Human Resource Management Review xxx (xxxx) xxxx

Contents lists available at ScienceDirect

Human Resource Management Review

journal homepage: www.elsevier.com/locate/hrmr

A critical review of algorithms in HRM: Definition, theory, and practice

Maggie M. Cheng*, Rick D. Hackett

DeGroote School of Business, McMaster University, Canada

ARTICLE INFO

Keywords:
Algorithm
Big data
HRM
Heuristics
Causality

ABSTRACT

The recent surge of interest concerning data analytics in both business and academia has been accompanied by significant advances in the commercialization of HRM (Human Resource Management)-related algorithmic applications. Our review of the literature uncovered 22 high quality academic papers and 122 practitioner-oriented items (e.g., popular press and trade journals). As part of our review, we draw several distinctions between the typical use of HRM algorithms and more traditional statistical applications. We find that while HRM algorithmic applications tend not to be especially theory-driven, the "black box" label often invoked by critics of these efforts is not entirely appropriate. Instead, HRM-related algorithms are best characterized as heuristics. In considering the implications of our findings, we note that there is already evidence of a research-practitioner divide; relative to scholarly efforts, practitioner interest in HRM algorithms has grown exponentially in recent years.

1. Introduction

The attributes of volume, velocity, and variety associated with big data (Laney, 2001) cannot contribute to insightful decision-making without developing and applying proper algorithms. As workforce digitization is creating "ever increasing volumes of data" (George, Haas, & Pentland, 2014), algorithms are crucial to the interpretation of the data in a manner that has the potential to add value. In Human Resource Management (HRM) specifically, the increased datafication of HRM practices is calling attention to the development and application of advanced HRM algorithms.

HR used to be viewed as one of the least data-driven of all the business functions (Bersin, 2012; Davenport, 2014; Martin, Wright, & Cowan, 2014); however, the availability of big data and associated algorithms has drastically changed the HR landscape. Major technological giants including Google, Microsoft, IBM, and LinkedIn have all launched software or platforms that enable the analysis of HRM practices and outcomes, including those related to hiring, compensation, employee engagement, and the management of turnover (Dignan, 2018; Meister, 2017; Walker, 2012; Walter, 2018). Although HR-related algorithms have been developed and applied to small data sets, examples of big-data algorithmically-driven recommendations receive much of the publicity. Deloitte, for example, found that a lack of grammatical errors on a large dataset of resumes was predictive of the performance of salespeople to a greater degree than were academic grades (Bersin, 2013a). Similarly, Xerox found that personality types predict turnover, such that those identified as creative tended to stay longer than those regarded as being inquisitive (Walker, 2012). Data-driven analyses by IBM revealed that employees who worked overtime without rewards or promotion were more likely to leave the organization (Alexander, 2015). Ultimately, the market for workforce analytics is projected to exceed 1 billion USD annually by 2022 (Zion Market

* Corresponding author at: DeGroote School of Business, McMaster University, 1280 Main St. West, Hamilton, Ontario L8S 4M4, Canada.
E-mail address: chengm22@mcmaster.ca (M.M. Cheng).

https://doi.org/10.1016/j.hrmr.2019.100698
Received 20 February 2018; Received in revised form 19 April 2019
1053-4822/

Please cite this article as: Maggie M. Cheng and Rick D. Hackett, Human Resource Management Review, https://doi.org/10.1016/j.hrmr.2019.100698

Research, 2017).

While the use of algorithms seems to be thriving in HRM practice, the scholarship concerning their use (including related analytical models) reflects a comparatively cautious, conservative outlook (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016; Cheng, 2017; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015). HRM researchers question, for example, the value of analytics-driven software for decision making; Angrave et al. (2016) concluded that there is little evidence to support the strategic value of these tools. Relatedly, Cheng (2017) warned that using analytical models without a strong basis for making causal inference is likely to result in spurious models that add little value to HRM practice. In all, some believe that the zealous embrace of algorithmic models in HRM practice will turn out to be a management fad (Angrave et al., 2016; Rasmussen & Ulrich, 2015).

The major aim of this paper is to provide a review of both high quality academic research as well as items in trade journals and the popular press concerning the use of algorithms in HRM. By doing so, we hope to help bridge the long-standing gap between academics and management practice (Bansal, Bertels, Ewart, MacConnachie, & O'Brien, 2012; Bartunek & Rynes, 2010; Ghoshal, 2005; Hambrick, 1994; Mowday, 1997; Pearce, 2004; Rousseau, 2006; Walsh, Tushman, Kimberly, Starbuck, & Ashford, 2007). In the past, researchers have indicated a knowledge gap caused by practitioners not being aware of impactful HR research findings (Deadrick & Gibson, 2009; Rynes, Colbert, & Brown, 2002; Rynes, Giluk, & Brown, 2007). However, the recent rapid development of algorithmic tools in HRM practices lead to concerns that management researchers may be at risk of being left irrelevant in fast-growing workplace applications of complex modeling (Phan, Wright, & Lee, 2017). As we will discuss below, such concern is not unfounded. Our analysis takes this discrepancy from the realm of speculation (Bartunek & Rynes, 2010; Phan et al., 2017; Walsh et al., 2007) to empirical evidence.

As part of our review, we address several research questions. First, we seek to provide clarification concerning the definition of algorithms in the HRM context, including how their application differs from traditionally used statistical approaches. Second, we assess the extent to which there are particular topics or issues within HRM that have attracted the interest of those who use algorithmic approaches. Third, we identify several especially pressing research questions given the state of the HRM algorithmic literature. Finally, in line with our goal of helping to bridge the divide between scholarship and practice, we examine the degree to which the answers to these questions depend on whether we are dealing with a research-oriented or application-oriented database.

2. HRM algorithm in context

As used in math, computer science, and related fields, an algorithm has a strict definition as an "unambiguous" specification in relation to problem solving (Rogers, 1967; Knuth, 1997; Boolos & Jeffrey, 1999). Unambiguity typically refers to three criteria of clarity: (1) each step in the algorithm is clearly-identified; (2) the inputs and outputs of the algorithm are well-defined; and (3) the algorithm has a guaranteed end point that produces a correct result (Rogers, 1967; Knuth, 1997). The underlying algorithmic logic between the inputs and the outputs of algorithms can be roughly separated into two categories: deterministic and probabilistic (Cormen, Leiserson, Rivest, & Stein, 2009, p. 114–116, 123). The most studied type of algorithms in math and computer science assumes a deterministic relationship between the inputs and outputs, which means that if an input A causes the output B, then A must *always* be followed by B. For instance, in one of the most famous algorithms, *the Traveling Salesman Problem (TSP),*[1] if the location of all cities were known, and the order that the salesman travel through each cities is fixed, the salesman will *always* travel the exact same total distance – not one mile more, not one mile less. The other type of algorithm is used to uncover probabilistic relationships between inputs and outputs, which means that the *occurrence of A increases the probability of B*. Informally, this type of algorithm is more often used when researchers are only exposed to imperfect knowledge of a real-life scenario, such as the relationship between smoking and lung cancer. An algorithm with a probabilistic nature employs a degree of randomness as part of its logic, therefore it does not guarantee correctness.

