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Using Machine Learning to Translate Applicant Work History Into Predictors of Performance and Turnover

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Work history information reflected in resumes and job application forms is commonly used to screen job applicants; however, there is little consensus as to how to systematically translate information about one's work-related past into predictors of future work outcomes. In this article, we apply machine learning techniques to job application form data (including previous job descriptions and stated reasons for changing jobs) to develop interpretable measures of work experience relevance, tenure history, and history of involuntary turnover, history of avoiding bad jobs, and history of approaching better jobs. We empirically examine our model on a longitudinal sample of 16,071 applicants for public school teaching positions, and predict subsequent work outcomes including student evaluations, expert observations of performance, value-added to student test scores, voluntary turnover, and involuntary turnover. We found that work experience relevance and a history of approaching better jobs were linked to positive work outcomes, whereas a history of avoiding bad jobs was associated with negative outcomes. We also quantify the extent to which our model can improve the quality of selection process above the conventional methods of assessing work history, while lowering the risk of adverse impact.

Keywords: selection, occupational analysis, data mining

Researchers and practitioners increasingly use massive databases of job applications produced by electronic application systems. These systems present challenges, as organizations need to contend with many applicants in a systematic and efficient manner (Flandez, 2009; Grensing-Pophal, 2017). Both human resource (HR) departments and consulting firms are evaluated based on time-to-hire and volume of qualified candidates (Gale, 2017). To keep the best applicants, organizations need to respond rapidly to individuals who may be sending out dozens of online applications (Ryan, Sacco, McFarland, & Kriska, 2000). Time pressures, the large volume of applications, the complexity of the decision task, and recruiters' biases and heuristics increase the chance of overlooking or misinterpreting candidate qualifications (e.g., Converse, Oswald, Gillespie, Field, & Bizot, 2004; Tsai, Huang, Wu, & Lo, 2010).

While standardized tests and inventories speed the acquisition of data, they overlook individualized applicant information. Facets of work history, including relevant work experience, tenure in previous jobs, and reasons for leaving previous jobs, are empirically and conceptually distinct from either cognitive ability or personality, and so can add significant predictive power in a selection battery (Ryan & Ployhart, 2014). Although job-relevant experience predicts performance, it is difficult to track job-relevance systematically across applicants' idiosyncratic work histories (Tesluk & Jacobs, 1998). For example, recruiters struggle to quantify the difference between an individual with 5 years of experience in childcare relative to someone with 3 years of experience in corporate training, or between a person who quit a previous job because of insufficient administrative support relative to an intrinsic desire to share knowledge. Lacking a system for organizing job history information, many organizations evaluate qualifications using idiosyncratic and cumbersome processes (Brown & Campion, 1994).

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To circumvent these problems, more organizations use large-scale data analytic techniques to comb through open-ended text fields in electronic applications. Most HR professionals are familiar with automated keyword searches of applications, a method that far predates the use of electronic systems (e.g., Peres & Garcia, 1962). The development of these lists, however, is seldom linked to a conceptual or theoretical understanding of qualifications. In the absence of this knowledge, the cognitive and information limitations of decision makers are built into the system in the stage of building keyword lists (Bao & Datta, 2014). Keywords are also often applied in a rudimentary scorekeeping method, with each word that matches the keyword list receiving equal weight independent of the context in which the word is used.

Recent developments in machine learning provide opportunities to summarize work history as rapidly as keyword methods, but in a more rigorous and comprehensive manner that can be linked to other research and practice. Broadly defined, machine learning consists of prediction algorithms, including text mining techniques that classify chunks of text into categories or order them based on a criterion (Mohri, Rostamizadeh, & Talwalkar, 2012). Unlike keyword searches focused on individual words, machine learning techniques find terms that co-occur, enabling better incorporation of context. These techniques can also calculate the importance of words, and algorithmically calculate the probabilities that a statement belongs across multiple categories. These methods are increasingly used measure individual differences and work motivation (de Montjoye, Quoidbach, Robic, & Pentland, 2013; Doyle, Goldberg, Srivastava, & Frank, 2017). Despite calls to apply these methodological developments in employee selection (Campion, Campion, Campion, & Reider, 2016; Chamorro-Premuzic, Winsborough, Sherman, & Hogan, 2016), to the best of our knowledge, machine learning and text-mining have not been systematically applied to translate information from standard application forms into predictors of subsequent work outcomes.

