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Chapter Draft: Big Data in Turnover/Retention

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Introduction

Managing talent inflows and outflows remains a top organizational priority. Given the substantial costs and consequences associated with talent loss, and the difficulties in fully explaining the phenomenon, employee turnover has maintained a central position in HR, OB, and I/O research and practice for many decades. Yet, for most of its history, turnover research has been guided, directed—and at the same time, constrained—by the data available to researchers, organizations, and their joint efforts in research collaboration. However, this is changing. Advances in technology, heightened company interest, and the proliferation of new and varied sources of information are giving rise to numerous interesting and provocative ways to understand employee movement and its effects on organizational functioning and performance. This chapter explores the potential applications of big data within the domain of employee turnover and retention, examining current practices and how they could evolve as researchers and organizations leverage big data in the coming years.

Overview

In this chapter, we examine how turnover research and practice can benefit from advances in big data by first describing characteristics of recent turnover research. Such an analysis provides a starting point for understanding the extent to which researchers already leverage big data in their design, measurement, and analysis. We then move to a discussion of prominent turnover theories at the individual and group levels as a guide to thinking about how big data could inform, change, and extend these perspectives. Finally, we develop four key means by which big data could strengthen understanding and management of employee turnover from theoretical, methodological, and practical standpoints.

Definitions

Defined simply, turnover involves people leaving organizations (Mobley, 1982). More formally, turnover represents “the degree of individual movement across the membership boundary of a social system” (Price, 1977, p. 4). Recognizing that not all departures are the same, leavers have been further differentiated into voluntary (employee-initiated) and involuntary (organization-initiated) types, and research has shown that the causes and consequences of each are conceptually and empirically distinct (e.g., Shaw, Delery, Jenkins, & Gupta, 1998). Other terms for voluntary turnover include quits and resignations, whereas involuntary turnover is sometimes described in terms of dismissals or terminations. Other dimensions of turnover include the extent to which turnover is avoidable and/or functional. Avoidability hinges upon whether the organization *could have* done something (within reason) to prevent a departure (Abelson, 1987), whereas functionality denotes the extent to which the organization *would have* done something to prevent the departure (Dalton, Todor, & Krackhardt,

1982), which is presumably based on leaver performance, replaceability, and/or willingness to rehire.

A great deal of turnover research focuses on predicting individual departures, which can be seen in the near-exclusive focus of turnover theory and research at the individual level from the 1950s forward. More recently, researchers have supplemented this understanding by studying causes and consequences of “collective turnover” or employee turnover at higher levels such as the group, work unit, or firm (Hausknecht & Trevor, 2011). This work appears under various labels—unit-level turnover, organizational turnover, collective turnover—but all are focused at understanding factors drive turnover *rates* and, in turn, how aggregate departures influence various group and firm-level consequences (e.g., productivity, customer outcomes, and financial performance). As we will discuss, this two-class distinction (i.e., individual and group/unit/firm) becomes important as we consider implications of big data for research design, measurement, and analysis.

Typical Approaches to Studying Turnover and Retention, 2009-2014

To begin, and to provide context for understanding what could (or should) change within turnover research in the realm of big data, we summarize typical characteristics of recent turnover and retention research. As the basis for this effort, we searched online databases for studies published between 2009 and 2014 with the word “turnover” or “retention” appearing in the title or as a keyword. For the sake of manageability, we restricted our search to six journals that are often viewed as top outlets for publishing turnover research: *Academy of Management Journal*, *Journal of Applied Psychology*, *Journal of Management*, *Organization Science*, *Organizational Behavior and Human Decision Processes*, and *Personnel Psychology*. We

reviewed Abstracts and the Method sections of these papers to ensure that the study included an actual measure of employee turnover. A total of 31 studies met our inclusion criteria. We then coded the following characteristics for each study: (1) sample size, (2) sample type (entry-level, managerial, executive), (3) level of analysis (individual, group, or firm), (4) turnover type (voluntary, involuntary, or total), (5) role of turnover (independent variable, dependent variable, or moderator), (6) data sources (self, manager, HR record, or public data), and (7) analytic methods (e.g., OLS, survival analysis, random coefficient modeling, and latent growth modeling).