The computational nature of algorithms in HRM research is no different than those from math and computer science and can be either deterministic or probabilistic. For instance, finding the best solution for workforce scheduling is very similar to TSP – once we know the distances between destinations, the rules of scheduling among employees, and the sequence of services, the nurse will always spend the same time to travel the same distance. These optimization problems based on established deterministic causal relationships are usually at the center of research in operations management field in business schools. On the other hand, most HRM researchers are interested in problems that are probabilistic in nature, for instance, whether conscientiousness increases the probability of better individual performance and how much effect it would have. The traditional regression models used in HRM research follow this probabilistic logic and are also algorithms in a broad sense. Since algorithms with a probabilistic nature do not guarantee correctness, researchers are particularly careful in applying them to make causal claims. Further discussion on this topic will be included in the latter part of this article.

Both categories of algorithms have significant practical value for HRM practices, yet we believe that algorithms that are probabilistic in nature would be more meaningful to HRM research due to several considerations. First, these algorithms are closely-connected to the kinds of questions that HRM field tries to answer, such as recruitment, selection, turnover, and performance management. Second, algorithms with non-definitive answers results in a certain level of randomness, which requires judgment from

[1] The traveling salesman problem (TSP) was first formulated in 1930 and is one of the most studied problems requiring optimization algorithms (Shmoys, 1985). It asks the following question: "Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city and returns to the origin city?" The problem is computationally difficult and has further applications in planning, logistics, or even DNA sequencing.

their users. Third, as a result, decisions regarding such algorithms may challenge the existing ethical framework of HRM practices. Therefore, this article is aimed at understanding how HRM research and practice use and interpret algorithms with a probabilistic nature, as well as sparking discussion on the need for guidance for their application.

3. Data and preliminary analysis

3.1. Collecting quality sources for review

Articles referring to algorithms in both HRM research and practice were identified using "integrative synthesis" review procedures (Rousseau, Manning, & Denyer, 2008), a systematic methodology to identify a comprehensive pool of literature. We searched two major multidisciplinary publication databases: ProQuest Databases and Web of Knowledge. ProQuest Databases covers multidisciplinary content from 90,000 authoritative publishers and includes business, social sciences, communications, and engineering. Web of Knowledge, previously known as Web of Science, is a comprehensive research platform encompassing 256 disciplines, including science, social science, the arts, and humanities, reflective of more than 12,500 high impact journals, 170,000 conference proceedings, and 70,000 books. Together, these databases cover both the academic and non-academic domains of interest.

To address concerns from management scholars that evidence-based reviews are susceptible to underplaying the importance of the quality of evidence (Barends, Rousseau, & Briner, 2014; Marler & Boudreau, 2017), we followed Barends et al. (2014)'s recommendation to evaluate each paper for the degree to which, for example, an explicit research question was formulated, followed by data collection and analyses designed to address the issue. We also followed the Marler and Boudreau (2017) approach by differentiating papers that were both peer-reviewed and members of the Journal Quality List; (Harzing, 2018) for business or organizational contexts, from those that were not. The JQL is intended to help academics to identify outlets that meet reasonable scholastic standards (Harzing, 2018) and is often used by universities to evaluate publications for the purposes of tenure decisions (Marler & Boudreau, 2017). JQL covers high-quality journals in multiple business-related disciplines with hundreds of those journals from Organization Behavior/Studies, Human Resource Management, Industrial Relations, Psychology, and General Management. Regarding non-academic sources, we deliberately limited our review to sources that are part of the ProQuest Business Premium Collection such that sources with less credibility (e.g. company websites, and individual blogs) were excluded.

3.2. HRM research vs. practice: the general trend of interest in algorithms

The protocols of "human resource algorithm," "talent algorithm," and "workforce algorithm" were used in conjunction with the targeted databases. Also, in our search for research content we used the following keyword combinations, each paired with "algorithm": recruitment and selection; personnel training; performance; turnover; job satisfaction; pay and compensation; and salary; yielding 10 protocols containing "algorithm".

Regarding the research-based search, a preliminary pool of 536 articles was found, but 385 of them were ultimately eliminated because they did not involve JQL (2018) list outlets. Of the remaining 151 publications, 24 were excluded because the algorithms involved were either unrelated to HR (e.g. other business disciplines, and various subfields of computer science) or did not directly describe an algorithm for HR purposes (e.g., the study of peoples' perceptions of algorithms). The result was that 127 high-quality publications met the criteria for our review.

Fig. 1(a) shows that the number of articles has grown steadily since 1974.

Turning to our search of practitioner literature, the primary protocols as used in the research search (human resource algorithm, talent algorithm, and workforce algorithm) yielded 728 non-academic entries from ProQuest Business Premium Collection. These included newspapers, magazines, trade journals, as well as wire feeds, blogs and, websites belonging to institutions. Given the large number of items uncovered by this initial effort, we elected not to use the additional protocols applied in the research-oriented search because we were confident that this initial effort sufficiently reflected the overall trends in practice.

As with the research-oriented findings, we confined our focus concerning practice to material that directly described the application of an algorithm to one or more HR functions. Thus, we first removed 144 articles that mentioned the algorithm-related keywords in general contexts. Second, 241 articles describing the use of algorithms outside of HR (e.g., finance, healthcare, media and fashion) were removed. Third, 35 articles that were general commentaries concerning the use of algorithms to HR, without any reference to specific HR functions, were removed. Lastly, we eliminated 86 overlapping items that reflected coverage of the same issue and/or event by multiple media events (e.g. XYZ company launches/kicks off/creates ABC algorithm). This resulted in 222 articles that described a computer algorithm that was specifically used in relation to one or more HR functions. Note that beyond the practitioner material we cite to illustrate various points in the paper, page constraints prevented us from providing a complete listing of this work here; a complete list of them is available from the corresponding author.

Fig. 1(b) shows a notable surge in coverage of HR-related algorithms in trade journals and mass media after 2014. Moreover, a comparison of the trendlines shown in Fig. 1(a) and (b) reveals that for many years research and practice-oriented interest in HR-related algorithms grew together, though in the past 5–10 years the practice content has grown at a much faster rate.