In an attempt to find low-cost and systematically assessed predictors of performance and turnover from applications, we draw on existing theories and use machine learning techniques to develop useful and novel measures of work history. In purely empirical applications of machine learning, researchers rely on hundreds of variables, train different algorithms using a training sample of the data and evaluate the performance of these algorithms on a test sample. Then, they regularize these algorithms and evaluate how the algorithm can improve employee selection in the specific organization (e.g., Aiolli, de Filippo, & Sperduti, 2009; Chalfin et al., 2016). They do not examine the importance of particular predictors, nor attempt to evaluate mechanisms driving the prediction. Further, lack of interpretability can make these selection models vulnerable to challenge from stakeholders within the organization and from legal cases alleging that the method is disconnected from job requirements (Klehe, 2004). Our approach contrasts with this atheoretic, "black box" prediction approach that may not generalize to other contexts, sheds little light on the underlying mechanisms, and is difficult to explain to decision makers, the public, courts, or other stakeholders.

We focus on three aspects of work history from application forms: (a) *work experience relevance* incorporating correspondence of knowledge, skills, abilities, and other attributes (KSAOs) from previous job titles and job descriptions with the current job; (b) *tenure history,* incorporating length of tenure in previous jobs; and (c) *attributions for previous turnover,* including a history of involuntary turnover, leaving to avoid bad jobs, and leaving to approach better jobs. This mix of predictors represents components of skill development and job requirements embodied in the U.S. Department of Labor's Occupational Information Network (O*NET; Peterson, Mumford, Borman, Jeanneret, & Fleishman, 1999), patterns of behavior and attitudes, and general motivation for work based on approach-avoidance models (e.g., Elliot & Thrash, 2002; Elliot & Thrash, 2010; Maner & Gerend, 2007). We use these prehire measures to predict performance across multiple domains, and both voluntary and involuntary turnover hazards (i.e., duration of employment until turnover occurs).

Besides these innovations on the predictor side, we are able to evaluate the proposed selection system using a broad set of outcome variables, and contrast this idealized system relative to the existing selection system. Barrick and Zimmerman (2009) opened out the criterion space to include both performance and turnover, and concluded that it is more cost-effective for organizations to assess candidates using constructs that predict both performance and turnover. Our data allow us to accomplish this by incorporating multiple perspectives on performance, including (a) client evaluation, (b) expert observations of performance, (c) more-objective measures based on standardized test results, and (d) voluntary and involuntary turnover hazards.

Linking Work History to Performance and Turnover

Most job applications request information related to work experience and history of job changes. In addition to these factual pieces of information, forms ask applicants about the content of previous job responsibilities and reasons for leaving previous jobs. Below we describe how we use these clues in work history to assess how well-acquainted applicants are with job-related KSAOs, their motivational tendencies linked to turnover, and the duration of previous employment.

Relevant Experience

Work experience is conceptualized in terms of whether the applicant has encountered work situations relevant to the requirements of the job for which s/he applies. Ployhart (2012, p. 24) proposed that "work experience is a broad, multidimensional construct that often serves as a proxy for knowledge." Quiñones, Ford, and Teachout (1995) and Tesluk and Jacobs (1998) emphasized the importance of the qualitative aspects of work experience, including the type of tasks performed which can be translated into work-related knowledge and skills.

