campion, & Braverman, 2001; Moss, 1926).

Among both practitioners and researchers, it is assumed that mechanically generated information from a set of personnel assessment methods can be used to predict applicants' future performance and job-related learning (e.g., learning in training and development programs). That is, recruiters are making decisions that assume the predictive validity of these selection measures. Schmidt and Hunter (1998) conducted a meta-analysis summarizing 85 years of research in personnel psychology and found that the validity of measures of 19 different selection methods (i.e., GMA tests, work sample tests, integrity test, conscientiousness tests, employment interviews (structured), employment interviews (unstructured) job knowledge tests, job tryout procedure, peer ratings, T&E behavioral consistency method, reference checks, job experience (years), biographical data measures, assessment centers, T&E point method, years of education, interests, graphology, and age) used in decision-making in hiring, training, and development varies significantly across different types of selection information. Their results showed that some work very well, whereas some work very poorly. For example, measures of general mental ability (GMA) (i.e., intelligence or general cognitive ability) strongly predicts job performance while graphology does not.

Scholars have also investigated how HR professionals, recruiters, and hiring managers make hiring decisions, largely explained by cognitive schema, signaling theory, and attribution theory (Perry, Davis-Blake, & Kulik, 1994; Bangerter, Roulin, & Konig, 2012; Knouse, 1989). Schemas include features or attributes associated with a particular category of membership. Specifically, role schemas contain sets of organized knowledge of role expectations, that is, how the observer expects an individual occupying a certain role to behave. And attribution theory is key role in selection whereby hiring personnel are actively seeking information about applicants' skills and abilities.

Several social cognitive theories are used to explain how job applicants' information is used in the pre-screening process to guide hiring managers' or recruiters' evaluations. The first is the *cognitive schema perspective*. The term schema describes the most general type of cognitive representation (Perry, Davis-Blake, & Kulik, 1994). Social-cognitive researchers have shown that cognitive schemas influence selectin decisions (Kulik & Clark, 1994; Martinez, Lengnick-Hall, & Kulkarni, 2014; Perry et al., 1994) when recruiters apply assumptions or perspectives about which types of applicant characteristics predict job performance. In addition, schemas include features or attributes associated with a particular category of membership. Specifically, role schemas contain sets of organized knowledge of role expectations, that is, how the observer expects an individual occupying a certain role to behave. A key responsibility of the recruiter is to determine the fit of the applicant to the job. In doing so, recruiters combine applicants' information to attribute certain characteristics (Brown & Campion, 1994) and employ role schemas to determine applicants' suitability for a specific job position. In other words, recruiters utilize their developed schemas to match their implicit understanding of the job requirements to information presented in an applicant's application or resume.

Another important theory applied to employee selection is *attribution theory* (Fiske & Taylor, 1991; Heider, 1958). The conception of attribution approaches was first found in Fritz

Heider's work in 1958. Heider stated that individuals contrive common sense explanations of the world to make sense of, predict, and control events. He suggested that individuals' explanations are not scientifically conceptualized, analyzed, or tested, and instead, they are naïve. Heider proposed that individuals make causal attributions about behaviors observed in other and perceived causality influences their responses and actions. Heider's work was subsequently developed by others in the field of psychology; most notably Harold Kelley (1967, 1973) and Bernard Weiner (1979), resulting in several complementary, and overlapping theories of attributions (Fiske & Taylor, 1991). Despite their differences, each of those theories attempts to explain how people draw causal inferences, what inferences people make, and the attitudinal and behavioral consequences of those inferences.

Attribution theory posits that people draw upon information cues in an attempt to determine whether the ultimate cause of the behavior is due to internal (dispositional) or external (situational) factors. This theory is key role in selection whereby hiring personnel are actively seeking information about applicants' skills and abilities. For example, previous research suggests that attribution theory is helpful in explaining conclusions drawn by recruiters in employment interviews (e.g., Silvester, 1997), from applications (e.g., Dipboye, Fontenelle, & Garner, 1984) and letters of recommendations (e.g., Knouse, 1989). Similarly, recruiters use resume information to form causal judgments regarding whether or not applicants possess certain work-related skills and abilities. Research shows that recruiters use resume information to draw conclusions about applicants' abilities, motivations, personalities, and job fits (Cole, Field, Giles, & Harris, 2004). Recruiters also conclude that the presence (or absence) of certain resume information is due solely to applicants' dispositional factors (Ross, 1977). Thus, the presence or absence of information, regardless of its relation to actual skills or abilities, may heavily in a recruiters' overall assessment of employability (Knouse, 1989).

Other applications of attribution theory in selection research include Tay and colleagues (2006) who examined locus of causality attributions as moderators on the relationship between interview success and following interviewing self-efficacy. They found that self-efficacy for interviewing was at higher levels among interviewers who believed that their success was due to internal factors (versus external). Thompson and colleagues (2015) also examined the locus of causality and studies the attributions from overqualified job candidates. Their results showed that candidates who made external attributions for overqualification were considered as a poorer fit for the job and were viewed less employable than candidates who made internal attributions by recruiters. Finally, Carless and Waterworth (2012) conducted a quasi-experimental study and found that experience recruiters differ their expectations about applicant's future job performance, responsibility for failure, and hiring recommendations based on applicants' abilities and efforts.

An important example of how attribution theory and cognitive schema area are applied in selection research is the work on how resumes are perceived and assessed by recruiters. Resume is an important component in presenting the applicants' qualifications and often serves as the first contact between an organization and a job seeker (Thoms, McMasters, Roberts, & Dombkowski, 1999). Since recruiters use the information from applicants' resumes to determine the next phase (interview versus rejection) in the hiring process, resume content has become critical for applicants to be successful during the application process. Scholars have put considerable effort to identify the determinants of resume screening decisions (e.g., Fox, Bizman, Hoffman, & Oren, 1995; Gardner, Kosloski, & Hults, 1991). In general, this work concludes that recruiters use information from resumes to make judgments about candidates' personal characteristics (e.g., personality), their qualifications (e.g., person-job fit), and their cultural fit (e.g., person-organization fit). For example, Cole and colleagues (2007) investigated the relationship between recruiters' pre-interview assessments of applicants' resume information and estimated applicants' employability for relevant job openings. Their results suggest that recruiters considered particular items to infer successful job performance. Based on the previous review, this research applies attribution theory to argue that information generated by AI (algorithm-based) decision aids is used by decision-makers to assess candidates' qualifications and employability.

Artificial Intelligence (AI) in Selection

Due to rapid technological development, artificial intelligence (AI) has become increasingly relevant for both theory and practice in recent years. Kaplan and Haenlein (2019) define AI as, "a system's ability to interpret external data correctly, to learn from such data, to use those learnings to achieve specific goals and tasks through flexible adaptation" (p. 15). AI refers to the idea that algorithms are capable to perform tasks that would normally require acting and thinking of a human being. AI creates the possibility to automate various activities related to the collection, storage, analyzing as well as retrieval of data. AI enables machines to detect different patterns in large amounts of data (Kumar, Rajan, Venkatesan, & Lecinski, 2019) and it helps to save time and effort and therefore also to reduce costs (Yang, Ozbay, & Ban, 2017).

Applications of AI have begun to permeate nearly every profession and industry, including HR. To better understand how AI works in HR and especially in the selection process. It is important to review how it works and the differences between HR automation and algorithm-based decision-making.

Algorithms are defined as a set of steps that a computer follows to perform a task (Castelo, Bos, & Lehmann, 2019). Pioneering literature from the 1950s demonstrated that very simple algorithms such as linear regression could outperform expert humans on tasks such as diagnosing medical and psychological illness (Dawes, Faust, & Meehl, 1989; Grove, Zald, Lebow, Snits, & Nelson, 2000; Meehl, 1954). Since then, rapid progress in the field of artificial intelligence has endowed algorithms with the abilities to understand and produce natural language, learn from experience, and even understand and mimic human emotions. Today, algorithms can outperform even expert humans at an increasingly comprehensive list of tasks, from diagnosing complex diseases (Simonite, 2014) to driving cars and providing legal advice (Krasnjanski, 2015). Algorithms can also perform seemingly subjective tasks, such as detecting emotion in facial expressions and tone of voice (Kodra, Senechal, McDuff, & Kaliouby, 2013).

In HRM, employers have begun to use algorithms and AI in a wide variety of ways. The first is in process automations. HR automation is a technology that works by automating recurring human resource processes and streamlining document-heavy tasks. Without sacrificing quality, it significantly reduces the time it takes to complete HR processes. It can handle many crucial administrative tasks, such as feeding data, creating files, and sharing documents. When processed manually, these types of tasks can take hours on end. Automation offers many benefits including helping to reduce printing and physical storage costs while offering convenient access to online files anytime from anywhere. Common HR automation examples include employee onboarding, offboarding, leave requests, expense claims, payroll, time management, employee benefits, and tax filing. The biggest difference is that HR automation is more relevant to improve work efficiency and productivity, and to reduce the time and cost by replacing more and more manually handled administrative work, whereas AI tools in HR help handle more complicated and data-driven tasks in all aspects of HR practices.

Algorithm-based HR decision-making (i.e., algorithms designed to support and govern HR decisions) (Leicht-Deobald, Busch, Schank, Weibel, Schafheitle, Wildhaber, & Kasper, 2019). The first step toward algorithm-based HR decision-making was the introduction of electronic performance monitoring during the last decades of the twentieth century. Electronic performance monitoring includes, for example, automated tracking of work times as well as internet; video-, audio-, and GPS-based observation of employee on the job (Stanton, 2000).

The technical capability of algorithms to meaningfully analyze data has largely expanded (Amoore & Piotukh, 2015; Ananny & Crawford, 2016; Dourish, 2016). According to common classification in management (Davenport, 2013; Souza, 2014), algorithms can broadly divide into three categories: descriptive, predictive, and prescriptive algorithms.

Generally, when employers use algorithms, the goal is to gather and apply data to make decisions in a faster, more efficient, and more objective manner. One common application is in recruiting and selection. In selection, leading AI-based tools available to employers primarily work by data mining and predictive matching.

Organizations use selection procedures such as the analysis of resumes, personality tests, and interviews to collect information from applicants as a foundation for their selection decision. Traditionally, HR professionals or line managers aggregate this information mechanically or judgmentally to make selection decisions such as whom to invite to a job interview or whom to take a job offer. Today, with technological advancements and increasing data availability, organizations can increasingly make use of algorithms for selection decisions. Examples of algorithms range from simple functions (e.g., aggregating scores from a personality test to arrive at a final score) to more complex functions (e.g., text mining of CVs). Regardless of their complexity, algorithm-based decisions differ from human decisions by combining data mechanically instead of holistically (Kuncel, Klieger, Connelly, & Ones, 2013).

The most prominent use of algorithms and AI in hiring is to mine available data (data mining) on applicants to predict who will succeed in a given position based on matching applicants to a model employee. The model employee is derived by using a training dataset based on existing applicants and employees that includes a target criterion such as job performance and a series of predictors such as the type of information gathered in a selection process through resumes, applications, selection testing, or any other source of available information.

Machine learning is then used to create an algorithm or formula by searching for patterns in the body of training data. This algorithm derived from historical data is then applied to data on a set of candidates to create fit scores and identify candidates who have selection information that most closely fits the information from the model employee. Hiring algorithms use the information on workers they have previously hired in order to predict which job applicants they should now select. Algorithms used to predict future success based on past success assume that organizations should favor applicants that are similar to those that have been successful in the past.

Hiring algorithms extract the traits of top-performing employees from training data and matched these traits against candidates to identify those candidates with the highest overlap. The algorithms then calculate an algorithmic recommendation per candidate such as a “match percentage score”. For example, the technology firm Xerox Service uses a recruitment algorithm to support HR managers in their hiring decisions, offering them a score of how well an applicant's qualifications fit a job (Peck, 2013). For example, resume screening algorithms incorporate some element of searching for patterns and predicting outcomes in an effort to improve hiring decisions based on a training dataset of resumes of successful existing employees. Similar to how search engine optimization works for websites, a resume screening algorithm looks for keywords, phrases, and text strings within the document itself. These keywords are usually the knowledge, skills, and abilities a company is looking for in the ideal candidate, and often include duties of the job. The algorithm will sift through a resume to match against the keywords and then score according to keyword match and fit.