3.3. Analysis of the literature by subfields

We now examine our findings by HR function. Regarding the research-oriented literature, it is notable that 105 of the 127 scholarly articles (82.7%) focused on solving the challenges of increasing "manpower" efficiency by optimizing the allocation, routing, and scheduling of a workforce. As explained earlier, this research applies deterministic logic that yield exact answers as opposed to the algorithms that are probabilistic in nature and better connected with the HRM field. Examples include rearranging activities of operators working in transportation (airlines, trucks, railways, ships, etc.); or in systems requiring on-demand services (call centers, hospitals, gas stations, etc.). This literature concerning the optimal operation of equipment and the provision of services is thus most representative of the use of algorithms in operations management and industrial engineering contexts (Cardoen, Demeulemeester, & Beliën, 2010; Edwards & Holt, 2009; Ernst, Jiang, Krishnamoorthy, & Sier, 2004; Nof & Hank Grant, 1991). Since, as explained earlier, our emphasis is on probabilistic algorithms, from this point forward, we focus on these applications, as reflected in the 22 remaining high-quality peer-reviewed papers. Also, irrespective of the algorithmic form involved, our interest is in the subset of HRM activities that view employees as investments with differentiated knowledge, skills, and abilities (Lado & Wilson, 1994; Noe, Hollenbeck, Gerhart, Wright & Eligh, 2016; Schuler & Jackson, 1987; Schuler & MacMillan, 1984; Wright et al., 1994) and/or strategic partners in the business (Barney & Wright, 1998; Caldwell, 2008; Lemmergaard, 2009; Holbeche, 2009) who can be a source of sustainable competitive advantage (Lado & Wilson, 1994; Noe, Hollenbeck, Gerhart, Wright & Eligh, 2016; Schuler & Jackson, 1987; Schuler & MacMillan, 1984), rather than deterministic algorithms, where the primary aim is to reduce labor costs.

Regarding the practice literature, our review revealed a similar pattern to that found with the academic literature. Of the 222 articles, 78 were scheduling, allocation and/or routing related, while 22 described HR-related automation, including automatic form filling and audio transcription. Thus, our subsequent focus was on the remaining 122 articles (a listing of the excluded articles is available from the corresponding author).

4. Comparison of the use of algorithms between HRM research and practice

4.1. Research articles

In the 22 remaining journal articles, algorithms are applied across many different HR concerns, in outlets that span multiple disciplines including management, industrial relations, operations management, economics, information systems, and statistics. Table 1 displays the outlets along with the topic(s) of interest, and the stated purpose of HRM algorithm.

At the individual-level of analysis, algorithms are widely used in the description and prediction of work-related attitudes such as job satisfaction (Aouadni & Rebai, 2016; Becker & Grilli & Rampichini, 2007; Hsiao, Jaw, Huan, & Woodside, 2015; Becker & Ismail, 2016; Kuron, Schweitzer, Lyons, & Ng, 2016; Liu, Chen, Lu, & Song, 2015; Somers & Casal, 2009). Relatedly, algorithms have also been developed to predict motivation (Canós-Darós, 2013) and employee turnover (Koch & Rhodes, 1981; Wang et al., 2017). In recruitment and selection, an algorithm has been used to predict future performance outcomes when a quota is imposed for minority group hiring (Kroeck, Barrett, & Alexander, 1983). In training and performance management, algorithms have been used to rank the importance of HR capabilities against developmental needs (Lin & Hsu, 2010), and to predict competency gaps in the management of software engineers (Colomo-Palacios, González-Carrasco, López-Cuadrado, Trigo, & Varajao, 2014).

At the macro-level, algorithms have been used to describe how ownership separations and acquisitions influence the composition of HR of organizations (Boudreau & Berger, 1985). They have also been used to reduce HR overhead (Strub, Lapinsky, & Abrahamson, 1994), to optimize HR-related investments (Gutjahr, 2011), and to analyze the alignment between various HR practices and the strategic capabilities of small and medium-sized enterprises (Fabi, Raymond, & Lacoursière, 2009).

Other applications include efforts to predict labor force participation (Hall, Racine, & Li, 2004). Bidding and arbitration behaviors in final offer arbitration have been modeled (Gerchak, Greenstein, & Weissman, 2004; Swartz, 2003). Hatfield and Milgrom (2005) endeavor to match contracts between individuals and organizations.

4.2. HRM research vs. practice: divergence by HR function

Articles from trade journals and the popular media also reference use of algorithms across a variety of HR functions. To compare the topics targeted in these literatures, we grouped the studies in terms of commonly referred to HRM concerns. For example, the Job Attitudes category includes algorithm studies related to job satisfaction, motivation, engagement, and happiness, while Recruitment and Selection includes algorithmic resume screening, selection algorithms, and online job matching. In Fig. 2, we use percentages to compare the literature pools given the large discrepancy in the total the number of articles in favor of practice over research.

Fig. 2 reveals that use of algorithms in areas such as Performance Management and Turnover draws attention from both researchers and practitioners, whereas in areas such as Job Attitudes, Collective Bargaining, Labor Participation, and Strategic HRM, there has been little or no interest among practitioners, relative to researchers. In contrast, the HRM functions of Recruitment and Selection, Training and Development, and Compensation have attracted more interest from practitioners than researchers. Accordingly, we now turn to a consideration of the research opportunities that exist in relation to these three areas of practitioner interest.

4.3. Research opportunities

In the course of reviewing both the scholarly and application-oriented literatures by HR function, several areas especially in need of research became apparent. We now consider some of these possibilities.

4.3.1. Recruitment: blind hiring algorithms

Our review reveals a growing trend in the use of "blind" screening algorithms to eliminate unconscious human bias by removing demographic markers from application materials, as their disparate influence on decision makers has been shown, for example, with regard to ethnicity (Kang, DeCelles, Tilcsik, & Jun, 2016) and gender (Moss-Racusina et al., 2012). While research designed to find viable interventions with a demonstrable positive impact are rare, we found media reports (e.g., Norberts, 2018) concerning the use of automated text processing software to reduce the cost and effort of conducting blind resume screening. In addition to fostering the blind review of candidates, there are algorithmic techniques that help remove gender bias in job listings. Textio, a software developer, analyzes the wording in the job listings that may inadvertently attract one gender over another (Silverman & Gellman, 2015). Their analyses, for example, suggests that use of the term "rock star" may attract more males than females, and that the phrase "high performer" should be used instead.

4.3.2. Training and development: A bottom-up, self-driven training system

The analysis of the practice-oriented literature revealed use of bottom-up training algorithms that empower employees to make decisions concerning the training content required for their jobs and/or make suggestions concerning training needs to their employer. As described by Walker (2012), statistics gathered from current and former Google employees are used to inform managers of likely training needs at various points in their career (Walker, 2012). Vencat (2006) describes a platform that employees at Cisco used to distribute videos, including content from YouTube channels, to promote learning across teams. At Whirlpool, a digital platform allows engineers to immediately create interactive webcast tutorials to correct product flaws which can be shared with other employees across 70 countries (Vencat, 2006). Among other opportunities, the research community has yet to address the impact of bottom-up, self-driven approaches to on-the-job training enabled partly by algorithmic platforms.