Table 1 lists coding results for the 31 studies. In terms of sample sizes, these studies ranged from 112 to 114,198 employees (mean = 6,649, s.d. = 21,717) in 45 to 1,255 teams (mean = 375, s.d. = 415) and in 1 to 718 organizations (mean = 130.47, s.d. = 235). Across the set of studies, 30 (97%) included entry-level employees in their samples, 7 (23%) included managers, and only 1 (3%) included executives (percentages exceed 100 because some studies included multiple job levels). Of the total, 23 studies (74%) examined individual-level of variables, while 13 (42%) and 3 (10%) respectively examined group- and firm- level variables. Further, 15 (48%) studies focused on voluntary turnover, 3 (10%) included involuntary turnover, and 13 (42%) considered undifferentiated or total turnover.

In most cases—26 of 31 studies (84%)—researchers studied turnover as a dependent variable, with 5 (16%) modeling turnover as an independent variable (e.g., predictor of firm performance), and 1 (3%) as a moderator. Across studies, 23 (74%) collected data from the employees themselves, 7 (23%) from managers, 1 (3%) from customers, 18 (58%) from company HR records, and 7 (23%) from publicly available sources (e.g., Bureau of Labor Statistics, National Longitudinal Survey of Youth, and industry blue books). Various analytic

methods were used in these studies, ranging from t-tests, MANOVA, and OLS regression to survival analysis, random coefficient modeling, and latent growth modeling.

[Insert Table 1 about here]

Looking across the pattern of results, we offer several observations regarding the extent to which big data already influences turnover research. First, it is fairly clear that in almost no case did we find a study that truly fits emerging big data definitions. According to Davenport (2014), the hallmarks of big data typically include one or more of the following characteristics: (1) massive size (e.g., file is too large to fit on a single server), (2) unstructured formats (e.g., not the typical row-and-column structure), (3) flowing/streaming data (e.g., continuous rather than static measurements), (4) diverse sources (e.g., social media, HR records, and external sources), and (5) new data collection methods (e.g., sensors, video). We consider each of these in turn relative to the literature and then discuss how big data could enhance future work in this domain.

Regarding size, we would characterize nearly all of the studies as fairly “small data” when considered against the backdrop of truly big data sets mentioned elsewhere (e.g., Wal-Mart’s collection of 2.6 *billion* megabytes of customer transaction data *per hour*; McAfee & Brynjolfsson, 2012). Most of the studies included fewer than 1,000 employees. This said, sample sizes were often adequate from sampling and statistical power standpoints, many were fairly large relative to others found in the literature, and some included very large sample sizes (e.g., 114,198 employees in Ployhart, Weekley, & Ramsey, 2009; further, although published prior to our inclusion window, Hom, Roberson, & Ellis, 2008 studied quit patterns among 475,458 professionals across 20 firms). Others include multiple observation periods, thus multiplying the size of the data sets considered. However, the majority of studies include data sets that are quite

manageable in size (e.g., the data set for Hausknecht, Trevor, & Howard, 2009 was less than 1 megabyte).

Looking at format, all of the studies included would fit the more traditional row-and-column format that typifies structured data rather than big data's usual foray into unstructured information (e.g., qualitative data, video data, and images). Quantitative survey data, demographic information, and publicly available sources were commonly represented, all of which fit a standard structure.

Concerning the dimension of continuous vs. static measurement, about three-fourths of the studies gathered measures at a single time point. Several others adopted three-wave or longer data collection periods (e.g., Ployhart et al., 2009; Van Iddekinge, Ferris, Perrewe, Perryman, Blass, & Heetderks, 2009), but in no case did researchers report "continuous flow" or "streaming data" that has been discussed elsewhere as a common big data ingredient (e.g., Davenport, 2014; George, Haas, & Pentland, 2014).

On the dimension of data source diversity, many of the studies did in fact incorporate data from multiple sources. Most commonly this involved merging internal sources (e.g., HRIS records and attitude survey data) with those external to the organization (e.g., Bureau of Labor Statistics unemployment rate data, customer satisfaction data, and benchmark data from industry reports). Looking across the 31 studies, the average number of predictor variables included in researchers' models was around 12 (including control variables). Most ranged between 7 and 15 and included data from multiple sources. It is on this dimension that existing research already seems to capitalize on the purported benefits of big data "variety."