Predictive algorithms are used to forecast what might be the results of certain past- pr real-time observations on future outcomes. Predictive algorithms determine the likelihood of such outcomes (or situations) to occur. Applied methods are advanced regression techniques, machine learning algorithms, and data mining approaches (Davenport, 2013; Souza, 2014). Typically, predictive algorithms provide a score that represents the possibility of an event to occur. An example is a recruitment algorithm developed by the technology firm Xerox Services. This algorithm works as an advanced support system for hiring staff in Xerox's call centers by offering a score of how well the applicant would fit the job (Peck, 2013). The algorithm behind this HR tool analyzes data provided by applicants via an online application tool and offers a cognitive skill assessment, personality test, and multiple-choice questions to see how well the applicant would deal with specific challenges on the job.

Discussion of algorithm-based decision-making often invokes a "mythology" centered on objectivity (Amoore & Piotukh, 2015; boyd & Crawford, 2012; Ziewitz, 2015). Technology firms suggest, for example, that algorithm-based HR decision-making increases efficiency, enables fact-based decision-making, reduces particularism, and offers solutions to talent shortage (Porter, 1996). An area where algorithm-based HR decision-making techniques could become particularly important is recruitment. In industries with a high fluctuation, such as retail or hotel chains, firms must scan a vast number of resumes per year and conduct a large number of interviews. In such a context, algorithm-based HR decision-making techniques could be helpful in reducing manual, labor-intensive processes. Providers of recruitment algorithms, for example, promise that “when using an automated process, all candidates are screened against the same criteria consistently” (Why, 2018). Vendors of HR tools promise that the results of algorithms are fairer and less biased than human judgment. Accordingly, those firms advertise the resulting staffing solutions as a means to help firms win the war for talent (Delle Donne, 2017). Most prominently, technology firms propose that algorithm-based HR decision-making is evidence-based, bias-free, and superior to human intuition.

Trust in Automation

Another stream of research to investigate how managers interact with an automation is the trust. Automated technology has been everywhere in the modern world society. Trust in automation influences people’s perception and reliance on technology applications and this concept has been the focus of a large amount of research over the past few decades. When human-automation perform optimally, the efficiency of working system can be improved significantly. However, using automation to increase efficiency is not always realized. Using automation can make simple tasks complicatedly. Facilitating appropriate trust in automation is critical to improve the efficiency and productivity of human beings. Then it is important for researchers and practitioners to understand the factors that influence conductors’ trust.

Automation was defined at "technology that actively select data, transoms information, makes decisions, or controls processes" (Lee & See, 2004. P. 50). Automation can perform complex, repetitive tasks quickly without error. Human-automation labor systems can be very efficient when the adoption equip people with more freedom to use their attention to where it is more needed. There are four primary types of automation systems: information acquisition, information analysis, decision selection, and action implementation (Parasuraman, Sheridan, & Wickens, 2000). Algorithm-based decision aid systems are used for the decision selection purpose for recruiters. Automated systems are different based on the amount of control human operators have over their functions (Parasuraman et al., 2000). Thus, automation-related accidents can happen for reasons like poor system design, software and hardware failures, operator misuse, and operator disuse, etc. (Parasuraman & Riley, 1997).

Introducing operators with appropriate levels of trust in automation systems can help reduce the frequency of misuse and disuse (Lee & See, 2004). However, it is too difficult to do it appropriately. For instance, the inconsistent characteristics of the operator can shift the trust formation process in unforeseen ways. Similarly, this helps understand how individual differences in recruiters would have different usage of algorithm-based decision aids in hiring and selection process; further lead to different applicants being hired.

Trust has been studied in various fields of research, such as psychology, sociology, political science, economics, and human factors. Scholars have tried to define the term and conceptualize it. One of the most influential review papers on trust from Mayer, Davis, and Schoorman (1995) has examined the antecedents and outcomes of organizational trust. Gefen, Karahanna, and Straub (2003) studied the role of trust and the technology acceptance model in online shopping context. Research has found that human-automation trust depends on the performance, process, or purpose of an automated systems (Lee & Moray, 1992). Performance-based trust varies on how well an automated system executes a task.

Research Questions and Study Plan

The dissertation presents two big sections on how recruiters' make hiring decisions when they are given algorithm-based decision aids in resume screening process. First part I investigate how recruiter's individual differences (age, level of education, data engineer experience, use of algorithm-based decision aids, high-technology industry, hiring recency, and algorithm aversion) influence recruiters' perceived usefulness to use algorithm-based decision aids in hiring process. This investigation is conducted using empirical survey questionnaire method. The research question formally addressed in the first part is "How recruiters' individual differences (age, level of education, and algorithm aversion, etc.) influence their perceived usefulness for algorithm-based decision aids in hiring process?"

The second part of this research explores the effects of different outputs of applicants from the Application Tracking System (ATS) influence recruiters' decision-making for applicants' employability. I aim to answer this research question: "How do recruiters rate applicants' employability when they are given different outputs with different combinations from bio data and AI data (i.e., 2 X 2)"; especially when recruiters are given contradictory rating scores from bio data and AI data (e.g., high bio data and low AI data, or low bio data and high AI data). How would recruiters make the hiring decisions?

Chapter 3 Hypothesis Development

Artificial intelligence as applied in employee selection can be considered as new technology and perceptions of this technology are likely to vary among individuals who are expected to accept and adopt AI in practice. This means that the existing behavioral models that have been used to study the acceptance of technology over time might be also applied to predict acceptance and use of AI in employee selection. These models include the Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1980), the Theory of Planned Behavior (TPB) (Ajzen, 1991), and the Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003). The most widely applied model used to study the adaptation of new information technology in the workplace is the Technology Acceptance Model (TAM) (Davis, 1986). By adopting Davis' (1986) Technology Acceptance Model to examine the AI resume-screening process, I propose that individual characteristics of recruiters themselves make a difference in their perceived usefulness to use AI or algorithm-based decision aids in employee selection. Specifically, I predict that a recruiter's age, level of education, data experience, AI use, technology background, hiring recency, and algorithm aversion will predict recruiters' perceived usefulness to adopt AI-based decision aids in the resume screening process.

Davis's TAM has been shown that it has equal predictive power to TRA and TPB, yet it is the most parsimonious of the three (Taylor and Todd, 1995; Mathieson, 1991). The Technology Acceptance Model (Davis, 1986) predicts individual use of technology in the workplace based on perceived usefulness and perceived ease of use. Perceived usefulness is the prospective user's subjective probability that using a specific application will increase his or her job performance within an organizational context (Davis, 1986). Perceived ease of use: the degree to which the prospective user expects the target system to be free of effort (Davis, 1986). The model uses perceived usefulness and perceived ease of use influence to predict behavioral intention to use and actual use of technology. The TAM model is particularly useful in that individual characteristics of the potential users can be integrated to predict perceived usefulness and perceived ease of use and therefore, by extension, use of the technology itself.

The theory supporting TAM follows the Theory of Planned Behavior (Ajzen 2002). The TAM maintains that the decision to use a particular IT follows four stages beginning with external variables used to predict beliefs about the technology. Users consider a range of external variables (such as their individual abilities, the type of IT, the task, and situational constraints) to evaluate the consequences of using an IT. Their overall evaluation is reflected in their beliefs about the usefulness of the technology and ease of use of the technology. In the second stage, these beliefs drive the attitude towards technology.

One key set of external variables is users' individual differences, such as personality, age, and education level. Studies have found that individual differences are significant factors in both end-user computing (Harrison & Rainer, 1992) and decision-support systems (Alavi & Joachimsthaler, 1992). Perhaps the most comprehensive study of how individual differences affect usage is by Agarwal and Prasad (1999), who studied how five individual differences (organizational role, tenure, education, experience, and training) directly affect IT adoption. Consistent with TAM, they found that TAM's belief constructs (perceived ease of use and perceived usefulness) fully mediated the impact of individual differences on users' attitudes and intentions to use IT.

Age differences have been known to play an important role in understanding human perceptions and behaviors in various research domains including organizational behavior (Goldberg, Finkelstein, Perry, & Konrad, 2004; Taylor, 1975) and psychology (Myerson, Kale, Poon, Wagstaff, & Smith, 1990; Salthouse, 1996). Due to the fast development of new technologies, different age generations are inevitably confronted with different generations of technologies.

Research suggests that older workers and those who have longer company tenure are more likely to be resistant to new technology (Kerr & Hiltz, 1982). Gattiker (1992) conducted a study of the acquisition of computer skills, and he found that there were significant effects for age in skill acquisition and retention. When the technology is significantly different from other existing technologies, probably because of habit or stability need, recruiters' age in the workforce might negatively influence beliefs.

Tarhini and colleagues (2014) proposed and tested a conceptual model of e-learning technology acceptance based on TAM. Their model extended TAM through the inclusion of subjective norms and self-efficacy as additional predictors and two individual differences, age and experience as moderators. They collected data from British students who used web-based learning systems in their study at a University in England. Age was found to moderate the relationships among most of the predictors and behavioral intention. A stronger relationship between perceived usefulness and behavioral intention was demonstrated for younger uses compared to older users.

Meanwhile, research also shows that age is not a significant role in classroom technology use by teachers. For example, Tweed (2013) conducted a study about technology implementation from teacher's age, experience, self-efficacy, and professional development to classroom technology integration. Her quantitative study results showed that based on the responses from 124 teachers from 2 school districts, teacher age did not play a significant role in the self-efficacy by teachers. Findings also indicated that teacher age did not play a significant role in the classroom technology use by teachers.

There is another perspective from technology readiness, Dutot (2014) found age to be negatively related with technology readiness, which means that younger people generally use new technologies more readily. However, some researchers also found that these effects are sometimes non-significant (Gilly, Celsi, & Schau, 2012). Thus, I propose:

H1a: Younger recruiters will be more likely to use the algorithm-based decision aids in resume screening than older recruiters.

H1b: There is no difference among younger recruiters and older recruiters regarding the use of algorithm-based decision aids in resume screening.

Prior research has also suggested that education has a negative effect on computer anxiety (Igbaria & Parsuraman, 1989). Education level has been found to be an important factor for the acceptance of a technology (Poon, 2008; Lymperopoulos & Chaniotakis, 2005). In addition, Vasarhelyi (1997) found that managers who had higher levels of education were better able to understand a marketing decision-support system, and better able to take advantage of it. Davis and Davis (1990) have also demonstrated that level of education is an indicator of a potential technology adopter's ability to learn. Lymperopoulos and Chaniotakis (2005) found that potential users' level of education was an important external variable that affected attitudes and intentions through perceived usefulness. So, I expect that there will be a positive relationship between recruiters' education level and their beliefs to adopt algorithm-based decision aids in resume screening.

H2: Recruiters with higher level of education will be more likely to use the algorithm-based decision aids in resume screening.

Research has established a positive relationship between experience with computing technology and outcome variables, such as computers and computing skills (Levin & Gordon, 1989; Harrison & Rainer, 1992). Some previous research suggests that teachers with more technology experience had a higher tendency of using technology in the classroom (Yueh, Huang, & Chang, 2015). Blut and Wang (2019) studied technology readiness, which aims to better understand people's propensity to embrace, accept, and use technologies. Maier (2016) suggests that the greater people's technology-related experience, the higher their technology readiness is. I further argue that the more experience people have, the more willing they will adopt and use technology in the future.

Similar to recruiters, I propose that recruiters who have had more exposure to computing technology or data analytics will be more likely to use algorithm-based algorithms or computer programs and those with technical backgrounds should be less intimidate by the use of such systems and more likely to perceive that decisions based on the rules of a specific programming language are useful.

H3: Recruiters with technical backgrounds will be more likely to use the algorithm-based decision aids in resume screening.

Artificial intelligence provides big data users to automate and improve complex predictive and descriptive data analysis that would have been time consuming and tedious if it was to be performed by humans (Surya, 2015). Large organizations have long understood the importance of technology. Technology companies have been the main beneficiary of AI, such as Google and Amazon have been successful with AI for product recommendations, targeted advertising, and forecasting demand. Tech companies have the resources to transfer and use AI in HR practices.

Non-tech companies are slow in embracing AI due to the lack of technology professionals or insufficient funding. Or they do not leverage AI's ability to make more frequent and granular decisions but keep following their old practices. With the experience or current implementation of AI in tech companies and non-tech companies, I propose:

H4: Recruiters that work in high-technology companies will be more likely to use the algorithm-based decision aids in resume screening than those in other industries.