4.3.3. Compensation

Relative to other HR concerns, the topic of compensation has been a neglected area of research (Gupta & Shaw, 2014). For example, a meta-analysis of research concerning the impact of financial incentives on job performance found only 39 studies over a 40-year timeframe (Jenkins, Mitra, Gupta, and Shaw, 1998); this relative lack of research interest remains unchanged (Gupta & Shaw, 2014). Relatedly, we did not find any research reflective of the practitioner-oriented trend of applying algorithms to designing compensation systems. For example, Google has been using a predictive algorithm to reduce attrition by making timely, flexible adjustments to compensation packages (Silverman and Gellman, 2018). In the United Kingdom, large banks are evaluating a pay system based on multilevel modeling that captures regional variations to attract and retain talent in different locations (Economists make a difference on pay, 2000). More broadly, HelloWallet offers an online diagnostic algorithm to compare employer-offered salary and benefits against open data sources from government (HelloWallet, 2012). From a research perspective, the impacts and effectiveness of these efforts are open questions.

5. Investigating the nature of HRM algorithms

5.1. Are HRM algorithms black boxes?

In addition to variations between the research and practitioner literatures regarding areas of relative interest, the nature of algorithms themselves tend to be portrayed differently. It is notable that the term "black box", while uncommon in the research literature, is widely adopted by practitioners, especially those who have a general discomfort that these applications are producing solutions that are mystical in nature (Boulton, 2017; Johnson & Ruane, 2017; Pasquale, 2015; Wilson et al., 2017). Wilson, Daugherty, & Morini-Bianzino (2017), for example, note that the "black box" nature of sophisticated algorithms made many executives uneasy, especially when the resulting recommendations conflicted with conventional wisdom. Relatedly, Johnson and Ruane (2017) note that hidden bias in an algorithm cannot easily be detected since "you cannot simply read the code to analyze what is happening." Boulton (2017) also warns against blind trust in algorithms generally, including in HRM contexts, because if "you're making decisions that impact peoples' lives you'd better make sure that everything is 100 percent."

In comparing our literature pools, the relative differences concerning references to a black box might be partially because the practitioner-oriented articles rarely discuss the details of the algorithms involved. In comparison, due to differences in mission and readership, the algorithms in our research-oriented pool were typically clearly-defined. The information provided usually consisted of detailed guidelines generated by humans and communicated to computers via coding. This is important since any missteps in the process will result in software failures. To address the level of clarity and transparency, we reviewed each of the 22 research papers for the degree to which the analysis protocols were clearly-defined with regard to: (1) independent variables and dependent variables used, (2) the methods of processing unstructured data (e.g. graphs/video/sound) involved; (3) goal of estimation/optimization (minimization or maximization) used, and (4) the sequence and priority of calculations.

First, most research articles clearly stated the independent and dependent variables used. For example, the most complex model used 78 factors reflective of eight categories as antecedents to predict employee motivation (Canós-Darós, 2013). Two papers employed historical data to predict the future decision-making of arbitrators, such that the algorithms involved could accommodate all previous events if necessary. In terms of dependent variables, most of the papers used only a single dependent variable though some used as many as three (Fabi et al., 2009; Hsiao et al., 2015). The simplest algorithm in the pool used two independent variables (home life and work attitude) to predict a single dependent variable, job satisfaction (Liu et al., 2015). One exception to the high level of clarity concerning the variables involved was Lin and Hsu (2010) who used the generic term "Decision Support System" instead of disclosing the details of their algorithm. Collectively our review revealed that when researchers use the term "algorithm" in place of traditional models, the algorithm typically includes more independent variables than is common in traditional HR research.

Second, none of the articles in our pool involved unstructured data. Nonetheless, there is an increasing trend to using unstructured data in fields such as social psychology. For instance, computerized-text analysis methods, including Linguistic Inquiry and Word Count (LIWC), were created and validated to count words in psychologically meaningful categories (Tausczik & Pennebaker, 2010). Related methods are widely used in marketing (Ludwig et al., 2013), strategic management (Crilly, Hansen, & Zollo, 2016; Nadkarni & Chen, 2014), and health management (Monrouxe, Rees, Enddacott, & Ternan, 2014). Image processing represents another new method of unstructured data analysis adopted by social psychologists. Wang and Kosinski (2018), for example, used deep neural networks to predict human sexual orientation from facial images shown on a dating website. Use of wearable sensors to measure geospatial data for social network analysis is also an emerging field in management research (Chaffin et al., 2017; Tonidandel, King, & Cortina, 2016). In any case, use of these methods in HRM scholarship is either absent or nascent.

Third, although the goals of algorithms estimation or optimization varied across studies, they were typically clearly stated. Several used algorithms to find the best fitting model to describe their data (e.g., Becker & Ismail, 2016; Canós-Darós, 2013; Colomo-Palacios et al., 2014; Hall et al., 2004; Hsiao et al., 2015; Koch & Rhodes, 1981; Somers & Casal, 2009) and for maximizing prediction. Some used algorithms for clustering (Fabi et al., 2009; Kuron et al., 2016) or generating simulated datasets and assessing proposed models (Boudreau & Berger, 1985; Kroeck, Barrett, & Alexander, 1983). Others aimed to minimize the sum of measurement errors as part of a construct measurement, e.g. measuring multiple facets of job satisfaction (Aouadni & Rebai, 2016).

Forth, the sequence or priority of operations in the algorithms used was also typically detailed. This includes the order of calculation in applications of Neural Networks or Genetic Algorithms (Aouadni & Rebai, 2016; Colomo-Palacios et al., 2014; Somers & Casal, 2009); two-step clustering algorithms (Fabi et al., 2009; Kuron et al., 2016) iterations of estimating likelihood functions (Gerchak et al., 2004; Swartz, 2003), the parameters and steps used in a simulation (Boudreau & Berger, 1985; Kroeck et al., 1983), the selection of parameters or models following a specific preference, e.g. using correlations instead of R^2, assigning smoothing parameters from large to small, and matching parameters to their weighting in the population (Becker & Ismail, 2016; Hall et al., 2004; Hsiao et al., 2015). Only two studies (Lin & Hsu, 2010; Strub, Lapinsky, & Abrahamson,1994) did not detail the mathematical decision-making embedded in their algorithms.

Given the above, we suggest that the “black-box” perception associated with using algorithms is only a reflection of the techniques used to process complex data. Factors contributing to the complexity of algorithms include the translation of graph/video/sound into binary variables, the automatic clustering of data points, the automatic assignment of various weights to large numbers of variables, and the generation of a global solution despite local heterogeneity. Thus, a complete understanding of the underlying computational complexity associated with some algorithms requires detailed knowledge from a variety of fields, including engineering, mathematics, and/or computer science. Importantly, since most management researchers lack this background, the “black box” label is appropriate to a limited extent, underscored by the lack of basic information concerning the algorithms described in the practice literature.