The key factor we assess is work experience relevance, defined consistent with prior work (e.g., Dokko, Wilk, & Rothbard, 2009) as the correspondence between the KSAO requirements of applicants' previous jobs and the job that the applicant seeks. KSAO-based matching of experience is a better predictor of performance than using titles and employment durations in previous jobs (Quiñones et al., 1995). The training and development literature (Blume, Ford, Baldwin, & Huang, 2010; Saks & Belcourt, 2006) similarly argues that repeatedly doing tasks contextually similar to those required for the focal job develops competency. Relevant job experiences are considered socially acceptable hiring criteria by job seekers, organizations, and legal systems as they are factual and job related (Hausknecht, Day, & Thomas, 2004; Klehe, 2004). Relevant work experience signals applicants' fit with the focal job. Applicants possessing relevant experience can make more informed decisions relative to those who have not had such direct interaction with core job tasks (Jovanovic, 1984). Individuals also tend to gravitate toward jobs that match their KSAOs (Converse et al., 2004; Wilk, Desmarais, & Sackett, 1995). In sum, work experience relevance, weighted by recency and tenure in each previous job, provides valuable information about applicants' level of knowledge, skills, abilities, interests, and values. Despite this, there are still few efforts to build a truly systematic scoring method for evaluating work experience relevance. Large databases of job titles and relevant tasks have been used in synthetic validation to assess entire selection measures or systems (Johnson, Steel, Scherbaum, Hoffman, Jeanneret, & Foster, 2010; Steel & Kammeyer-Mueller, 2009), but such tools have not been used to predict individual applicant performance.

We propose that machine learning can be used to match occupationally relevant KSAOs to job requirements. We operationalize work experience relevance by measuring the similarity between the KSAOs required for applicants' previous jobs and the required KSAOs for the job for which the applicant has applied. Starting with the previous jobs' self-reported titles and job descriptions provided by the applicants in their application form, we categorize each previous job into the standard O*NET occupations. As a machine learning technique, words from self-described job titles and job descriptions are matched with best fitting O*Net job titles probabilistically. These probabilities form estimates of the level of different work characteristics the individual has encountered in previous jobs. Profile analysis techniques measure the similarity between each applicant's past profile and the profile of the focal job. We then weight the KSAO match based on the tenure in each previous job and the recency of each job to give a better sense of the quantity of experience (e.g., Quiñones et al., 1995).

> *Hypothesis 1:* Work experience relevance, assessed through machine learning, is (a) positively related to performance and (b) negatively related to turnover hazard.

Tenure History

There is a consensus among organizational psychology researchers and practitioners that past behavior is the best predictor of the future behavior (e.g., Barrick & Zimmerman, 2005; Owens & Schoenfeldt, 1979; Wernimont & Campbell, 1968). Job applications provide information regarding behavioral tendencies based on the applicant's average length of time spent in previous jobs, which we term "tenure history." A person with a questionable tenure history has a record of changing jobs after a relatively short period of time, whereas a more reliable tenure history is indicated by many spells of long tenure. The existence of different typical levels of tenure history across jobs has been noted in several theoretical and empirical works (e.g., Judge & Watanabe, 1995; Maertz & Campion, 2004). As noted by Barrick and Zimmerman (2005) "while most turnover models view intent to quit as an immediate precursor to actual turnover, some individuals may be predisposed to quit even before starting the job" (p. 164). Peripatetic tenure history could also signal other problems, such as poor skills or low motivation. Short tenure in previous jobs may reflect a generally poor work ethic, correlated with consistently lower levels of organizational commitment and a higher likelihood of turnover (Mathieu & Zajac, 1990). Also, job applicants with poor levels of skills or motivation are expected to have lower average tenure in their previous jobs as they either involuntarily or voluntarily leave the job as they lack dispositional conscientiousness for their work (Barrick & Zimmerman, 2009; Griffeth, Hom, & Gaertner, 2000).

> *Hypothesis 2:* Tenure in previous positions is positively related to (a) performance, and negatively related to (b) voluntary and (c) involuntary turnover hazard.

Attributions for Previous Turnover

Machine learning is well-suited to examining open-ended text regarding one's attributions for leaving past jobs. We start from the premise that turnover attributions extracted from job applications are valid signals of traits and dispositions toward work. Individuals vary greatly in the attributions they make for prior turnover (Lee, Mitchell, Holtom, McDaneil, & Hill, 1999). Attributions or motives related to turnover may be indicative of a persistent orientation toward work across multiple jobs, as noted in previous work on the consistency of job attitudes (e.g., Newton & Keenan, 1991; Staw & Ross, 1985). This approach to coding open-ended information as indicative of stable characteristics has a long history (Lee & Peterson, 1997; Spangler, 1992). Like previous text coding research, our approach looks at attributions for previous events (Burns & Seligman, 1989; Staw, McKechnie, & Puffer, 1983). Machine learning approaches circumvent the unreliability of alternative approaches through a standardized method of coding. Machine learning allows us to identify words or phrases that signal applicants' relatively stable psychological characteristics based on a priori categories. For example, an applicant can write that s/he left the previous job because of excessive stress or poor working conditions. This means the person was seeking to avoid a bad job, although he or she did not explicitly use words like "leaving a bad job," or more abstract theoretical terms like "avoidance motive." Although there are several contextually specific reasons for leaving previous jobs, such as continuing education, relocation, or caregiving, we only focus on attributed reasons that signal relatively stable behavioral and attitudinal characteristics.