Finally, in terms of data collection methods, most of the studies gathered information using more traditional means such as online/paper surveys or company records. In no case did researchers report newer data collection methods stemming from sources such as social media, sensors, or video.

Looking across the five characteristics, it is clear that turnover research to date fits often more traditional definitions of data size, structure, measurements, sources, and methods. This leaves open numerous opportunities to supplement existing knowledge with new studies that take advantage of the features common to big data. Before considering these possibilities, it is useful to consider dominant theoretical perspectives in this domain (particularly since turnover theory is not necessarily constrained by data availability). In the following section, we briefly review extant turnover theory to understand how big data could be used to test, change, or extend current thinking in this domain. Despite the appeal of big data, it is our belief that theory-driven approaches should dominate future efforts to understand and predict employee turnover. Otherwise, there is the risk of identifying empirical patterns that do not replicate, cannot be explained, and therefore add little to science and practice. On the other hand, it is also useful to consider how access to big data could allow for inductive approaches to theory generation, a point we revisit in our conclusion.

Turnover Theory at Individual and Organizational Levels

Our approach to reviewing theoretical perspectives is meant to provide a brief rather than comprehensive overview of the dominant perspectives in the area. The interested reader is encouraged to review the original sources and other detailed reviews for more information (e.g.,

Holtom, Mitchell, Lee, & Eberly, 2008; Hom & Griffeth, 1995; Hom, 2011; Maertz & Campion, 1998).

Individual-level turnover theory

March and Simon's (1958) model of organizational equilibrium advanced the notion that turnover is jointly determined by employees' *ease of movement* (i.e., alternative employment prospects) and *desirability of movement* (i.e., job satisfaction). It represented one of the earliest efforts at formalizing a model of employee turnover and remains consequential in guiding researchers' thinking today. Notably, March and Simon are credited for recognizing the fact that quit decisions are constrained by market alternatives, and for laying the foundation for thinking about the major determinants of ease and desirability of movement.

Following and building upon March and Simon (1958), a number of influential articles and books appeared that included refined frameworks of the turnover process (Mobley, 1977; Porter & Steers, 1973; Price, 1977). In one form or another, Hom (2011) suggested that these models aim to capture *how* (i.e., via specification of mediating mechanisms between cognitions and withdrawal; Mobley, 1977) or *what* drives employees to quit (i.e., specifying organizational and environmental determinants, Price, 1977). Subsequent to this work, further modifications, empirical tests, and literature reviews followed, all of which have served to develop a strong foundation for understanding likely drivers of individual employee turnover (e.g., Hom, Griffeth, & Sellaro, 1984; Price & Mueller, 1981; Steers & Mowday, 1981). Despite their promise, and as several critics have noted, the predictive power of these frameworks has been underwhelming, rarely explaining more than 25% of the variance in turnover (Hom, 2011; Maertz & Campion,

1998). Such findings led researchers to propose alternative conceptual perspectives that better explained how, when, and why people leave or stay.

Lee and Mitchell's (1994) unfolding model of employee turnover represents one such endeavor, representing a major shift in thinking about the employee turnover process. Noting limitations of the traditional attitudes and alternatives view of March and Simon (1958) and later descendants, these authors proposed a series of alternative "decision paths" that employees might take prior to departure. They formalized the notion that employees sometimes leave abruptly without an alternative in hand (and with or without experiencing dissatisfaction) after experiencing "shocks" that prompt thoughts of quitting (e.g., unsolicited job offers, changes in personal situation). A growing number of empirical studies provide support for the key contributions made by the unfolding model beyond traditional views (Lee, Gerhart, Weller, & Trevor, 2008; Lee, Mitchell, Holtom, McDaniel, & Hill, 1999; Lee, Mitchell, Wise & Fireman, 1996).

Researchers have also supplemented traditional thinking about why employees leave by thinking more deeply about why they *stay*. Emerging research on job embeddedness—i.e., the extent to which employees have links to other people and activities, fit with the organization and community, and the degree of sacrifice associated with leaving—reveals incremental value in predicting turnover (and other job outcomes) beyond traditional determinants found in earlier theories (Jiang, Liu, McKay, Lee, & Mitchell, 2012; Lee, Mitchell, Sablinski, Burton, & Holtom, 2004; Mitchell, Holtom, Lee, Sablinski, & Erez, 2001; Swider, Boswell, & Zimmerman, 2011).