5.2. The role of theory is deemphasized in the use of HRM algorithms

In the research we reviewed, algorithms largely take the place of traditional statistical models, typically without highlighting the differences involved. This is important because the use of traditional statistical approaches such as multiple regression (Cohen, Cohen, West, & Aiken, 2003) are intimately linked with the desire to test a theory. Specifically, a complete theory has at least four essential “building blocks” – factors (variables, constructs, concepts), mechanisms (causal relationships), rationale (underlying psychological, economic, or social dynamics), and contextual conditions (who, where, when) (Dubin, 1978; Whetten, 1989). Hence, the statistical approaches traditionally used in HRM research have been chosen to align with the testing of theory reflected by “boxes (constructs)” and “arrows (causal relationships)”, and the underlying rationale and boundary conditions being sufficiently discussed. In comparison, theory is downplayed in HR-related algorithmic applications; underlying complex calculations take on the role of model-building instead. Thus, for example, with the exception of Becker and Ismail (2016) who specify that their study is intended to assess Hult's (2005) existing model of job attitudes, most of the research in our database emphasizes *what* their algorithms are capable of doing (e.g. handling complex antecedents, dealing with a biased sample, processing categorical or ordinal variables, predicting nonlinear relationship between variables) and/or their mathematical deduction, rather than how such algorithms test a theory. Theory-related discussion was either minimal or non-existent, especially in studies involving more than 10 antecedents.

In comparison, in applying traditional HRM models, researchers first form causal hypotheses derived from theory. The hypotheses typically consist of a causal description between theoretical constructs, for instance, job satisfaction, turnover intention, and turnover behavior. Some of the constructs may be directly observable (e.g. turnover—whether the employee left the organization); others are not (e.g. turnover intention). As such, researchers attempt to operationalize the unobservable constructs to bridge theoretical constructs with observable measurement. Only then can they collect observational data based on justified observable measurement, make statistical inferences, and draw statistical conclusions concerning the statistical significance of effect sizes. These statistical conclusions are essentially associations with strong theoretical causal support and are eventually interpreted as research conclusions for making practical or policy recommendations. In sum, the major source of inferring causality in traditional HR research is through theoretical discussion such that much of the research relies heavily on theory to support causal arguments.

In some of the research we reviewed predictive modeling, defined as a statistical model or data-mining algorithm for the purpose of predicting new or future observations (Shmueli, 2010; Shmueli & Koppius, 2011), was the explicit goal. For instance, the stated aim of Hall et al. (2004) was to improve the mathematical predictive power of categorical variables using nonparametric methods, using female participation in the workforce as an example. Colomo-Palacios et al. (2014) used Artificial Neural Networks to predict the competency gaps in key management personnel when the relationships among variables of interest were nonlinear. Hsiao and his colleagues (2015) applied Fuzzy Set Qualitative Comparative Analysis to predict happiness-at-work and the job performance of hospitality employees. A crucial feature among all these predictive models is the temporal forecasting of the dependent variables involved. Nonetheless, predictive modeling has been criticized as "atheoretical" or "unacademic" and is sometimes disregarded for the purposes of theory testing (Shmueli, 2010). Often, the debate concerns "whether prediction per se is a legitimate objective of economic science, and also whether observed data should be used only to shed light on existing theories or also for the purpose of hypothesis seeking in order to develop new theories" (Feelders, 2002). Importantly, statisticians emphasize the value of statistical prediction (Findley & Parzen, 1998; Friedman, 1997), noting that observed variables can have greater relevance in estimation than artificially constructed ones (Geisser, 2017). In the end, predictive modeling based on more powerful calculation capabilities to analyze large, rich datasets may give rise to new hypotheses and help uncover new causal mechanisms useful in theory testing (Shmueli, 2010).

Some of the research we found was descriptive. In descriptive modeling, theoretical discussion is either absent or informally characterized (Freedman, 2009). Relative to predictive modeling, where the aim is to improve predictive accuracy, descriptive modeling is focused on fully capturing the associations among relevant variables and fitting a regression model. Strictly speaking, descriptive models aim to present data in a succinct manner, but not for the purpose of causal inference or prediction per se. For instance, Hsiao et al.'s (2015) study involving the use of an algorithm with four conditions or antecedents that identify and characterize a high performing hospitality employee is descriptive. In fact, none of the antecedents involved (including whether the frontline employees are happy at work; whether they work well with other employees, whether they ever cause peer conflicts, or arrive to work on time) were subject to a rigorous causal analysis or theoretical discussion as part of the algorithmic estimation. In other words, we can infer from the dataset that people in a specific organization who fit a set of criteria happen to be high performers, but we cannot say with certainty that people in the target organization who fit these criteria will be high performers in the future, nor can we conclude that if we help them improve on one or more of the antecedents (e.g. warn them to avoid conflict with co-workers, encourage them to arrive at work on time), that improved performance will result.

In summary, most of the algorithm-related HR research is either descriptive or predictive, and hence cannot be classified as theory-driven. Causal testing as suggested by theory is not evident in the reviewed journal articles. Rather, the mechanisms connecting the variables involved are presumed unknown. Discovery without a priori assumptions dominates this literature.

5.3. HRM algorithms are heuristics

Algorithms used in HRM might best be characterized not as "black boxes" but as "glass boxes" because they are reflective of some, but not all, components of a theory. That is, these algorithms usually consist of a large list of clearly-defined variables, drawing out certain predictive or descriptive "patterns" without defining their causal direction. Most of the research either predicts variables of interest to the HR function (e.g., competence gaps; employee happiness; labor participation, turnover, etc.) or provides a descriptive estimation of them (e.g., job satisfaction, alignment between HRM and strategic capabilities, etc.), without addressing matters of causality. Only in one paper was it noted that the level of prediction achieved might vary considerably as a function of changes in the historical data used (Colomo-Palacios et al., 2014); yet even here there was no explicit statement of boundary conditions. As such, much of the algorithmic HR research approximates a theory, while attempting to maximally account for the phenomenon in question from incomplete sources of information. Hence, we regard most research applications found in our review as heuristics, which by definition, are approaches to problem solving that offer sufficient, practical solutions that are not necessarily optimal or perfect (Kahneman, Slovic, & Tversky, 1982).

Heuristics are a compromise of two criteria, i.e., the need to use simple methods requiring less resources, and the need to sufficiently distinguish between good and bad choices (Pearl, 1984). For humans, they relieve the cognitive load associated with decision making (Kahneman et al., 1982); for computers, they reduce computational time. Examples include the educated guess, intuitive judgments, rules of thumb, or common sense (Pearl, 1984). While heuristics work well under many circumstances, they are relatively simplistic in nature, which can result in bad choices. For instance, a rule of thumb is that white mushrooms are edible, yet some are actually highly toxic and could be deadly to humans. In HRM, stereotyping and racial profiling are examples of heuristics with potentially negative consequences if applied.