To systematically evaluate reasons applicants describe for leaving previous jobs in our data, we use supervised machine learning techniques. We trained a small sample of data (3% of the data) and manually categorized applicants' reported reasons for leaving a past position into four categories: (a) involuntary, (b) avoiding bad jobs, (c) approaching better jobs, and (d) other reasons. This is shown in Table 1. We then trained the algorithm on these data and it "learned" to evaluate the probabilities that different words and word combinations predict belonging to each category. Then it read the remaining data, which we call the test sample (97% of the data), and applied what it learned from the co-occurrence of terms and phrases and their probability distributions over the four categories of reasons in the training sample to recognize the semantic patterns and themes in applicants' reported attributions for leaving previous jobs. The algorithm then delivered probabilities that each text aligns with each of the four categories.

It is reasonable to believe that applicants might not disclose the actual reason for their leaving. However, in this study, the main

Table 1
Sample of the Training Dataset

Attributions for turnover	Reasons for leaving
Involuntary	Low student enrollment budget hold back from state
Involuntary	School closed due to low enrollment
Involuntary	Reorganization after turnaround transferred management back to Dutch owners
Involuntary	Company went under due to economic situation
Involuntary	Position eliminated due to recession
Avoid a bad job	The school wasn't a good fit for my teaching style
Avoid a bad job	I was unhappy and I resigned my position
Avoid a bad job	I was pretty much burned out
Avoid a bad job	Air pollution no health insurance low pay
Avoid a bad job	Bad management not enough hours
Approaching a better job	Interested in having a more challenging position
Approaching a better job	I'm interested in education and am now pursuing my dream
Approaching a better job	I love working with kids my passion is in teaching and promoting learning
Approaching a better job	A new professional challenge and an opportunity for professional growth
Approaching a better job	Advancement in career opportunity to grow personally and professionally
Other	Birth of my daughter
Other	I had a baby
Other	Relocated for family illness
Other	Husband's job was transferring
Other	Began Master of Education program

question is not whether the applicants reported the verifiable reasons organizations record for turnover, but whether applicants' self-reported attributes provide information useful in predicting future performance and turnover. Our model focuses on psychological processes filtered through self-presentation motives, memory distortions, and attributional biases to produce a description of prior turnover. Moreover, our hypotheses focus not primarily on answering theoretical questions about the variables we have included in our model, but rather, whether machine learning algorithms grouped around theoretical concepts established in prior research can predict subsequent work behavior.

History of involuntary turnover. An attribution of involuntary turnover reflects a situation in which the applicant reports that the organization made the decision to end the employment relationship. As an example of our machine learning process, reasons related to involuntary turnover include "I was laid off due to a budget cut," "my position was eliminated because of budget cuts," or "my position was eliminated and I was excessed." Words and phrases associated with budget, cut, eliminate, position, and layoff are expected to co-occur in reasons related to involuntary turnover. In our machine learning approach, algorithms learn these words and phrases are related to one another in a training sample, and applies the rule on the rest of the data by searching for similar relationships among words in the test sample. The algorithm then categorizes each individual reason for leaving given by applicants into corresponding categories by calculating the probability distribution of that information. The algorithm repeats this process in the test sample and finds their probability distributions over the categories predefined in the training sample.