As mentioned earlier, research has established a positive relationship between experience with computing technology and outcome variables, such as computers and computing skills (Levin & Gordon, 1989; Harrison & Rainer, 1992). This suggests that hiring managers or recruiters who have had more exposure to hiring experience with algorithm-based decisions aids are more likely to perceive those decisions based on the rules of a specific programming language are useful and helpful. SHRM data shows that on average, every corporate job opening attract 250 resumes, but only 4 to 6 of these applicants will receive an interview and only one will get an offer for the job. The average amount of time a recruiter spends review a resume is 6 seconds. People may argue that is not enough time to make a decision. But recruiters do not have time to review all applicants' resumes thoroughly. Using AI technology at the initial screening process would help rank and score potential applicants and recruiters can spend more time on the resumes that warrant more attention. This process would save time for recruiters in organizations and help them make better hiring decisions. There are other aspects companies claim to have from AI in recruitment, such as better candidate experience and more objective decision-making. No matter which one, companies benefit from AI technology in recruitment, therefore, companies are more likely to adopt and use AI technology in hiring and selection once they have benefited from its usage. Therefore, I propose that there will be a positive relationship between recruiters' prior experiences and the intention to use algorithm-based decision aids in hiring process.

H5: Recruiters who have had experience using algorithm-based decision aids will be more likely to use algorithm-based decision aids in resume screening than those who have not had experience using algorithm-based decision aids.

Over the years, companies around the world have adopted various hiring algorithms in order to win the war on talent (Bogen & Rieke, 2018) because they can catch wider job candidate pools and lower recruitment costs (Yam & Skorburg, 2021). To make the hiring process more efficiently and attract qualified candidates at the same time, organizations are utilizing algorithms to automate screening and ranking in the recruitment process. There is evidence that algorithms can increase efficiency by shortening time to assess and score, reaching a broader talent pool, and reducing costs in recruitment (Zhang & Yencha, 2022). According to the Global Recruiting Trends 2018 LinkedIn report, the most important benefits of using hiring algorithms are saving time and money (LinkedIn, 2018). Since 2020, as national labor shortage drags on, organizations and workers suffer consequences of the "Great Resignation" (Klotz, 2021), also known as the "Big Quit". More and more companies have adopted AI to speed up the early back-and-forth emails and other communications with applicants and quickly get good candidates in front of recruiters. Thus, I propose:

H6: Recruiters who have hired employees more recently will be more likely to use algorithm-based decision aids in resume screening than those who have hired less recently.

It has been suggested that AI will enable organizations to more efficiently interact with job candidates, develop more accurate candidate profiles, better grade and rank qualifications during the screening process, and more quickly reach out to qualified candidates. For example, IBM (2018) advertised its HR artificial intelligence algorithm Talent Watson as empowering "HR teams to increase the efficiency and quality of their operations." While technology companies and business consultants have praised the usefulness of algorithm-based decisions in HR. Their use and usefulness depending on the willingness of HR decision-makers to embrace the technology and integrate this information into selection and talent decisions. However, the degree to which hiring managers and recruiters will actually use this information in hiring decisions is unknown. In this section, I will present recruiting decision-makers with a set of outputs that require them to integrate information from AI decision-aids with traditional biodata information on job candidates to assess candidates' employability.

As algorithmic prediction and decision-making have become more widely used in many applications, there has been some theory development and emerging research on whether individuals are likely to accept these recommendations in different contexts. In decision-making literature, some research supports the popular assumption that people often do not rely on algorithmic decision aids and prefer to rely on human judgment (e.g., Yeomans et al., 2019). This behavior is called algorithm aversion (Dietvorst, Simmons, & Massey, 2015). The literature on algorithm aversion is rooted in the medical field with the debate in the clinical (i.e., human thought) and statistical judgment in medal diagnosis or treatment (Meehl 1954; Dawes et al., 1989). This research shows that statistical data interpretation is superior to clinical judgment; however, humans show a tendency to resist statistical judgment purely. Some research shows that evidence-based algorithms have more accurate predictions than do human forecasters;

however, when forecasters make the decision whether to use a human forecaster or a statistical algorithm, they often choose the human forecaster (e.g., Dietvorst et al., 2015; Yeomans, Shah, Mullainathan & Kleinberg, 2019).

Studies have extended this resistance to the research of algorithmic decision support or algorithm-based decision aids when compared to human advice (Promberger and Baron 2006; Alvarado-Valencia and Barrero 2014). For instance, Elkins, Dunbar, Adame, and Nunamaker (2013) found that expert users feel threatened by system recommendations when they have contradicting judgment and they tend to disregard system recommendations. However, the countercurrent research stream has also shown that individuals are not always averse to algorithms (e.g., Logg, Minson & Moore, 2019; Thurman, Moeller, Helberger & Trilling, 2019); this behavior was termed as algorithm appreciation (Logg et al., 2019). Logg and colleagues have conducted six experiments and the results show that people advocate more to advise from an algorithm than from a person. Their experiments have covered aspects of visual stimulus, the popularity of songs and romantic attraction, etc. Similarly, Thurman and colleagues (2019) have conducted a study with data from 53,314 participates from 26 countries and their results show that accumulatively, the audience believes that algorithmic selection guided by a user's past consumption behavior is better than getting news from editorial curation.

Previous research (e.g., Cole et al., 2007) on how recruiters derive perceptions of applicant characteristics from resume information uses cognitive schema and attribution theory to explain how judgments are made about candidates. I apply the same theory here to suggest that recruiters also make judgments about candidates based on information from AI decision aids. In other words, recruiters should view information such as a fit score generated by an AI algorithm as another piece of selection information that indicates certain characteristics of the candidate.

When faced with information from both biodatas drawn from a resume and algorithm-based decision aids (score) on applicant's resumes, recruiters' algorithm appreciation or aversion will affect how the recruiter incorporates the applicant's AI scores in hiring recommendations. Thus, I propose:

H7: Recruiters with algorithm aversion will be less influenced by algorithm-based decision aids in resume screening.

While screening a resume, a recruiter matches job requirements with the resume's content categories to make a decision on whether or not to move the applicant to the next round of recruitment. As I have discussed, applicants' educational background, working experience, and extracurricular activities are related to hiring decisions. However, not only the content on the resume would influence recruiters' hiring decisions, job, itself influence recruiters' decision-making results. Finally, I investigate whether the type of jobs associated with hard, or technical and soft or social skills assessed influences recruiters' use of Ai information in the decision-making process.

To understand the variety types of skills required in jobs, it is helpful to first refer to the broader concept of competency. Mirabile (1977, p. 75), defined competency as: "knowledge, skill, ability, associated with high performance on the job, such as problem-solving, analytical thinking, or leadership. Some definitions of competency include motives, beliefs, and values". Spencer and Spencer (1993, p. 9) define competency as, "An underlying characteristic of an individual that is causally related to criterion-referenced effective and/or superior performance in a job or situation." These underlying characteristics are part of an individual's human capital and can predict behavior in a wide variety of situations and job tasks. Competencies are then thought to be comprised of specific knowledge, skills, and abilities and are considered to be associated with an individual's job performance (Hendarman & Cantner, 2018). Part of the selection process is identifying and matching employee competencies with job requirements.

Competencies can be divided in research and practice among hard skills and soft skills. Hard skills describe explicit behaviors and skills. Hard skills are skills that can produce something that is visible and direct. Hard skills can be assessed from technical tests or practical tests. Hard skills are skills that are easily documented and formed (Lee & Choi, 2003; Sousa & Rocha, 2019; Borrego, Morán, Palacio, Vizcaíno, & García, 2019; Cifariello, Ferragina & Ponza, 2019; Bashir & Farooq, 2019; Attia & Salama, 2018), easily articulated (Haamann & Basten, 2018), and include specific knowledge (Afsar, Masood & Umrani, 2019). In addition, hard skills can be identified, documented, and transferred between company activity units (Lombardi, 2019).

Hard skills can be described in general and are also based on the specific context in which these skills are used. Rainsbury, Hodges, Burchell, and Lay (2002) defined hard skills as skills related to technical aspects to perform several tasks in work. Hard skills are cognitive and are influenced by intellectual quotient (IQ) (Muhammad, Ariyani, Sadikin, & Sujana, 2019; Kenayathulla, Ahmad & Idris, 2019; Tsotsotso, Montshiwa, Tirivanhu, Fish, Sibiya, Mlangeni, Moloi, & Mahlangu, 2017; Fan, Wei & Zhang, 2017) and include indicators such as counting, analyzing, designing, comprehensive knowledge, modeling, and critical thinking. While predominantly in nature, some researchers have also applied the concept of hard skills in management. For example, Azim, Gale, Laolor-Wright, Kirkham, Khan, and Alam (2010) referred to hard skills in the context of project management as processes, procedures, tools, and techniques (Gale, Duffey, Park-Gates, & Peek, 2017; Laker & Powell, 2011).

Soft skills are often referred to as interpersonal skills. The contrast hard skills in that they are harder to define and can be very personal (Chen, Baptista, Ragsdell, & An, 2018; Holford, 2018; Khoshorour & Gilaninia, 2018; Zebal, Ferdous & Chambers, 2019) and difficult to formulate and share naturally (Deranek, McLeod & Schmidt, 2017; Asher & Popper, 2019) Soft skills are rooted in actions and experiences, values, and emotions (Boske & Osanloo, 2015; Kawamura, 2016; Hartley, 2018).

Soft skills are often categorized as personal knowledge or knowledge obtained from interactions with other individuals (Muñoz, Mosey, & Binks, 2015; Stewart, Schiavon, & Bellotto 2017; Rothberg & Erickson, 2017). Soft skills are not easily articulated and converted to hard skills (Mohajan, 2016; Prasarnphanich, Janz, & Patel, 2016; Spraggon & Bodolica, 2017).

Compared to hard skills, soft skills tend to be transferable between jobs or industries but are more difficult to quantify on a resume. Different jobs require different skills, in the resume screening stage, recruiters will look for hard skills and soft skills to gauge how well a candidate will be able to perform the core components of the specific job. Recruiters should be capable of analyzing the relative use of the skills to help organizations determine what kind of employee is suited for the job in a certain business sector (Lumague, 2017).

Because hard skills are easier to define, measure, and signal in a selection process, I propose that recruiting decision-makers will be more likely to integrate information from AI decision aids in assessing candidate qualifications. Specifically, I suggest that when presented with conflicting information from biodata and from AI decision aids for hard skills recruiters will be more likely to base assessments on the AI decision aids than the biodata. By contrast, soft skills are more difficult to define, measure, and signal in a selection process. I predict that recruiting decision-makers will be less likely to use AI decision aids when assessing the qualifications of candidates for jobs that require significant soft skills.

Algorithm–based decision aids are based on the data analyses for hiring algorithms, by contrasting two jobs – HR assistant and data engineer. I expect recruiters would have different perceptions and emphases for the comparison from applicants' resume information to make the hiring decision. Thus, I propose that:

H8: Recruiters will be more likely to use algorithm-based decision aids for jobs that require technical skills in assessments of employment suitability.

Chapter 4 Methodology

Hypotheses were tested using data from 394 managers with hiring experience. Managers were surveyed twice with the first survey to collect individual characteristics and perceived usefulness of algorithm-based decision aids for resume screening. A follow-up survey asked these same managers to rate eight job applicants using a policy-capturing experimental design that presented manipulated candidate profiles that appear as outputs from an Applicant Tracking System (ATS). These candidate profiles included information about the candidate experience and education as taken from a resume and the output of an algorithm-based decision aid that reported candidate fit scores for a specific job. Profiles of eight candidates were developed using a 2X2X2 design which contrasts biodata fit (high vs. low), AI score fit (high vs. low), and job requirements (HR assistant vs. data engineer). The within-subject factors of AI score, biodata fit, and job requirements were presented to respondents in random order, and they were asked to rate the employability of each of the eight candidates.

Participants

Participants of this study were recruited through Prolific, which is an on-demand platform that enables large-scale data collection by connecting researchers to participants around the globe. It is headquartered in Oxford, United Kingdom, and was founded in 2014). During the study period, the sample was selected from Prolific participants in the U.S. and the U.K. who are English speaking, over the age of 18, and full-time employed with managerial experience.

A total of 500 participants from a total sampling frame of 10,489 eligible Prolific participants responded. In the first wave, participants were paid $2 to take an initial survey that collected demographic information, experience with employee hiring, and perceptions of AI decision aids. After receiving the responses, I excluded 19 respondents who reported that they do not have any experience making hiring decisions. One week later, I sent out the second survey to the remaining 481 participants and 394 (81.9%) responded. Participants were compensated with $3.00. I took the final 394 respondents for the analysis.