Computer software reflective of heuristics can also result in erroneous judgements during trade-offs to achieve computational speed and efficiency. Recommendation algorithms used by major news websites may capture a pattern of reading baseball stories and start to "push" news items regarding various baseball teams to the user, without knowing that the user is interested only in one team. Most importantly, as aforementioned, HRM algorithms of a probabilistic type are not exempt from errors and biases. For example, in an organization with a dominant demographic group (e.g. young, Caucasian, males), an algorithm programmed to predict "a good candidate" based on the past performance of employees may inappropriately favor the demographics of the existing workforce.

Beside the biases associated with the application of heuristics (e.g., Kahneman et al., 1982), some researchers (Gigerenzer & Goldstein, 1996; Gigerenzer & Todd, 1999) highlight the positive aspect of heuristics, i.e., that in an uncertain world, smart heuristics or rules of thumb help us adapt to the environment by contributing to better decisions with less effort. To illustrate, Gigerenzer and Selten (2002) identified situations in which "less is more" by illustrating the value of several heuristics as part of a "fast and frugal" toolbox. In developing the toolbox, they created a series of algorithms in which less knowledge can make better prediction. The hypothetical "secretary problem" is an example, in which applicants are randomized and interviewed one by one. To maximize the chance of selecting the best applicant, the first 37% of the applicants should be sampled, followed by selecting the first candidate thereafter who is regarded as better than all the previous ones (Seale & Rapoport, 1997; Todd & Gigerenzer, 2003). Though this heuristic likely could not be used in practice given legal and ethical constraints, it illustrates the counterintuitive argument that some simple algorithms can outperform more complicated ones despite the reduced effort, such that simple heuristics can "make us smart (Gigerenzer & Todd, 1999)."

In fully considering the findings of our review we propose a definition of HRM algorithm as follows:

HRM algorithms are computer programs of a heuristic nature[2] *that use economical input of variables, information, or analytical resources to approximate a theoretical model, enabling an immediate recommendation of screening, selection, training, retention, and other HR functions.*

6. Advancing HRM theory & practice using algorithms as heuristics

Given our view that HRM algorithms are most appropriately regarded as heuristics, we now consider some of the related implications with regard to inferring causality in research and avoiding adverse impact when HRM algorithms are used in practice, and in theory building.

6.1. Algorithms and causality issues in HRM

As discussed earlier, it is important to acknowledge that HRM algorithms are predominantly predictive or descriptive. Therefore, unlike empirically-tested theories grounded in causal inference, these algorithms should not be used in isolation to directly inform decision-making. Confidence in decision making can be fostered by gaining an understanding for previously uncovered patterns among variables to avoid inferences based upon spurious relationships and endogeneity issues. Two common causes of endogeneity are: (1) confounding variable(s) that mask the true underlying cause of the relationship between independent and the dependent variables; and (2) reverse causality involving variables in the model. Importantly, manipulating independent variables based upon spurious findings will not necessarily result in the anticipated effects on the outcome variables of interest. A classic example of the impact of a confounding variable involves the positive correlation between city-based ice cream sales and the rate of swimming pool drownings, with more sales and drownings linked with high summer temperatures. Reducing ice cream sales during summer months would have no impact on drownings.

There is potential for some relationships uncovered by HRM algorithms to be an unsound basis for decision-making. For instance, at Deloitte, Bersin, (2013a,b) used textual analysis to identify several factors correlated with success among sales professionals, one of which was the lack of typographical or grammatical errors on resumes. Nonetheless, Cheng (2017) cautioned that a selection policy based on the variable is risky. This results from the implication that typos and grammatical errors are a suitable proxy for a latent quality that has a causal bearing on future sales performance. This may not be an appropriate inference in multinational contexts involving English-as-second-language applicants.

Antonakis et al. (2010) suggested six methods for inferring causality in non-experimental settings. Two of the more broadly applicable options involve using statistical adjustments, and quasi-experiment designs. Statistical adjustment or measuring and controlling for all possible causes of y, is the simplest way to help ensure causality inferences (cf. Angrist & Krueger, 1999). However, while it is relatively easy to control for some variables (e.g., employee demographics) it is virtually impossible to rule out all the possible causes of variance in y. Variations in childhood experience, for example, may contribute to developing individual emotional processes and personality, but it is not viable to design an algorithm for employee selection that would account for this variation.

The use of quasi-experiment designs to test for causality lacks the element of random assignment to the treatment or the control group that characterizes the gold standard of experimental design. To help deal with this shortcoming, Antonakis et al. (2010) suggest that simultaneous-equation models, regression discontinuity, difference-in-differences models, as well as Heckman selection models, be used to establish causality when certain assumptions are met. Table 2 briefly describes the essence of each of the highly recommended approaches.

6.2. Algorithms and adverse impact in HRM practice

Understanding that HRM algorithms are essentially heuristics is crucial to avoiding the potential for adverse impact that they may introduce to HRM practice. For instance, it would be fair to say that the algorithms that produce fast recommendations concerning selection likely involve stereotyping or profiling. Hall et al. (2004), for example, demonstrated a non-parametric method in which demographic variables were included as independent variables (e.g. age, number of children). To guard against the replication of historical biases and the potential for adverse impact against protected classes, policies are needed that delineate boundaries around how these algorithms can be used to inform decision-making. There is also the potential for adverse impact even when demographics are not directly involved. For example, in Hsiao et al. (2015), a person who never arrives late to work fits the top performer criteria, but it may be that such a person is especially likely to be single or married without young children.

Interestingly, in 2016, the European Union (EU) ratified the General Data Protection Regulation (GDPR) intended to protect EU residents guaranteeing them more control over their personal data and limiting the free movement of personal data collected or processed by an organization (Tankard, 2016; Wachter, 2018). One aspect of the regulation requires that any algorithms used for

[2] Please note that here by heuristics we refer to *how* researchers use algorithms instead of *what kind* of algorithms they are using. We are aware of the distinction in math and computer science on exact algorithm, heuristic algorithm, and approximation algorithm, however we are not referring to heuristic algorithm here.

decision making must be explainable by those who engineered them (Kean, 2018). Aligned with the spirit of the GDPR, we propose that not only the collection of data related to individuals be protected, but also that HR-related algorithms be regulated such that employers be required to: (1) Disclose to applicants/employees the nature of any decision-making made solely by algorithms; (2) Ensure the right of individuals to contest the outcome of decisions based solely on algorithms; and relatedly, (3) Have sufficient expertise to address challenges to algorithmic decision making.