Although we cannot be certain that individuals in our sample did experience involuntary turnover, we can use their attributions of involuntary turnover to predict behavior. Such attributions are important because they may reflect administrative decisions, but also reflect a tendency for an individual to focus on the role of external actors in shaping their behavior. The first issue relates to the more factual component of involuntariness. Several studies have found that employees who involuntarily leave their jobs tend to be lower performers compared to those leaving voluntarily (Barrick, Mount, & Strauss, 1994; Barrick & Zimmerman, 2009). Even in the case of layoffs, the selection of which individuals are terminated is often reflective of poor performance. Davis, Trevor, and Feng (2015) further note that individuals who have a history of being laid off tend to have more negative attitudes toward subsequent jobs, and in turn, are more likely to quite these subsequent jobs. The second issue relates to internal mental processes which drive individuals to describe their prior turnover to involuntary components (Wang, Bowling, & Eschleman, 2010). Such descriptions are consistent with a lower sense of personal responsibility and agency. Machine learning scores differentiate a statement "I was laid off due to budget cuts in my last job," from "After I was laid off, I sought a job that better matches my career goals." The former statement is scored as a totally involuntary attribution whereas the latter statement is scored as only a partially involuntary attribution because it blends an external attribution with personal control. In many other cases, the extent to which the employer or employee is truly the initiator of a job separation is not so clear-cut. In such ambiguous situations, individuals who are less agentic will recall and describe the event as completely involuntary, whereas an agentic individual may recall and describe the event as purely voluntary. The combination of the characteristics that lead an employer to terminate an employment relationship as well as the characteristics of an individual to recall and report this termination as mostly or entirely involuntary point in the same direction:

> *Hypothesis 3:* Applicant attributions of previous turnover as involuntary, as assessed via supervised machine learning, is (a) negatively associated with performance, and (b) positively associated with voluntary turnover hazard.

History of avoiding bad jobs. An extensive research tradition has differentiated individuals based on their long-term, dispositional motivational orientations. Scholars have come to find an important distinction between an "avoidance" disposition and an "approach" disposition (Elliot & Thrash, 2010). An avoidance disposition is associated with a tendency toward noticing negative or threatening features of the environment, experiencing anxiety when confronted with negative information, and behavioral attempts to avoid the resulting negative emotional stimuli (e.g., Diefendorff & Mehta, 2007; Elliot & Harackiewicz, 1996; Ferris et al., 2011). A focus on avoiding negative outcomes has been linked to attention to minimal standards of job performance, characterized by trying to find "minimally sufficient" levels of effort (Förster, Higgins, & Idson, 1998). While individuals with a strong avoidance focus may be able to complete core job tasks at a very basic level by showing up on time and completing strictly defined duties, efforts to innovate, exert extra effort, or seek advancement in one's career generally suffer (Elliot & Harackiewicz, 1996; Elliot & Sheldon, 1997). Moreover, it is also possible that individuals who attribute previous quitting to problems with their former workplace are behaviorally prone to externalize blame for negative events (Maier & Seligman, 2016). An avoidance focused attribution for job changes will also be associated with higher probability of turnover. Evidence clearly suggests that a disposition toward avoidance motivation is associated with lower levels of job satisfaction (Lanaj, Chang, & Johnson, 2012) which is a key antecedent of turnover (e.g., Schleicher, Hansen, & Fox, 2011; Trevor, 2001). Individuals who are avoidance focused will also be more prone to exit a job when problems arise, based on their generalized tendency to cope with problems by avoiding them.

> *Hypothesis 4:* Applicant attributions of previous turnover to avoiding bad jobs, as assessed via supervised machine learning, is (a) negatively associated with performance, and (b) positively associated with voluntary turnover hazard.

History of approaching better jobs. Several studies describe how an approach motivational orientation is positively associated with positive work outcomes (e.g., Diefendorff & Mehta, 2007; Elliot & Harackiewicz, 1996; Ferris et al., 2011). The approach orientation can represent itself in seeking a better fit, following one's passion, or looking for opportunities for advancement and development. Wrzesniewski, Dutton, and Debebe (2003) identified that interpreting one's work as a calling to be sought out is linked to more enjoyment, greater satisfaction and spending more time at work which all result in better performance and lower levels of turnover. Other studies found that a positive desire for one's work can positively contribute to long-term performance (e.g., Baum & Locke, 2004; Bonneville-Roussy, Lavigne, & Vallerand, 2011; Vallerand et al., 2008). Other studies have found that people who framed their work positively (e.g., as having positive effects on others) were more effective and more resilient in the wake of setbacks (Blatt & Ashford, 2006).