Male accounted for 52.5% of participants. Participants' ages ranged from 20 to 70 with an average of 42 years old. The majority of participants (87.1%) identified as Caucasian. The participants reported high educational attainment with 69.6% having at least a bachelor's degree and 25.1% holding a graduate degree. The participants worked in for-profit businesses (58.6%), non-profit (17.3%), and government (16.5%) with the remaining self-employed (7.1%). The industrial of the participants varied: 34.5% reported having work experience in HRM, and 10.9% had working experience as a data engineer or a data scientist. 28.4% of respondents had worked in a technology-related industry.

Materials

This dissertation follows procedures similar to a number of studies examining resume information (e.g., Cole et al., 2007). To help participants better understand the applicants' candidacy, job descriptions were created for HR Assistant (Figure 1) and Data Engineer (Figure 3). I started with reviewing a sample of job descriptions from current job openings on professional hiring platforms (e.g., Indeed (www.Indeed.com) and LinkedIn (www.linkedin.com)) with specific titles (HR assistant and data engineer). Based on this review, job descriptions were developed which included responsibilities, job requirements, and educational level requirements. This was compared to the same information for these titles on the Occupational Network or O*Net (www.onetonline.org), the nation's primary source of occupational information developed under the sponsorship of the U.S Department of Labor/Employment and Training Administration.

I used an experimental policy-capturing design which included information on eight job candidates. To develop the candidate profiles, I first reviewed available examples of profiles from commercial Applicant Tracking Systems (ATS) and AI-based resume screeners for content, format, and graphic design. A candidate profile template was designed that contained specific biodata (i.e., educational background and working experience) and out an output from an AI-based screener which included an overall fit score and a "predictive fingerprint" for the candidate with five dimensions. Five dimensions for HR assistant were communication, teamwork, critical thinking, HR experience, and extracurricular leadership. Five dimensions for data engineer included programming languages, analyze, manipulate, and process data, clean raw data by statistical software, design instruments to collect data, and interpersonal skills. Figure 2 and Figure 4 present 4 different manipulations for HR assistant position and data engineer position, respectively. These templates were qualitatively reviewed by HR professionals with experience using commercial ATS and AI-based resume screeners who confirmed that these templates contained similar content and graphic design of the systems that it was intended to represent.

At first, the levels of a candidate's educational background and working experience were manipulated at three levels (low, medium, and high); and a candidate's AI fit score was manipulated at two levels (low and high). Then because of the consistency of educational background and working experience, the candidate profiles were further developed to represent two levels for biodata (low and high) of educational background and working experience; and two levels (low and high) for AI fit scores for two different jobs (HR assistant vs. Data engineer). Participants were given all possible combinations (2x2x2). The candidate name

“Morgan Smith” was selected to be neutral for both gender and ethnicity and was the same across all eight candidate profiles.

After completing candidate profiles, I conducted a pilot test by using a survey of 127 undergraduate and graduate students. Students were given extra credits by their professors as compensation for their participation. A survey link was sent to students’ UTA email addresses. Each student was shown either the job description for the HR assistant position or the Data engineer position. Then manipulated candidate profiles were randomly assigned to students with a 2x2 design, which contrasted low and high levels of biodata (educational background and working experience) and AI predictive fit score. After reviewing the profiles, students were asked to rate the demands-abilities fit of a candidate by answering the three-item scale from Resick, Baltes, and Shantz (2007) with a Cronbach’s alpha of .881. There items were: “I believe that the applicant’s skills and abilities match those required by the job description”, “The knowledge, skills, and abilities of this applicant match the requirements of this job”, and “this applicant possesses the skills and abilities to perform this job.” Results from the pilot test demonstrated that respondents perceived significant differences in low/high conditions for biodata ($t=1.487, p<.07$) and AI fit ($t=6.468, p,.001$). There were no significant differences in the qualification ratings for the HR assistant compared to the Data engineer.

Sample

I used Prolific; an online platform that helps researchers recruit participants for research. Prolific verifies and monitors participants with sophisticated checks and researchers can get fast and quality data. Prolific also offers screening processes with specific criteria for potential participants. To avoid the potential problem of respondents’ ‘social desirability’ (Arnold and

Feldman 1981), I did not disclose the true objectives of this study to the participants; the introduction at the beginning of the survey simply told them that the purpose of this study was to investigate how HR recruiters and managers assess job candidates' qualifications to make the hiring decisions. Moreover, the participants were promised that I would ensure their privacy by keeping all responses anonymous.

Respondents were screened to be English speaking and full-time employed with managerial experience. Prolific showed 10,717 eligible participants from the U.S. and U.K. I aimed 500 participants and sent out the survey with demographics, two job descriptions from HR assistant position and Data engineer position (See Figure 1 and Figure 3). Participants were asked to rate the job requirements along with several dimensions of technical and soft skills. With a short period of time, I received 500 responses. Each participant was paid $2. To address common method bias concerns, I used a pre-determined time-lag in between each administration (Pdosakoff, MacKenzie, Lee, & Podsakoff, 2003). A week later at Time 2, the second survey was sent to the previous participants with 8 different manipulations (See Figure 2 and Figure 4) in a random order. Participants were asked to rate the applicant's employability. The final data set contained 394 eligible participants, which was also the analysis based on. Each participant was paid $3 for the second wave data collection.

Measures

Recruiters' demographics

Participants were asked to report demographics including age, gender, ethnicity, level of education, and managerial experience, etc. Participants' ages ranged from 20 to 70 with an average of 42 years old. Participants were asked to report on their level of education. All respondents reported having at least a high school diploma. 43.9% reported having a bachelor's degree and 25.1% reported having a master's degree/MBA or above. In the analysis, participants' level of education was aggregated into a measure of bachelor's degree or above as 1 versus high school diploma, some college, and associate degree as 0.

Hiring Experience

Participants were asked to answer the question "When's your last hiring?" with responses options from "within a month", "within six months", "within a year", and "within three years". In analysis, responses were aggregated into a measure of hiring experience within six months or less as 1 versus a year or longer as 0. Nearly three-quarters (73.6%) of the respondents reported they had hired within the last six months or less.

Technical Background

There were two questions used to ask for respondents' technical background. The first question asked participants, "How many years of working experience have you had as a Data engineer or Data scientist?" Most respondents reported zero experience (81.7%) with the remaining respondents ranging from .5 to 30 years of experience. The average years of experience across all respondents was analyzed as .69 years. Respondents were asked the second question: "Are you working in a high-technology industry?" with answers "Yes" or "No". Nearly a third (30.2%) of respondents reported that they are currently working in a high-technology industry.

Use of Algorithm-based Decision Aids

Participants were asked the question "Have you ever used an artificial intelligence-based decision aid to help screen resumes?" with five answers: "Never", "Very rarely", "Rarely", "Occasionally", and "Frequently". More than one-fifth (21.6%) of respondents reported that they had experience using artificial intelligence-based decision aids previously with a mean response of 1.42.

Algorithm Aversion

While algorithm aversion has been widely studied across several fields, there is no common or agreed upon survey measures. In a systematic review of 61 studies conducted from 1950 to 2018 Burton, Stein & Jensen (2018) concluded that algorithm aversion was most commonly observed from individual decision-making behavior rather than measured as an individual characteristic through surveys. For this study items for algorithm aversion in hiring decisions were adapted from an unpublished thesis by Melick (2020). Six items were selected in this research with a Cronbach's α =.806, which was considered to be reliable. These items included the question, "It is more appropriate to select new employees using a formula designed to predict job performance than to select new employees using professional judgments" The complete scale items are in Table 3.

Usefulness of Algorithm-based Decision Aids

The usefulness of algorithm-based decision aids wea measured by using five items from Agarwal and Prasad (1999). Respondents were provided with a fictional product description which describes an algorithm-based decision aid for resume screening (See Appendix B). After reviewing the description, respondents were asked to rate the usefulness. There were five items from Agarwal and Prasad (1999) measures of technology usefulness as part of their Technology Acceptance Model (TAM). To be consistent with this research, these five items were modified by adding the referent "Using AI-based employee selection…" at the beginning of each item. Example items were "Using AI based employee selection would enable me to accomplish tasks more quickly" and "Using AI based employee selection would improve my job performance"

Participants were asked to rate all items on a 5-point Likert scale, with strongly disagree and strongly agree as the two endpoints (See Appendix C). Five items were selected in this research with Cronbach's α =.891, which was considered to be reliable.

Employability

Employability was measured by using a four-item scale developed by (Singer & Bruhns, 1991) and Kristof-Brown (2000). Four items were: "How likely that you would be interested in interviewing this applicant?" "How likely is it that you would recommend this applicant to be hired?" "How confident do you think that this applicant would succeed in the organization?" and "Taking everything into consideration regarding this applicant's given output, your overall evaluation of this applicant is high". Participants were asked to rate these four items on a 5-point Likert scale, with "Not at all" to "Extremely" as the two endpoints (See Appendix D). Across the eight conditions, the items had Cronbach's alpha which ranged from α = .901 to α = .967 which was judged to be reliable (See Table 1)

Results

Preliminary Analysis. First, Descriptive statistics for all variables in the study were computed using SPSS v28**.** Table 2 provides the means, standard deviations, and zero-order correlations for the study variables. The discriminant validity of the perceptual measures of algorithm aversion and the usefulness of algorithm-based decision aids were assessed using Principal Components analysis with Varimax Rotation. Table 3 shows the rotated component matrix for the two scale items and indicates the measures. To examine the factor structure and discriminant validity among these two variables, I conducted a confirmatory factor analysis (CFA) in Mplus 7.0 (Muthén & Muthén, 2012). First, one-factor model with eleven items from both perceived usefulness and algorithm aversion was tested in Mplus. Then the two-factor model with five items on perceived usefulness and six items on algorithm aversion were tested in Mplus. The results of the CFA analysis (Table 4) showed that the three-factor model that specified perceived usefulness, algorithm aversion, and employability by their respective items were statistically significant, with reasonable overall measurement model fit (χ^2 [87] = 330.13; confirmatory fit index [CFI] = .928; Tucker-Lewis index [TLI] = .913; root mean square error of approximation [RMSEA] = .085 with 90% confidence interval [CI] [.076, .095]; square root mean residual [SRMR] = .046). The three-factor model proved to be a significantly better fit (RMSEA= .085) than a two-factor model (RMSEA=.110; p<.001, ΔRMSEA=-.025, ΔCFI=.029, ΔTLI=.042) and a one-factor model (RMSEA=.110; p<.001, ΔRMSEA=-.066, ΔCFI=.227, ΔTLI=.199).

Manager Characteristics. Hypotheses 1-7 were first tested using an OLS regression predicting the usefulness of algorithm-based decision aids as the dependent variable. The results in Table 5 indicate that the model was significant (F=19.427, p<.001) explained 26.1% of the variance in perceived usefulness of algorithm-based decision aids. Hypothesis 1 predicted that older recruiters would be less likely to use algorithm-based decision aids for reviewing resumes. Recruiter age was significant in the model (t=2.58, p<.05) with a negative coefficient. This indicates that perceived usefulness of algorithm-based decisions aids declines with age and supports Hypothesis 1a. Hypothesis 2 predicted that more educated recruiters would be more likely to use algorithm-based decision aids. The results suggest recruiters who had earned a bachelor's or graduate degree rated algorithm-based decision aids do not rate algorithm-based decision aids more useful.

Hypotheses 3 and 4 predicted that recruiters with technical backgrounds were more likely to use algorithm-based decision aids. I tested these by asking recruiters how many years of experience they had as a data scientist or engineer (Hypothesis 3) and whether they worked in a high-technology company (Hypotheses 4). Years as a data scientist and working in a high-technology company were not significant and these hypotheses were not supported.

Hypothesis 5 predicted that recruiters who had previously used algorithm-based decision aids would be more likely to find them useful. The use of algorithm-based decision aids was significant (t=2.309, $p<.05$) and positive indicating that recruiters who had used these systems more frequently in the past were more likely to find them useful. Hypothesis 5 was supported. Hypothesis 6 predicted that recruiters who had the experience of hiring more recently would be more likely to find algorithm-based decision aids to be useful. Recruiters who had hired within the last six months perceived significantly (t=2.195, $p<.05$) more usefulness of algorithm-based decision aids for reviewing resumes. Finally, we predicted that recruiters who reported higher levels of algorithm aversion would be less likely to use algorithm-based decision aids. Algorithm aversion was significant (t =10.751, $p<.001$) and negatively related to usefulness of algorithm-based decision aids. Algorithm aversion had the largest effect size of the predictors of usefulness and Hypothesis 7 was supported.