6.3. Algorithms and HRM theory building

While algorithms do not typically allow for strong causal inferences, this does not mean that they are necessarily irrelevant to developing and verifying HRM theory-based models (Shmueli, 2010; Shmueli and Koppius, 2010). They can, for example, provide the foundation for new hypotheses, uncover new measures, suggest improvements to existing models, and help in assessing the explanatory power of theories. Using Hsiao et al. (2015) as an example, it might be hypothesized that conscientiousness (arriving on time) interacts with collegiality (avoid conflict, work well with others) to ultimately enhance performance. In the process, the extent to which on-time arrival reflects conscientiousness in the workplace could be evaluated. New measures and new hypotheses, in turn, may result in improvements to predictive modeling of job performance. Predictive modeling can also offer a straightforward way to compare competing theories by comparing their predictive power and thereby inform further research efforts.

Importantly, it is also possible to extract considerable value from descriptive or predictive algorithms to inform decision-making. Specifically, as implied earlier, algorithm-based research can be viewed as an exploratory step in the quest to establish causality, and/or as a post-hoc effort to assess causal theories. Over time, we should look to establish methodological standards regarding the use and interpretation of algorithms based on a clear understanding of the types and functions of the various algorithmic models. Triangulation between causal and non-causal modeling can be valuable in this regard. It should be possible, for example, to develop a weighted algorithm that draws from various theories of employee performance and turnover (cf. Harrison, Virick, & William, 1996) and develop new measures for constructs such as conscientiousness and honesty that are less susceptible to social desirability or faking. Given that we located only 22 high-quality research papers, there are obviously many remaining opportunities for scholarly work.

7. Discussion and conclusion

Research is required to better define the nature and characteristics of the range of algorithms used, especially in HRM practice. Also, as implied earlier, the findings in this regard are likely to have regulatory implications from a public policy perspective, especially as the popularity of algorithmic applications in HRM practice grows. For example, to what degree is adverse impact associated with HRM algorithms used in practice? If it is a problem, to what degree can the biases be reduced? What level of accuracy would be considered “good enough” and does the answer depend on the specific HR issue under consideration? Are there variables that should not be included in algorithmic models intended to predict human behaviors, e.g., ancestry information that ends up in the public domain? At present, questions of this nature are not attracting much attention, but we see the potential for that changing. In a manner analogous to the pressures social media companies such as Facebook are facing tied to violations of privacy that were contrary to stated policy (Gallagher, 2018), biased algorithms may conflict with stated organizational diversity goals. Moreover, research has already begun concerning the steps that organizations may need to take in order to increase the perceived authenticity of algorithms (Jago, 2019).

As documented earlier, resulting from the ready availability of the tools required, there is a research opportunity concerning HR-related algorithms that tap into unstructured data. The gaps include, but are not limited to, the analysis of text, images, spatial data, voice, and video. There is a need to evaluate the extent to which these sources of data can inform HRM decision making. HRM researchers are in danger of falling behind other fields in this regard, and possibly HR practice as well. Hitachi, for example has been using social badges or sensors to monitor their employees' mood and social interaction for years, and there are claims in the practitioner literature that 60% of companies are already using applicant tracking systems that apply textual analysis techniques in recruitment and selection (Bersin, 2013b; Bersin, Mariani, & Monahan, 2016). The implications of these and other practices need to be evaluated from a research perspective. Textual analysis, for example, could be used to extract multiple variables that may be relevant to recruitment and selection, while spatial data may be useful in analyzing social networks for team building and facilitating knowledge sharing.

The lack of research in this regard is consistent with our overall finding that the growth of scholarly interest in HR-related algorithms pales in comparison to the surge of applications in HR practice. As such, we have the beginnings of another wide gap between HRM research and practice. By targeting the research opportunities identified in this review, researchers can seize the opportunity to close the academic-practitioner divide concerning use of HR-related algorithms and avoid having their contributions disparaged as “arcane” (Walsh et al., 2007) and “ceremonial” (Bartunek & Rynes, 2010).

Appendix A

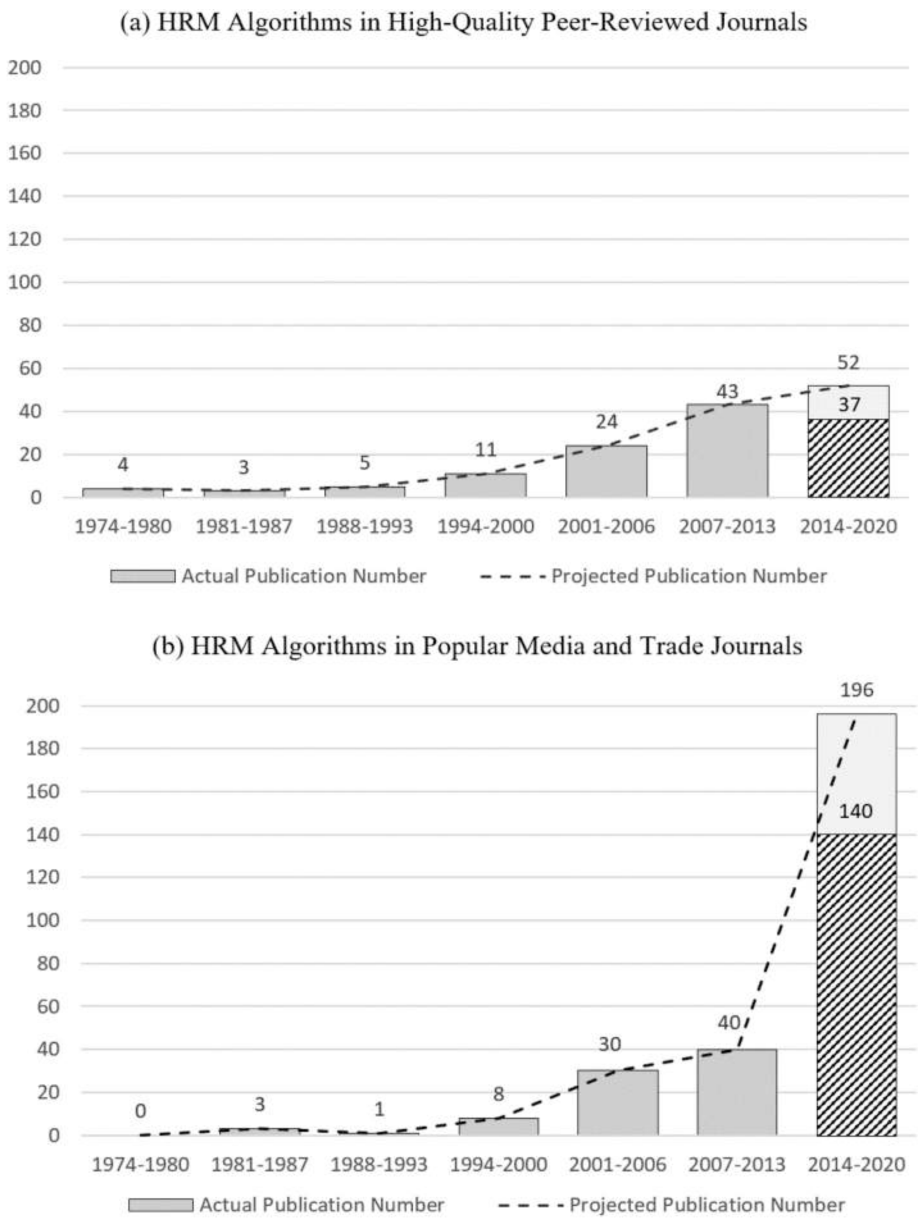

Fig. 1. Published articles on HRM algorithms over time.