> *Hypothesis 5:* Applicant attributions of previous turnover to approaching better jobs, as assessed via supervised machine learning, is (a) positively associated with performance, and (b) negatively associated with voluntary turnover hazard.

Method

Data and Sample

We used data from 16,071 external applicants for teaching positions at the Minneapolis Public School District (MPS) between 2007 and 2013. The district hired 2,225 of the applicants. Of these, 1,756 stayed with the district at least until the 2012–2013 academic year, when the district introduced its teacher-effectiveness evaluation system, data from which we obtained our performance measures. Institutional review board (IRB) approval was granted by University of Minnesota (IRB Protocol #: 1510S79046, study title: Improving Human-Resource Management in Urban School Districts).

MPS is one of the largest school districts in Minnesota, serving over 30,000 students each year and employing around 2,800 total teachers in recent years. The school district teaching staff is 86% White, 6% African American, 2% Hispanic, 4% Asian, and 1% Native American. It serves a diverse population of students, many of whom are economically disadvantaged. MPS serves about 70% students of color, 21% English language learners, and 65% students eligible for free or reduced-price lunch.

The district publicly posts vacancy announcements. Typical teaching positions include elementary, high school math, or special education. Applications are submitted via a series of electronic forms that elicit semistructured text similar to that commonly found on a resume. The central human-resources department does a light screening to ensure each applicant meets minimal qualifications, such as having required licenses. School-based hiring teams conduct interviews and make offers. According to the district, more than 90% of offers are accepted.

For each application, we have data on position and self-reported applicant characteristics. These included a detailed work history with job title, job description, reason for leaving, and start and end dates for each previous job. Half of applicants' past positions were in 51 teaching occupations (their titles include the stem "teach*"). The other half were in 663 nonteaching O*NET occupations. The three most frequent were first-line supervisors of office and administrative support workers, educational guidance school counselors and vocational counselors, and social and human service assistants. Some applicants also disclosed race and gender, although this was not required. For hires working in the 2012–2013 academic year or after, we were able to link application information to performance data. We have information on turnover for all participants who were hired.

Measures

Work experience relevance. We automated measurement using four steps: (a) map past position job-title and job-description text to O*NET occupation codes, (b) map occupation codes to O*NET KSAO space, (c) measure distance in KSAO space between the past and desired position, and (d) average this distance across all the applicant's past positions using a weighting function that favors more recent and longer-held positions.

For the first step, we used supervised machine learning techniques to develop an algorithm that classified self-reported job titles and job descriptions into an O*NET standardized occupation code. Supervised classification is recommended for theory-driven studies and for cases in which a strong, external, ground-truth dataset exists on which to train the algorithm. Such classifiers were developed by learning the characteristics of different classes from a training sample of preclassified documents (Feldman & Sanger, 2007; Mohri et al., 2012). We used a naive Bayes Classifier, the most prevalent text classifier in machine learning (Feldman & Sanger, 2007; Mohri et al., 2012). We trained the algorithm against the ground truth of the official O*NET (O*NET, n.d.) occupational descriptions and job titles. We trained the classifier using a dataset comprising O*NET's detailed job descriptions and alternative job titles for each of 974 occupations as displayed on O*NET's web page. From the text on each occupation's O*NET web page, we made a "bag of words" for each O*NET standard occupation containing its description and commonly reported job titles associated with the occupation. We then trained the classifier on these data. Technical details are included in the Appendix.

Next, we ran the trained algorithm on the self-reported job description and job title from each applicant regarding a past position. The algorithm mapped this to a standardized O*NET occupation. To validate the classification, we took a random sample from the self-reported previous jobs, and hired a research assistant to classify the job descriptions into O*NET occupations. A senior undergraduate student in HR classified a random sample of 500 self-reported job titles and job descriptions. She searched for each self-reported job in O*NET online database, read the descriptions of occupations, and decided which O*NET occupation is closest to the self-reported job title and job description. We compared the predicted occupation from the naive Bayes classifier with the Research Assistant' (RA)'s classification to calculate the agreement rate between human and machine classifications. They agreed in 92% of the cases in the sample.