Hypotheses 1-7 were then tested using experimental data which asked managers to rate the employability of candidates. Because data on employability of multiple candidates was collected from each survey participant, this raises the potential for correlated errors for regression analyses (Greene, 1993). Acknowledging the nested nature of data, the second part of analysis of this dissertation adopted hierarchical linear modeling (HLM; Bryk & Raudenbush, 1992) to test the effects of seven individual characteristics (age, level of education, date-relevant working experience, high-technology background, previous AI use, hiring recency, and algorithm aversion) on recruiters' hiring decisions on applicants' employability. Moreover, research has suggested HLM as a suitable technique for policy-capturing studies (Aiman-Smith, Scullen, & Barr, 2002).

The use of HLM allows for examination of variables at more than one level of analysis; namely, within subjects (Level 1) and between subjects (Level 2). In current research, the within-subject predictors (Level 1) were the three manipulated dimensions (Bil/AI/HR) of the outputs from the applicant tracking systems. The between-subject predictors (Level 2) were recruiters' individual characteristics (i.e., age, level of education, date-relevant working experience, high-technology background, previous AI use, hiring recency, and algorithm aversion). Participants' perceived employability for applicants were regressed on the participants individual characteristics to identify the participants' idiosyncratic model. Then I followed Hofmann, Griffin, and Gavin's (2000) suggestion of investigating the between-recruiter variation before testing the hierarchical models. The null model results indicate that there was significant between-recruiter variance in the dependent variable (employability for candidates) (γ_{00} = 3.02-3.11). The variation in the residuals in Level 1 was significant (σ=1.65).

The HLM estimated a two-level with ratings of candidates (Bio x AI x HR) were entered into the model as Level 1within variables and a random slope for AI, the seven individual characteristics (i.e., age, level of education, date-relevant working experience, high-technology background, previous AI use, hiring recency, and algorithm aversion) were entered into the Level 2 model as between variables predicting employability and the slope of AI from Level `. To ensure meaningful interpretations of the parameter estimation and to refrain from specific organization effects, I grand centered Level 2 predictor variables before testing hierarchical linear models (Hofmann & Gavin, 1998).

As reported in Table 6, Bio data (γ=.554, $p < 0.01$), AI (γ=1.815, $p < 0.01$), job type (HR Assistant vs. Data Engineer) (γ=-.380, $p < 0.01$) were the important predictors of the AI's relationship with recruiters' perceptions of applicants' employability. Age (γ=-.008, $p < 0.05$) and use of AI systems (γ=.137, $p < 0.01$) were important predictors of recruiters' ratings of candidates' employability. These two supported Hypothesis 1 and Hypothesis 5, which was also consistent from the previous regression analysis. But hiring recency (γ=-.001, $p < 0.05$) and algorithm aversion (γ=-.036, $p < 0.005$) were not significant factors in the relationship between AI and employability. Hypotheses 6 and 7 were not supported, which was contradictory to the OLS regression analysis. Level of education (γ=-.161, $p < 0.05$), data engineer experience (γ=-.018, $p < 0.05$), and high-technology industry (γ=-.120, $p < 0.05$) were not significant predictors for employability. Hypotheses 2, 3, and 4 were not supported in HLM analysis. These three factors were not significant predictors from both analyses.

Types of Skills Required

Hypothesis 8 proposed that recruiters would place relatively greater weight on the information from algorithm-based decision aids for jobs that require greater technical skills than jobs that require greater social skills. To test Hypothesis 8, I examined the influence of AI information on the employability ratings of four candidates for Data Engineer versus four candidates for HR Assistant. As a manipulation check, respondents were first asked to about the skills required for the job descriptions for HR Assistant and Data Engineer along eight dimensions. Respondents were asked, "Based on the previous job description to what degree do you think that the following skills are required?" Following Deming & Kahn (2018) skills were divided between technical skills (problem solving, research, critical thinking, math and statistics) and social skills (communication, teamwork, collaboration, negotiation, and presentation). Respondents were asked to rate the skills required for both jobs from "Not at all important" to "Absolutely essential". These items were averaged together to represent technical skills and social skills respectively with Cronbach's alpha ranging from $\alpha = .690$ for HR Assistant social skills ($\alpha = .724$ for HR Assistant technical skills) to $\alpha = .757$ for Data Engineer social skills ($\alpha = .698$ for Data Engineer technical skills). Means for technical and social skills for the two jobs are presented in Table 7. Paired-sample t-tests indicate that respondents rated the HR Assistant job as significantly higher in social skills ($t= 16.112$, $p<001$) and the Data Engineer to require significantly higher technical skills ($t = 24.951$, $p<.001$).

To test this hypothesis, I analyzed the policy-capturing data with a General Linear Model (GLM) using the mixed linear model with repeated measures procedure in SPSS v.26 with fixed effects for the three conditions (AI, biodata, and job type). This study used the GLM approach with the respondent as a nested variable in the analyses. Results of the GLM analysis are detailed in Tables 8 and 9. The model shows significant main effects for Biodata fit ($F= 412.377$, $p<001$) and for AI fit ($F=4380.405$, $p<.001$) indicating that the intended manipulations for the resume information and the decision-aid information were effective. Respondents rated candidates as more employable with higher levels of Bio data and higher levels of AI fit. More importantly the interaction for job type (HR) and AI fit was also significant ($F=98.222$, $p<.001$) indicating that the respondents reacted more positively to AI fit data from algorithm-based decision aid for the Data Engineer. This supports Hypothesis 8 that recruiters are more likely to use information from an algorithm-based job aid when the job requires technical skills compared with social skills. This is illustrated in Figure 5 and 6 which show the estimated mean employability from the model for AI Fit (Figure 5) and Biodata Fit (Figure 6). The relative increase in rated employability as AI fit from the algorithm-based decision aid moves from low to high is significantly larger for the Data Engineer job than the HR assistant job. The opposite is also true as Biodata fit has a stronger relationship with employability for the HR Assistant job than the Data Engineer job.

Chapter 5 Discussion

Companies have increasingly adopted artificial intelligence (AI) technologies in their personnel recruiting and selection process. More specifically, AI applications can be found in various stages of recruiting, such as writing job advertisements, analyzing video interviews via facial recognition software, and screening of applicant resumes or applications. More and more organizations have claimed that AI has made their hiring process faster and more efficient. However, despite the popularity of AI applications in recruiting and selection practices, this subject is still an emerging topic in academic literature. I seized the opportunity to investigate how AI and algorithm-based decision aids have been adopted and deployed by recruiters in the resume screening process.

This study investigated how recruiters integrate information on various types of information when they evaluate resumes for job candidates' employability or hire-ability. Using manipulated outputs from the application tracking system, I explored whether recruiters' individual characteristics, bio fit score and AI fit score generated by the AI hiring software had effects on employability for job candidates when recruiters make the hiring decisions or recommendations.

The results of this research suggest that several individual characteristics impacted recruiters' decision-making in resume screening. More specifically, younger recruiters were more likely to use algorithm-based decision aids in resume screening than older recruiters; which aligns the argument from Morris and Venkatech (2000) that age reduces perceived behavioral control because self-efficacy and cognitive skills decrease as people age (Morris & Venkatesh, 2000; Brigman & Cherry, 2002). They further argue that the reason that age increases the effect of subjective norms is older workers have a greater need for affiliation. Moreover, older workers are more likely to have routinized habits and they are difficult to change (Harrison & Rainer, 1992; Majchrzak & Cotton, 1988). Older recruiters have their familiarized habits and process in resume-screening and are less likely to adopt the new technology tools in hiring process. Even though some researchers have argued that age does not make a difference for people relevant to technology (Gilly et al., 2012), the result from this dissertation still shows that age was a significant predictor for hiring managers' perceptions of the usefulness of algorithm-based decision aids.

Second, the results suggest that recruiters' level of education and technological background did not make a difference in their decision-making with algorithm-based decision aids in resume-screening, which was conflicting with the second hypothesis. There are two major reasons that might explain the reason. First, even though artificial intelligence has been a hot topic in recent years, except for professionals in engineering or computer science fields, ordinary people have limited understanding of the true concepts or very shallow level of understanding about AI's applications. AI in hiring process is based on algorithms, which is hard for respondents to understand. Second, among the 394 respondents, only 10.7% had working experience as a data engineer or data scientist, even for these participants with relevant working experience or working in the high-tech companies, it might be difficult or different for them to understand the usage in human resource field; or, they might work for other options and did not have experience in recruiting. Future studies can investigate a larger sample size with more professionals in hiring and selection.

Third, the results showed that recruiters who have had experience using algorithms or hired more recently with algorithm-based decision aids were more likely to use AI tools in resume screening. The use of artificial intelligence in the hiring process has increased in recent years. Companies have turned to data analytics to screen candidates' resumes and applications.

Traditionally, recruiters or hiring managers spend a large amount of time reviewing applicants' resumes or applications. Companies face challenges to find the right applicants with the right talent. The appearance of hiring algorithms claims that AI can make the hiring process faster and more efficient. Recruiters or hiring managers who have used this technology in recent years probably have experienced efficiency and convenience and are more willing to adopt AI in future hiring.

Fourth, inspired by Dietvorst et al.'s (2015) conceptualization of algorithm aversion, the rejection of algorithmically generated insights, I included algorithm aversion in this study. Many new software used in hiring and selection are based on algorithms. Complex hiring algorithms use data science to correlate the performance of large numbers of employees with data gathered on candidates. People's understanding and opinions about algorithms can be contradictory. Early studies of algorithms in decision making suggested that people tend to dismiss input from algorithms even when given information about the algorithm's superior performance (Dietvorst et al., 2015). Previous study findings also suggested the opposite opinion: in some situations, people rely more on algorithmic advice than human advice, which is called "algorithm appreciation" (Logg et al., 2019). The result suggested that respondents with algorithm aversion were less likely to adopt algorithm-based decision aids in the resume screening for the perceived usefulness of algorithm-based decision aids. Human interaction has been considered an important component in hiring for both recruiters and applicants. A recent review article showed that there is a perception among candidates and recruiters that AI is worse than humans (Will, Krpan, & Lordan, 2022). Most of the respondents in this study did not have rich hiring experience, highly possible, they had experience been hired by their organizations, which explains why they were less likely to adopt algorithm-based decision aids in resume screening.

The last hypothesis of this research was to investigate how the job type itself has effects on recruiters' decision-making with algorithm-based decision aids. To make the overt distinction in different jobs, this study used two different jobs: HR Assistant versus Data Engineer to compare. HR Assistant requires more social or soft skills such as communication, teamwork, collaboration, and negotiation skills, whereas Data Engineer requires more technical or hard skills such as math, statistics, research, and problem-solving skills. When presented with these two different jobs, the result suggested recruiters were more likely to use algorithm-based decision aids to hire for jobs with more technical skills. Technical or hard skills are more easily quantified by algorithms; social or soft skills are harder to quantify. Recruiters and hiring managers make use of interviews to see what makes their applicants succeed with different skills. Candidates reveal more soft skills in the interaction in the interviews. All of these explain why hiring managers were more likely to use AI or algorithm-based decision aids for Data Engineer positions.

Meanwhile, the data used in the OLS regression was cross-sectional and the participants actually responded eight different manipulations from the survey. It created the between-subject and within-subject analysis potentials. Thus, this study also adopted HLM to test the first 7 hypotheses. At the first level analysis, the results showed that there were significant variances in the dependent variable – employability, which means recruiters' decision-making on employability varied based on the bio data, AI data, and the job type from the manipulations they rated.

At the second level analysis, seven individual characteristics were tested on participants' employability ratings. Results showed that when participants were reviewing the outputs from the application tracking system with different combinations of the applicant's bio date rating (high/low school and working experience), AI fit scores (high/low predictive fingerprints) and two different jobs, individual characteristics age and the previous experience for the use of AI systems from respondents significantly predicted their ratings on applicants' employability. Age had a negative effect on employability, which means with recruiters' decision-making for hiring recommendations when they adopted the algorithm-based decision aids. Both OLS and HLM analyses supported age was a significant predictor, which also aligns to what technology acceptance model indicates that older recruiters were less likely to be able to process complex information processing tasks (e.g., Birren, Woods, & Williams, 1980) and older recruiters had a more difficult time adapting to changes in the work environment (Forteza & Prieto, 1990). Algorithm-based decision aids or hiring algorithms are relatively new concepts in the working place, organizations are learning to adopt and making use of the new tools; however, older recruiters might still believe more in their own experience to make the hiring decisions, especially when they are not very familiar with the new technology methods.