Group/organizational-level turnover theory

Although not absent from early (i.e., pre-1990s) discussions, much less attention was been paid to developing theoretical models of the causes and consequences of employee turnover at the group, work unit, and firm levels. One notable exception was Staw's (1980) framework that outlined the likely positive and negative organizational consequences of turnover (as well as moderating conditions). In terms of positive outcomes, Staw reasoned that turnover could increase innovation, reduce conflict, and increase internal mobility. The range of hypothesized negative outcomes included increased selection and training costs, operational disruption, and demoralization of membership. Aside from a handful of empirical papers (e.g., Mueller & Price, 1989; Terborg & Lee, 1984), much of the early period in turnover research was dominated by individual-level research.

By the late 1990s and early 2000s, however, researchers began to take a more formal look at how aggregate levels of employee turnover influence social capital and organization performance (e.g., Dess & Shaw, 2000), and, in turn, theorized and investigated possible determinants of voluntary and involuntary turnover rates (Shaw et al., 1998). A series of studies by Shaw and colleagues (e.g., Shaw et al., 2005a, 2005b, 2009) as well as others (e.g., Batt, 2002) paved the way for later work aimed at understanding turnover antecedents and outcomes at group and firm levels. In 2011, Hausknecht and Trevor summarized extant research to date on turnover at the collective level (i.e., group, unit, or firm) and developed a conceptual framework that included a range of determinants (e.g., HR practices, collective attitudes, and other collective characteristics) and consequences (e.g., productivity, firm performance, and customer outcomes). More recently, researchers have taken a closer look at the composition (and thus meaning) of collective turnover rates (Hausknecht & Holwerda, 2013) and have offered richer theoretical accounts that specify the emergent nature of collective turnover in explaining how human capital

leads to firm performance (Nyberg & Ployhart, 2013). Meta-analyses at the collective or organizational level have also emerged, highlighting known findings while pointing out how much remains to be learned (Hancock, Allen, Bosco, McDaniel, & Pierce, 2013; Heavey, Holwerda, & Hausknecht, 2013; Park & Shaw, 2013).

Turnover Theory, Methods, and Big Data

When considered alongside one another, we see many opportunities to leverage big data for theory testing at both individual and group levels. In this section, we highlight several such possibilities. As background, we quote a recent review of employee turnover by Hom, Mitchell, Lee, and Griffeth (2012) who summarized the traditional turnover research design as follows: “measure antecedents (e.g., job satisfaction) with surveys or personnel records; track employees for 6 months to 2 years; identify stayers and voluntary leavers from records; and then statistically estimate predictor-quit relationships” (p. 833). In addition, Allen and colleagues conducted a major review of the common approaches or “analytical mindsets” that underlie the design and execution of turnover research (Allen, Hancock, Vardaman, & McKee, 2014). We highlight selected findings from their analysis throughout the chapter, but note here their conclusion that “the bulk of turnover research is quantitative, conducted in field settings, at the individual level of analysis, utilizing correlational designs, with a heavy reliance on survey measures and regression-based methods” (Allen et al., 2014, pp. S76-78). Given these typical design choices, we offer several directions for turnover research that may better fit with the big data elements described above.

Studying dynamic processes. At the individual level, turnover scholars have long advocated for better understanding of the temporal dynamics underlying quit decisions (Mobley,

1982; Steel, 2002). Indeed, advances in analytical methods have allowed researchers to capitalize on the collection of repeated measurements of key antecedents (e.g., Kammeyer-Mueller, Wanberg, Glomb, & Ahlburg, 2005; Sturman & Trevor, 2001). Given the heavy focus in turnover theory on understanding process, leveraging big data methodology (e.g., the notion of continuous/streaming data collection from new and inventive sources such as mobile, social media, and/or sensor networks) may reveal more reliable insights about the patterning and processes underlying decisions to quit. Longitudinal and time-series studies could become more the norm rather than the exception going forward, often regarded as a substantial improvement over static or “one-shot” measurement approaches (e.g., Steel, 2002). For example, within the unfolding model paradigm, organization-initiated shocks could be modeled more carefully in terms of effects on attitudes and subsequent departures (e.g., Ballinger, Lehman, & Schoorman, 2010).