In the second step, each past position's standard occupation was mapped to a point in KSAO space. O*NET provides detailed information about the required level and/or importance of different abilities, knowledge, skills, vocational interests, values, and styles for each occupation. This gave each occupation-o a profile, x_o, in a high-dimensional KSAO space.

In the third step, we operationalized work-experience relevance with a profile similarity index (PSI), measuring the similarity between an applicant's past occupation and the occupation sought. A PSI is a single value representing the extent to which a past occupation and the prospective one are (dis)similar across multiple variables (Converse et al., 2004; Edwards & Harrison, 1993). We used *profile level* which measures dissimilarity and measures the extent to which scores in one profile tend to be higher or lower than scores within another profile. As is common, we used the L2 (Euclidean) distance between the two profiles (Converse et al., 2004; Edwards & Harrison, 1993). Letting a index the past position, b index the desired position, i index the dimensions of KSAO space, the profile level measures dissimilarity as,

$$R_a = -\left(\sum_i (x_{ai} - x_{bi})^2\right)^{\frac{1}{2}} \quad (1)$$

To measure relevance R_a, we reverse coded distance, using the negative sign above.

Finally, to aggregate information across an applicant's entire work history, we take a weighted average of R across all the applicant's past jobs. Applicants in our sample average 3.18 previous jobs (SD = 2.2). To account for the duration and recency of experiences, we define a weight for each previous job as the integral of the decay function of both the elapsed time since the person left the previous job (E_a) and their tenure in that job (T_a). The weight accorded to past position-a is,

$$w_a = \int_{E_a}^{E_a+T_a} e^{-rx}dx \quad (2)$$

A higher decay parameter (r) implies a faster rate of decay in KSAOs over time. For r = 1, current KSAOs become irrelevant in about 5 years. For r = .5, it takes about 10 years. In Minnesota, where the school district is located, teaching licenses expire after 5 years, and renewal requires more than 100 hr of professional development. We chose r = 1 to match this 5-year decay. The correlation between weights yielded from a decay function with r = 1 and r = .5 is 0.95 and the correlation between work-experience relevance variables created using those weights is 0.97. Our aggregate measure of work-experience relevance is the w_a-weighted average R_a across the applicant's past positions, which we then standardized across applicants.

Tenure history. We defined tenure history as the average deviation of applicant's tenure in prior jobs from the median tenure in each occupation category. Barrick and Zimmerman (2005) used average tenure in previous jobs to measure this. However, average tenure differs across occupations because of occupational characteristics unrelated to individual tendencies. To address this issue, we collected median tenure in an applicant's relevant prior occupation category, reported on the department of labor's website (United States Department of Labor, Bureau of Labor Statistics, n.d.). For each past position, we computed the difference between the applicant's tenure and relevant median tenure. Each applicant's tenure history is the average deviation across prior positions.

Attributions for turnover history. To systematically categorize self-reported turnover reasons, we hand-coded a randomly selected set of attributions into each of the main three topics (i.e., involuntary, approaching a better job, and avoiding a bad job) or a fourth, residual category capturing all other topics. In the training data, if the applicant's turnover attributions provided more than one topic, we broke the text into specific topics (additional lines in the training sample). In the process of improving our training sample, we started with manually coding a random sample of 100 attributions, trained the algorithm on that sample, and ran the trained algorithm on a validation sample that we had set aside. We increased the size of the hand-coded training sample gradually and repeated the process until we obtained algorithm accuracy of 90%, which occurred with a training sample size of 1,000 attributions. To ensure that the final training sample was accurately hand-coded by the authors, the RA rated a random sample of 100 from the final training sample. The agreement between the RA rating and our rating was 100%. At this point we trained a supervised naive Bayes classifier on the final training sample. Next, we had the trained classifier algorithm score each of the 34,601 turnover attributions in the whole dataset. For each past job, this delivers a probability distribution that sums to one across the four possible attributed reasons for leaving. To check the accuracy of this classification, the RA categorized a random sample of 350 classified turnover attributions that were not in the training sample. There was a 93% agreement between the machine and RA classification.