Another variable – the use of AI systems was also a significant predictor in both analyses. Respondents answered the questions "Have you ever used an artificial intelligence-based decision aid to help screen resumes". Results showed that their previous experience of using AI systems significantly predicted their employability ratings on applicants. Hiring algorithm have been used or preached for its efficiency. Technology companies say that hiring algorithms are designed to help hiring managers spend less time manually reading resumes that do not match job requirements. Even though hiring can be more complicated and more analytical. For organizations or recruiters that have used it before, they were benefited by its efficiency. Thus, the use of AI systems in the previous experience in resume screening made a difference on their employability ratings.

Unlike as the significant predictors in technology acceptance models to the dependent variable, level of education, data engineer experience, and high-technology industry were not significant predictors in both analyses. Potential explanation can be the limitation of the sample in this study. Even though the sample size was good and composed with actual working professionals, the targeted participants with hiring experience, especially hiring experience with AI systems were limited. They might work in the high technology companies with high level of education, but they are not familiar with hiring and selection field, and not fully understand how AI systems have been used in resume screening process. The future study could narrow down the sample to get more rigorous responses.

The last individual characteristic variable – algorithm aversion was a significant predictor in the first analysis, and it was negatively related to the perceived usefulness of AI based employee selection, which means that the greater the algorithm was, the lower the usefulness of AI based employee selection tools for participants. However, when participants were given manipulative outputs with more information about the applicant, algorithm did not have any effect on participants' ratings on applicants' employability. Participants might process the decision-making process heavily based on the information given on the outputs and less likely been influenced by the algorithm preferences in that specific process. Possible reasons could be: first, the measurement items used in this study were not very good measures; I took six items from a previous thesis and tested with exploratory factor analysis and confirmatory analysis. Even though the analyses results showed that those items were statistically significant measures, they might not capture the essentials of algorithm aversion concept. Second, there might no such concept as algorithm aversion, especially when participants were given manipulative outputs from applicant tracking systems, further research is needed.

Limitations

Although the method section has successfully tested all the hypotheses, there are some concerns in the study. First of all, all the individual characteristics and perceived usefulness were collected at Time 1 in a cross-sectional study which raises common method bias concerns. Second, respondents were given eight different manipulations and rated employability almost at the same time, which means nearly repeated measurements not involving time were used in the ratings and there are sources of nesting. Using Ordinary Least Square regression to test the data set might violate the statistical assumption of independent observations (Kenny & La Voie, 1985) and result in biased estimates of the relations between variables (Dreher, Ash, & Hancock, 1988).

Although this study provides rich data from the practitioners, the experimental study that is required by policy-capturing research raises some concerns. One issue is that participants were asked to read two job descriptions and eight outputs from the application tracking system and to make well-reasoned decisions on that information in a short period of time. To minimize the possibility of participants skimming through the material, I manipulated a small number of cues and presented only eight concise and simple outputs, these numbers are conservative when compared with other policy-capturing studies (e.g., Brannick & Brannick, 1989; Judge & Bretz, 1992). In addition, I instructed participants with an anticipated time frame. High within-person consistency ratings and the reasonable time frame suggest that respondents did pay attention to the task during the entire experiment.

A second concern is the limited individual characteristics. While this study has tested several major individual characteristics (age, level of education, hiring experience, and algorithm aversion, etc.). There are other individual characteristics have been tested in technology acceptance model, such as personality. Researchers have investigated the effect of personality on Internet use (McElroy, Hendrickson, Townsend, & DeMarie, 2007) and conceptualized personality through the Big Five model and the Meyer-Brigges Type Indicator (MBTI). Their results showed that before controlling for computer anxiety and self-efficacy, extraversion, and openness to experience predicted buying on the Internet. After controlling for computer anxiety and self-efficacy, openness to experience predicted Internet use. Future studies should include more predictors with other individual characteristics (organizational tenure, cultural differences, emotion, and habit, etc.) to a more comprehensive understanding about their effects on recruiters or hiring managers decision-making.

Third, this research first used a cross-sectional survey to examine the relationship between recruiters' individual characteristics and perceived usefulness of algorithm-based decision aids. It raises common method bias concerns. And using OLS regression to test the data set might violate the statistical assumption of independent observations. However, the second part of the analysis adopted HLM, and it allowed for examination of variables at more than one level analysis. It was also the appropriate method for policy-capturing experimental design.

Fourth, as noted in the previous discussion, the selection criteria for the sample respondents were full-time employed managers with hiring experience. Even though many respondents had hiring experience, they might have less experience in hiring than professional recruiters and HR professionals, especially with the use of algorithm-based decision aids in the screening process. Future studies should target hiring professionals with more experience with AI tools and identify the differences from managers who review resumes and make hiring decisions less often. However, compare to studies heavily rely on student data, this research has adopted better data with professionals with actual working experience to test all the hypotheses.

Finally, with the concept algorithm aversion being tested in both regression and hierarchical liner modeling, the results were the opposite. When participants were asked to rate their perceived usefulness of algorithm-based decision aids, algorithm aversion was a significant predictor for their perceptions; however, when participants were reviewing manipulated outputs from applicant tracking system with algorithm-based decision aids and were asked to rate job candidates' employability, algorithm aversion was not a significant predictor for their hiring recommendations. These contradictory results require further research to explore, examine, and test the concept of algorithm aversion with more rigorous measurement items, which further validate and enhance the findings in this research.

Future Research Directions

This dissertation has built a good foundation for future research. First, when tested the effects from individual characteristics from recruiters on their perception of the usefulness of AI, cross-sectional data was used in the analysis. Participants self-reported their perception, and it was only a short exposures with the technology name in question. Future study could expand the time frame for data collection to reduce the concerns from common method biases and enlarge the rating time frame for participants to make more objective ratings. For example, participants' demographics could be collected at Time 1, and perceived usefulness of AI and manipulation ratings for employability could be collected at Time 2. Previous

Second, this research presents the evidence that some individual characteristics influence hiring managers' decision-making with algorithm-based decision aids for job candidates. There are other individual characteristics such as personality traits should be considered. Svendsen and colleagues (2011) investigated the degree to which users' assessments of the core constructs of

TAM are influenced by their personality. They used a web-based survey to ask users to read a description of a software tool before completing personality inventories and TAM core constructs. Their results indicated that personality influences the TAM beliefs. Extraversion had significant and positive relation to behavioral intention. Openness to experience was also a significant predictor to perceived ease of use in TAM. Future research should consider and test personality traits to investigate their impact on recruiters' decision-making to contribute this research theme.

Third, the current research frame only focuses on the early stage of hiring with applications and resume screening from recruiters' perspectives. Recruiters' individual characteristics do make a difference for their hiring decisions towards job applicants. To expand the research theme, future research also can investigate how job candidates perceive the AI recruitment. Esch and colleagues (2019) investigated how potential candidates perceive the use of AI as part of the recruitment process and whether or not it influences their likelihood to apply for a job. Their results found that attitudes towards organizations that use AI in the recruitment process significantly influences the likelihood that potential candidates will complete the application process. The used anxiety in their theoretical framework and found that anxiety is naturally present when AI is part of the recruitment process, however, the anxiety does not really affect the completion of job applications. Thus, they claimed that organizations do not need to spend money to hide their use of AI in recruitment process. In their research, a cross-sectional design was employed with online survey platform participants. More research is needed in this field to investigate how job candidates perceive or react to AI tool in the recruitment process.

Fourth, the current research focuses on the early stage of recruitment and selection. It investigates recruiters' decision-making in resume screening. To move forward, researchers can conduct longitudinal research to include outcome variables, such as job performance from applicants who were hired by different recruiters. The purpose of hiring and selection is to find the good performers through different selection methods and selection states. To connect recruiters' decision-making process with performance outcome variables, this would help hiring managers understand their decision-making difference on the performance difference from candidates, which offers more comprehensive understanding and assistance in future hiring.

Finally, in this research, I focused on different skills required for job positions, only two different jobs were included in the experimental design; however, there are other categorization in the literature. For example, Cole and colleagues (2004) adopted the typology for personality from Holland's (1996) to study conventional jobs and enterprising jobs and how recruiters perceive information from resumes for hiring recommendations. Future research can include more types of jobs and investigate how different types of jobs combined with algorithm-based decision aids influence recruiters' decision-making.

Practical Implications

The findings of this study have significant implications. First, individual characteristics influence recruiters' decision-making in resume screening when they are equipped with AI tools. Recruiters with different ages, different level of education, different hiring experience, and different preferences make hiring decisions differently. Therefore, it is important to understand individual characteristics that matter for employee selection. When new employees are hired by organizations, their characteristics affect how they behave and perform and further influence how the company perform. Organizations should offer recruiters training programs with the information and tools that they need in recruiting. Especially with new technology tools, recruiters should have the opportunity to learn how to make use of the AI tools and how to make good selection decision and learn how different individual characteristics have effects on their decision-making and try to mitigate those effects. Except for the individual differences included in this research, there are other individual characteristics, or the interaction of different individual characteristics. Future research could include and examine a more comprehensive understanding from recruiters and facilitate organizations better understanding how new technology could be used in the employment selection process.

Second, even though there has been a number of research talking about AI in hiring and selection. Most of the articles are theoretical arguments. This research offers empirical study results from practitioners. Theoretical research papers have summarized the history of AI in HR, data analytics in hiring and selection, the practical adoption of AI in hiring, personalized hiring experience. This empirical study offers more robust test results about how recruiters' individual characteristics and how different outputs with bio data and AI data, combined influence recruiters' decision-making in resume screening. The results help researchers and practitioners better understand recruiters' decision-making process, which is a great contribution to the literature and a good reference for organizations to train recruiters for future hiring.

Third, the results also provide evidence that different jobs along with other information from the application tracking system outputs influence recruiters' decision-making when they were given information from both AI and traditional information like educational background and working experience. It reflects those recruiters have different skill emphases on different jobs, when they are equipped with new hiring tools, recruiters were more likely to use AI generated fit score to make the decision for hard skill-relied job, such as data engineer.

Conclusion

The reason behind the introduction of AI in the modern organizations is the gigantic growth of data and information not being managed efficiently by organizations. Due to this reason, more and more organizations have used some degree of digital transformation, and rely on this type of technology. Hiring is an extremely difficult process. HR professionals are recognizing that this valuable data plays a major role in effective decision-making, when it comes to talent management and individual performance. Recent research shows that AI is becoming a key driver behind job-candidate matching and automating communications with candidates (Nunn, 2019). It is increasingly important for HR to understand how information generated by AI tools influence decision-makers. Many organizations have used AI related systems in their hiring and selection process. It further indicates that it is critical to understand the individual and situational characteristics that influence how recruiters understand and incorporate this information into their decisions and actually can select and hire more qualified job candidates.

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Table 1

8 Manipulated Conditions and Cronbach's α

Condition	Bio	AI	HR	Cronbach's α
Condition 1	0	1	1	.957
Condition 2	1	0	1	.958
Condition 3	1	1	1	.901
Condition 4	0	0	1	.901
Condition 5	1	0	0	.949
Condition 6	0	1	0	.967
Condition 7	1	1	0	.902
Condition 8	0	0	0	.932

Note. *Bio 1=High, 0=Low*
AI 1= High, 0=Low
HR=1, Data engineer=0

Table 2.

Mean, Standard Deviation, and Correlations among Variables in the Study

	Variables	*M*	*SD*	1	2	3	4	5	6	7
1	AI Decision-Aid Usefulness	3.17	0.82							
2	Age	42.12	10.7	-0.102*	--					
3	College Degree	0.70	0.71	0.001	0.15	--				
4	Years as Data Engineer/Scientist	0.11	0.31	-.018	-.071	.183**	--			
5	High-Technology Industry	1.7	0.46	-.035	.047	-0.83	-.274**	--		
6	Use of AI Systems	5	1.38	.158**	-.057	-.069	.113*	-.056	--	
7	Hired Within Six Months	1.7	0.31	-.075	.057	-.062	.026	0.12	-.132**	--
8	Algorithm Aversion	2.22	0.64	.476**	.031	.015	.095	-.034	.107*	-.010

Note. $N = 394$ $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

Table 3.