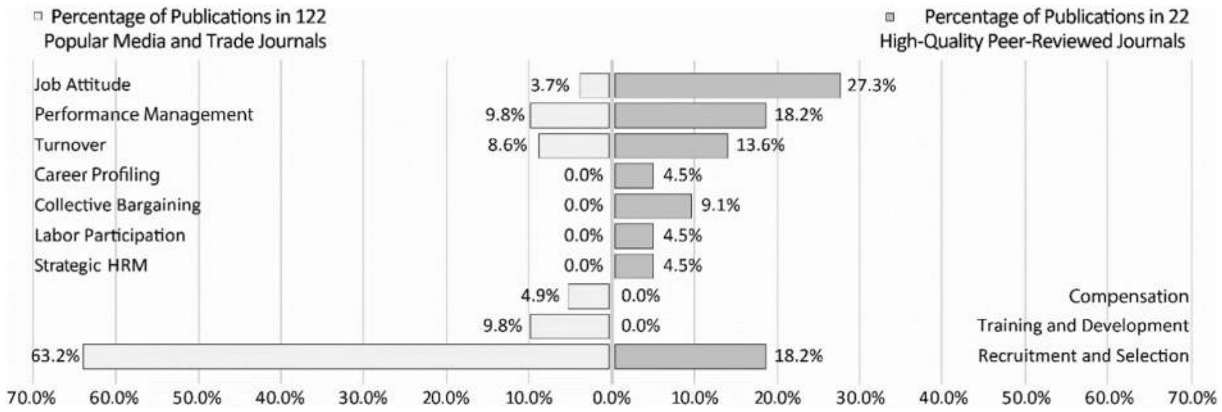

Fig. 2. Comparison of percentages of publications in popular media and trade journals.

Table 1
Peer-reviewed Journal Articles on HR Topics.

Study Authors	Journal	Subject area[a]	Purpose of the Algorithm in HRM
Koch and Rhodes (1981)	Journal of Vocational Behavior	Organization Behavior/Studies, Human Resource Management, Industrial Relations	To predict the turnover of female workers
Kroeck et al. (1983)	Journal of Applied Psychology	Psychology	To predict recruitment and performance outcomes under imposed quota for minorities
Boudreau and Berger (1985)	Journal of Applied Psychology	Psychology	To describe how ownership separations and acquisitions influence human resources
Strub et al. (1994)	The Journal for Quality and Participation	Operations Research, Management Science, Production & Operations Management	To reduce HR overhead
Swartz (2003)	Journal of Business and Economic Statistics	Economics	To analyze bidding behavior in final-offer arbitration
Hall et al. (2004)	Journal of the American Statistical Association	Economics	To predict female labor force participation
Gerchak et al. (2004)	Group Decision and Negotiation	General & Strategy	To estimate the arbitrator's hidden judgments in final offer arbitration
Hatfield and Milgrom (2005)	The American Economic Review	Economics	To match the bilateral contracts between individuals and organizations
Gilbert and Strauss (2007)	Technometrics	Operations Research, Management Science, Production & Operations Management	Using constant social interaction data (phone calls, e-mails, co-authorships, scholarly references or citations) to predict the same variables in the future
Grilli and Rampichini (2007)	Structural Equation Modeling: A Multidisciplinary Journal	Marketing	To estimate the job satisfaction of graduates
Fabi et al. (2009)	Journal of Small Business and Enterprise Development	Entrepreneurship	To analyze the alignment between the HRM practices and strategic capabilities of SMEs
Gutjahr (2011)	OR Spectrum	Operations Research, Management Science, Production & Operations Management	To optimize the investments of human resources over time into a given set of project classes with known competence requirements and known returns
Somers and Casal (2009)	Organizational Research Methods	General & Strategy	To model nonlinearities in the job satisfaction–job performance relationship
Lin and Hsu (2010)	Industrial Management and Data Systems	Operations Research, Management Science, Production & Operations Management	To decide the importance ranking of HR capabilities to be developed
Canós-Darós (2013)	Management Decision	General & Strategy	To identify the most motivated employees
Colomo-Palacios et al. (2014)	Information Systems Frontiers	Management Information Systems, Knowledge Management	To predict the competence gaps in key management personnel
Hsiao et al. (2015)	International Journal of Contemporary Hospitality Management	Tourism	To predict hospitality employees' happiness-at-work and managers' assessments of employees' quality of work performance
Liu et al. (2015)	Structural Equation Modeling: A Multidisciplinary Journal	Marketing	To investigate whether peoples' home life and job attitude could influence job satisfaction

(*continued on next page*)

Table 1 (*continued*)

Study Authors	Journal	Subject area[a]	Purpose of the Algorithm in HRM
Kuron et al. (2016)	The Career Development International	Organization Behavior/Studies, Human Resource Management, Industrial Relations	To investigates the relationship between "new career" profiles and two sets of career factors: agency (i.e. career commitment, self-efficacy, and work locus of control), and career attitudes (i.e. salience and satisfaction)
Aouadni and Rebai (2016)	Annals of Operations Research	Operations Research, Management Science, Production & Operations Management	To measure job satisfaction
Becker and Ismail (2016)	European Management Journal	General & Strategy	To assess the job attitude model
Wang et al. (2017)	Information Systems Frontiers	Management Information Systems, Knowledge Management	To evaluate the risk of employee turnover

[a] Categorization of subject areas of journals is based on the 63th Edition of Journal Quality List (JQL) published on 29 July 2018. JQL is compiled and edited by Anne-Wil Harzing, http://www.harzing.com

Table 2
Econometric methods to infer causality.
(Adapted from Antonakis et al., 2010).

Econometrics methods		Brief description
Statistical adjustment	Finding all causes	Measure and control for all causes of *y* (impractical and not recommended)
	Propensity score analysis	Compare individuals who were selected to treatment to statistically similar controls using a matching algorithm
Quasi-experiment design	Simultaneous-equation models	Using "instruments" (exogenous sources of variance that do not correlate with the error term) to purge the endogenous *x* variable from bias.
	Regression discontinuity	Select individuals to treatment using a modeled cut-off.
	Difference-in-differences models	Compare a group who received an exogenous treatment to a similar control group over time
	Heckman selection models	Predict selection to treatment (where treatment is endogenous) and then control for unmodeled selection to treatment in predicting *y*.

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