Principal Components Analysis Rotated Component Matrix

	Component	
	1	2
It is more appropriate for hiring managers to make hiring decisions based on their professional judgment than to make hiring decisions based on mathematical formulas designed to predict success at work.		-.731
Hiring decisions that are based on mathematical formulas designed to predict success at work are more accurate than decisions that are based on the professional judgment of the hiring managers.		.736
Selecting new employees using the professional judgment of the hiring manager is more effective than selecting new employees using a formula designed to predict job performance.		-.737
It is more appropriate to select new employees using a formula designed to predict job performance than to select new employees using professional judgment.		.750
It is more effective for employers to use computerized text analysis to screen resumes for applicants than for employers to decide which applicants to interview based on hiring managers' review of resumes.		.700
Using hiring managers' review of resumes is more likely to identify high quality applicants than using computerized text analysis to screen resumes.		-.623
Using AI based employee selection would enable me to accomplish tasks more quickly.	.747	
Using AI based employee selection would improve my job performance.	.872	
Using AI based employee selection would improve the quality of the work I do.	.870	
Using AI based employee selection would enhance my effectiveness on the job.	.890	
Using AI based employee selection would make it easier to do my job.	.789	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Factor loading less than .04 are suppressed.
Rotation converged in 3 iterations.

Table 4.

Confirmatory Factor Analysis with Two Models

Model	$\chi^2(df)$	*p-value*	RMSEA	SRMR	CFI	TLI	ΔRMSEA	ΔSRMR	ΔCFI	ΔTLI
Model 1 Factor all items	572.589 (44)	.000	.176	.115	.738	.672	-	-	-	-
Model 2 factors Use of AI Algorithm aversion	246.808 (43)	.000	.110	.054	.899	.871	-.066	-.061	.227	.199
Model 3 factors Use of AI Algorithm aversion Employability	330.13 (87)	.000	.085	.046	.928	.913	-.025	-.008	.029	.042

Note. CFI comparative fit index, TLI Tucker-Lewis index, CI confident interval, RMSEA Root Mean Square Error of Approximation; χ^2= Chi-squared Statistic, df=degrees of freedom.

Table 5.

OLS Model Results, Predicting Usefulness of Algorithm-based Decision Aids

	Beta
Intercept	2.183
Age	-.009*
College Degree	.008
Years as Data Engineer/Scientist	-.244
High-Technology Industry	-.055
Use of AI Systems	.094*
Hired Within Six Months	.016
Algorithm Aversion	-.609**
Overall Model F	19.427***
R^2	.261
Adjusted R^2	.247
Df = 393	

† $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 6
Hierarchical linear modeling results for employability.

	Estimate Sig.
Level 1	
Intercept	2.118 **
Bio	.554 **
AI	1.815**
HR	-.380 **
Level 2	
Age	-.008*
College	-.161
Data Experience	-.018
High-Technology Industry	.120
Use of AI	.137 **
Hiring Recency	.001
Algorithm Aversion	.019
Overall Model F	19.427***
R^2	.261
Df=393	

Note: Entries are estimations of the fixed effects with robust standard errors. *$p < 0.05$; **$p<0.01$

Table 7.

Skills Requirements Manipulation Check

		Mean	N	Std. Deviation	Std. Error Mean
Technical Skills	HR Assistant	3.291	394	.626	.038
	Data Engineer	4.174	394	.490	.030
Social Skills	HR Assistant	4.104	394	.526	.032
	Data Engineer	3.577	394	.619	.037

Note.
Technical skills included problem solving, research, critical thinking, math, and statistics.
Social skills included communication, teamwork, collaboration, negotiation, and presentation.

Table 8.

Estimated Marginal Means Fitted Model

	Biodata Fit	AI Fit	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Data Engineer	Low	Low	2.218	.042	2.136	2.299
		High	3.730	.042	3.649	3.812
	High	Low	2.749	.042	2.667	2.830
		High	4.336	.042	4.255	4.418
HR Assistant	Low	Low	1.572	.042	1.491	1.654
		High	3.635	.042	3.553	3.716
	High	Low	2.089	.042	2.007	2.171
		High	4.219	.042	4.137	4.300

a. Dependent Variable: Employability.

Table 9

GLM Model Parameter Estimates

	Estimate	Std. Error
Intercept	4.22	.042 ***
Data Engineer [HR=.00]	.118	.055
Biodata [Bio=.00]	-.584	.055 ***
AI [AI=.00]	-2.12	.055 ***
[Bio=.00] * [AI=.00]	.067	.078
[Bio=.00] * [HR=.00]	-.022	.078
[AI=.00] * [HR=.00]	.554	.078 ***
[Bio=.00] * [AI=.00] * [HR=.00]	.007	.110
-2 Restricted Log Likelihood	5801.133	

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

Table 10.

Type III Tests of Fixed Effects

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	374.000	22945.559	***
HR	1	2571	189.903	
Biodata	1	2571	412.377	***
AI	1	2571	4380.405	***
Bio * AI	1	2571	1.669	
HR * Bio	1	2571	.110	
HR * AI	1	2571	98.222	***
HR * Bio * AI	1	2571	.005	

a. Dependent Variable: Employability.

Figure 1. HR Assistant Job Description

Job title: HR assistant

Duties & Responsibilities:

- Facilitate the process of recruitment, including sourcing candidates, scheduling interviews, and issuing offers of employment
- Conduct new hire orientations
- Support inquiries and requests related to the HR department
- Assist with collecting payroll from supervisors, auditing for accuracy, and turn in on weekly basis
- Manage hiring of employees through staffing partners to include interviews, payroll, rollovers, invoicing, etc.
- Manage employee compensation and benefits

Requirements (skills & qualifications):

- Strong leadership and coaching skills, to include empathy and consider yourself to be a "people person".
- Excellent verbal and written communication skills
- Advanced computer skills, experience with HRIS strongly desired
- Excellent problem-solving abilities required
- Detail oriented, good time management and organizational skills

Education: Bachelor's degree in HRM or Business Administration

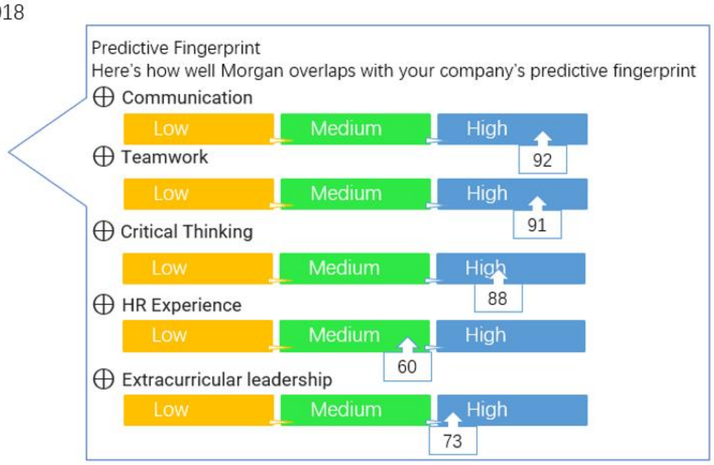
Compensation:

- Competitive salary

Figure 2. HR Candidate Profiles

Morgan Smith
Tarrant County College, 2018

Fit Score: 91 (High)
Overlap with your predictive fingerprint



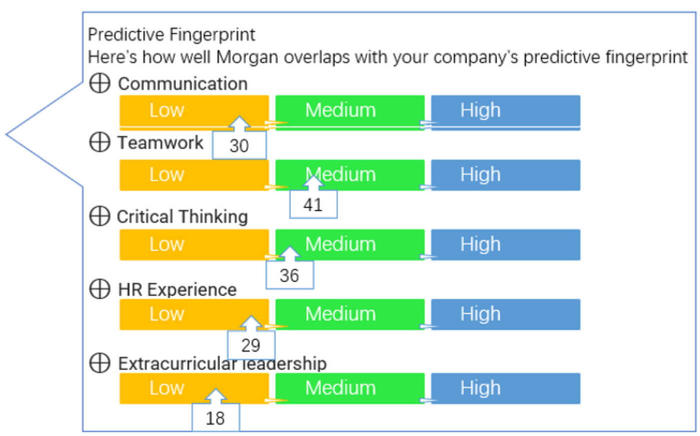
Insurance sales agent – C&G Consulting Group LLC. Houston, TX.

- Customize insurance programs to suit individual customers.
- Explain coverage options to the customers.
- Monitor insurance claims to ensure equitable settlement for both client and insurer.

Updated: October 24, 2021

Morgan Smith
Rice University, 2018

Fit Score: 31 (Low)
Overlap with your predictive fingerprint



HR Assistant – Amazon. Houston, TX.

- Maintained employee data and kept updated accounts of all employment records.
- Assisted in recruiting and training of new employees for the marketing and IT teams.

HR Associate – The Bartech Group. Houston, TX.

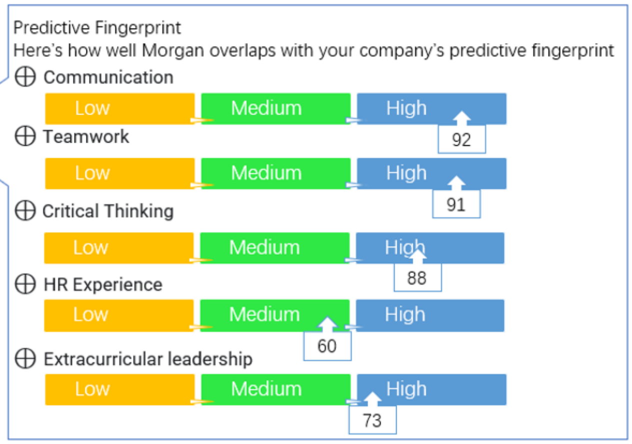
- Inputted changes into HRIS and related to merit, promotion, transfer, termination, new hire, benefits and personal information.
- Supported multiple HR professionals with various tasks and duties to ensure that all policies and procedures were fully followed.

Updated: October 24, 2021

Figure 2. HR Candidate Profiles (Continued.)

Morgan Smith
Rice University, 2018

Fit Score: 91 (High)
Overlap with your
predictive fingerprint



HR Assistant – Amazon. Houston, TX.

- Maintained employee data and kept updated accounts of all employment records.
- Assisted in recruiting and training of new employees for the marketing and IT teams.

HR Associate – The Bartech Group. Houston, TX.

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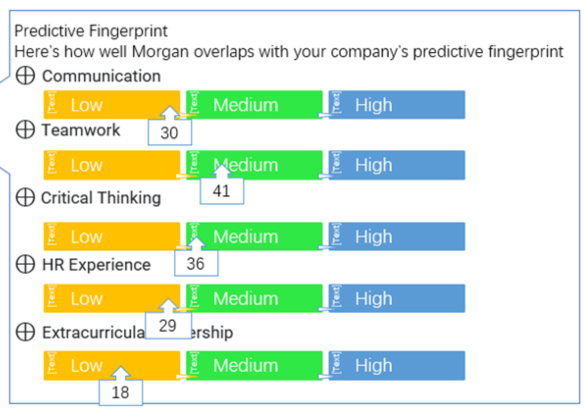
- Supported multiple HR professionals with various tasks and duties to ensure that all policies and procedures were fully followed.

Updated: October 24, 2021

Morgan Smith
Tarrant County College, 2018

Fit Score: 31 (Low)
Overlap with your
predictive fingerprint



Insurance sales agent – C&G Consulting Group LLC. Houston, TX.

- Customize insurance programs to suit individual customers.
- Explain coverage options to the customers.
- Monitor insurance claims to ensure equitable settlement for both client and insurer.

Updated: October 24, 2021

Figure 3. Data Engineer Job Description

Title: Data Engineer

Responsibilities:

- Provides plan with data, reporting and analyses that enable data driven decision making.
- Provides summary analyses in written and oral presentation settings.
- Builds database from scratch. And prepares complex presentations.
- Develops system test cases and documents results, research system issues and documents findings.

Requirements:

- Understanding of database objects (entities, attributes, constraints, relationships, joins, etc.)
- Good logic-building skills
- Ability to write DDL/DML/DQL (any RDBMS) queries
- Good technical presentation & delivery skills
- Exposure to any programming language (C, C++, VB, Python, R, etc.)
- Ability to translate business requirements into non-technical, lay terms
- High-level written and verbal communication skills
- Experience with other relational databases, BI reporting and data discovery tools is preferred (PowerBI, Tableau, SQL Server, Snowflake, MS Azure

Education: Bachelor's degree in Science, Technology, Engineering or Mathematics

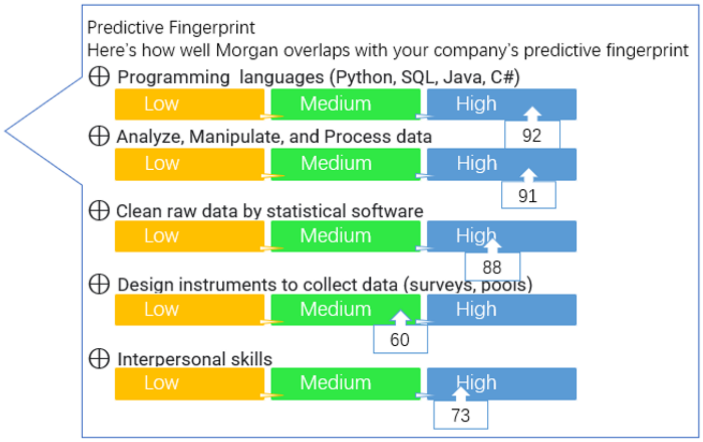
Compensation:

- Competitive salary

Figure 4. Data Engineer Candidate Profiles

Morgan Smith
Tarrant County College, 2018

Fit Score: 90 (High)
Overlap with your
predictive fingerprint



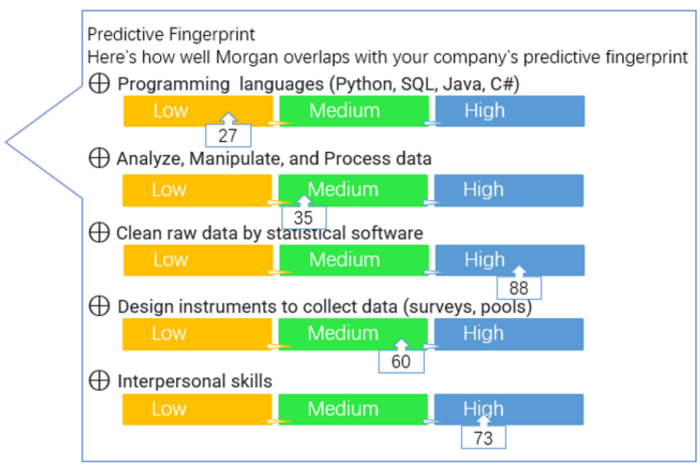
Insurance sales agent – C&G Consulting Group LLC. Houston, TX.

- Customize insurance programs to suit individual customers.
- Explain coverage options to the customers.
- Monitor insurance claims to ensure equitable settlement for both client and insurer.

Updated: October 24, 2021

Morgan Smith
Rice University, 2018

Fit Score: 30 (Low)
Overlap with your
predictive fingerprint



Data engineer – Microbiome Foundation. Austin, TX.

- Increased the efficiency of the data fetching by about 30% using query optimization and indexing
- Automated ETL processes, making it easier to wrangle data and reducing time by as much as 40%

Data engineer – Reilly Group, Austin, TX.

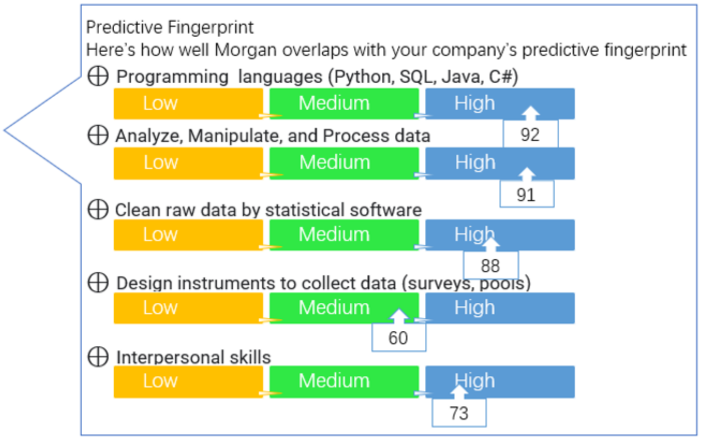
- Automated the manual data reconciliation process between the different sources, increasing data accuracy and efficiency by 90%
- Developed Pig scripts for data analysis and perform transformation.

Updated: October 24, 2021

Figure 4. Data Engineer Candidate Profiles (Continued.)

Morgan Smith
Rice University, 2018

Fit Score: 90 (High)
Overlap with your
predictive fingerprint



Data engineer – Microbiome Foundation. Austin, TX.

- Increased the efficiency of the data fetching by about 30% using query optimization and indexing
- Automated ETL processes, making it easier to wrangle data and reducing time by as much as 40%

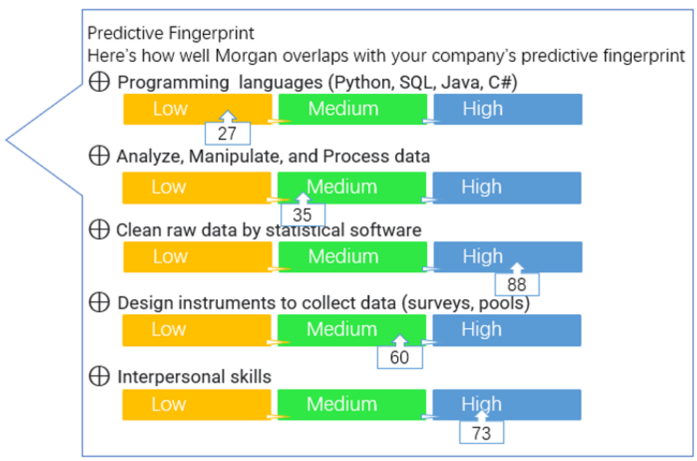
Data engineer – Reilly Group, Austin, TX.

- Automated the manual data reconciliation process between the different sources, increasing data accuracy and efficiency by 90%
- Developed Pig scripts for data analysis and perform transformation.

Updated: October 24, 2021

Morgan Smith
Tarrant County College, 2018

Fit Score: 30 (Low)
Overlap with your
predictive fingerprint



Insurance sales agent – C&G Consulting Group LLC. Houston, TX.

- Customize insurance programs to suit individual customers.
- Explain coverage options to the customers.
- Monitor insurance claims to ensure equitable settlement for both client and insurer.

Updated: October 24, 2021

Figure 5 Mean Employability Algorithm Fit for HR Assistant vs. Data Engineer

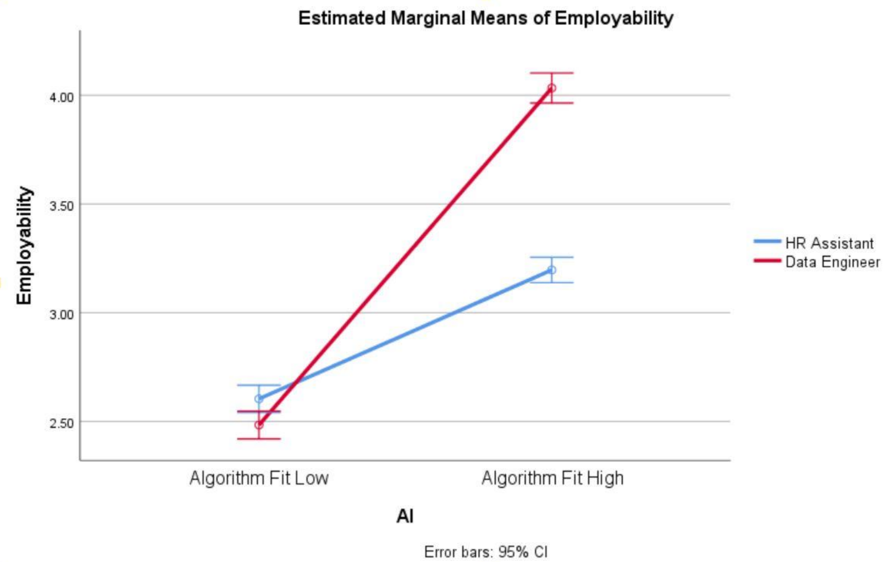
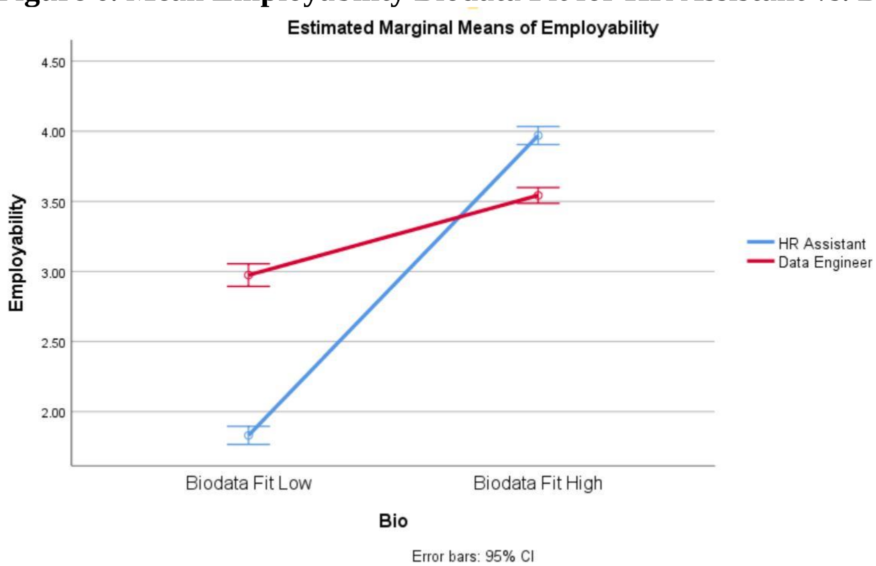


Figure 6. Mean Employability Biodata Fit for HR Assistant vs. Data Engineer



Appendixes

Appendix A – Predictor Information from Job Applicants

Method to Collect Predictor Information	Method to Combine Predictor Information	
	Judgmental	Mechanical
Judgmental	Pure Judgment	Trait Ratings
Mechanical	Profile Interpretation	Pure Statistical
Judgmental & Mechanical	Judgmental Composite	Mechanical Composite

Source: Adapted from Gatewood, Field, and Barrick (2015), *Human Resource Selection* (8th ed., p 652). Cincinnati, OH: Southwestern. Table is abridged version of the original.

Appendix B-Algorithm Aversion Measures

Please review the following statements and indicate the level of your agreement of each statement:

1= Strongly disagree

2= Disagree

3= Neither disagree nor agree

4= Agree

5= Strongly agree

1. It is more appropriate for hiring managers to make hiring decisions based on their professional judgment than to make hiring decisions based on mathematical formulas designed to predict success at work.
2. Hiring decisions that are based on mathematical formulas designed to predict success at work are more accurate than decisions that are based on the professional judgment of the hiring managers.
3. Selecting new employees using the professional judgment of the hiring manager is more effective than selecting new employees using a formula designed to predict job performance.
4. It is more appropriate to select new employees using a formula designed to predict job performance than to select new employees using professional judgment.
5. It is more effective for employers to use computerized text analysis to screen resumes for applicants than for employers to decide which applicants to interview based on hiring managers' review of resumes.
6. Using hiring managers' review of resumes is more likely to identify high quality applicants than using computerized text analysis to screen resumes.

Appendix C-Usefulness of Algorithm-based decision aid measuring material

The following questions describe competing products that use artificial intelligence (AI) algorithms to screen resumes for employers. Please read the descriptions and give your impressions of the products.

"A smart recruiting solution, HireTrack uses the cognitive power of artificial intelligence to scan through resumes and social profiles to pick the best talent based on culture fit. Its predictive analytics capability omits the task of conducting candidate surveys or making questionnaires, where advanced algorithms pre-qualify the applicants to enhance the interview process. The AI-tool has been built to match talent with extreme accuracy through the power of machine learning and natural language processing."

Appendix D-Usefulness of Algorithm-based decision aid Measures

Please review the following statements and indicate the level of your agreement of each statement:

1= Strongly disagree

2= Disagree

3= Neither disagree nor agree

4= Agree

5= Strongly agree

1. Using AI based employee selection would enable me to accomplish tasks more quickly.

2. Using AI based employee selection would improve my job performance.

3. Using AI based employee selection would improve the quality of the work I do.

4. Using AI based employee selection would enhance my effectiveness on the job.

5. Using AI based employee selection would make it easier to do my job.

Note: items were selected from *Agarwal & Prasad (1999).*

Appendix E-Employability Measures

Please review the following statements and indicate the level of your agreement of each statement:

1= Strongly disagree

2= Disagree

3= Neither disagree nor agree

4= Agree

5= Strongly agree

1. How likely that you would be interested in interviewing this applicant?

2. How likely that you would recommend this applicant to be hired?

3. How confident do you think that this applicant would succeed in the organization?

4. Taking everything into consideration regarding this applicant's given output, your overall evaluation of this applicant is high.

Note: items were selected from *Singer & Bruhns (1991)* and *Kristof-Brown (2000)*.