The types of data needed to track turnover processes dynamically involve collecting repeated measures of key antecedents over a theoretically-appropriate time period. A common rule of thumb is to collect at least three, and preferably more, observations per individual over the period of interest (e.g., Ployhart & Vandenberg, 2010). Historically, it is relatively atypical for a study to measure turnover predictors such as job satisfaction or perceived alternatives more than once. In fact, among the studies reviewed here (see Table 1), the modal number of times that predictors were measured was one. The strength of empirical tests of theories that involve temporally-ordered mediational chains (e.g., Lee et al., 1996; Steel, 2002) will remain limited if researchers continue to rely on single-shot measures of turnover antecedents.

The benefits of collecting antecedents on multiple occasions is starting to be seen in turnover research. As one example, Chen and colleagues departed from the traditional research

design by collecting multiple measures of job satisfaction and turnover intentions from multiple samples over time (Chen, Ployhart, Anderson, Thomas, & Bliese, 2011). Drawing upon multiple theoretical accounts (e.g., within-person spirals: that people act on not just levels of attitudes such as satisfaction but also trajectories that develop over time), they hypothesized and found support for the incremental prediction offered by job satisfaction *change* in explaining turnover intentions beyond static job satisfaction levels. Such insight only becomes accessible via repeated-measures designs so that one can treat the *variability* in work attitudes or related constructs as an important determinant in its own right. Of course, stable characteristics need not be collected on multiple occasions (e.g., demographics), but it seems safe to say that the vast majority of turnover antecedents are indeed likely to be dynamic in nature. It is here where big data—specifically, the increased granularity afforded by repeated measurements (George et al., 2014)—has significant potential to enhance research and practice.

As one possible means of increasing measurement frequency, researchers might partner with organizations to implement data collection methods that are less obtrusive. For example, periodically presenting a brief survey to employees on their mobile device or as they log in to a company portal could provide the necessary data without the encumbrances of a more formal standalone survey. Employees may be more willing to complete multiple measures over time if the data collection medium allows for simple and efficient responses.

Evaluating context. Classic and emerging work shows that quit decisions are influenced by factors that extend beyond the quality of one's immediate work environment. A host of non-work, social, and economic contextual factors have been identified as likely having either directly affecting turnover or moderating relationships between known antecedents and quit decisions. Researchers have called for better understanding of context within turnover research

for many decades (e.g., Schwab, 1991), but it is apparent that much remains to be understood about the conditions under which various antecedent-turnover relationships are strengthened or weakened. For instance, Allen et al. (2014) reported that the majority of turnover studies (54%) focused on direct effects only, whereas just 30% addressed moderation.

Consistent with the themes of big data, addressing context involves supplementing internal (often survey-based and self-reported) predictor data with measures that reflect the broader social and economic environment within which employees reside. For example, Trevor (2001) supplemented repeated-measures job satisfaction data with a composite measure of unemployment that included both local and occupation-specific information. Such data, available freely from the Bureau of Labor Statistics, offers a tangible means of addressing context and is consistent with the big data theme of integrating diverse sources. As another example of addressing context, researchers have begun to explore the social dynamics that influence turnover. One study reports that coworkers' embeddedness and job search influence individual quit decisions beyond other individual and group-level antecedents—i.e., that turnover is “contagious” (e.g., Felps, Mitchell, Hekman, Lee, Holtom, & Harman, 2009). In a similar vein, researchers have documented that turnover occurs in clusters based on employee's communication networks (Krackhardt & Porter, 1985, 1986). Further network-based studies of turnover are needed that build upon and extend these initial findings.

There are several possible means by which researchers could continue to address context via multisource data. For example, with the rise of big data, social network data should become much easier to access, which would likely benefit both individual and collective-level understanding of turnover (e.g., Dess & Shaw, 2001). Researchers could measure connections to individuals inside the firm (more internal connections might promote embeddedness and increase

retention) as well as those externally (where more connections may increase exposure to alternatives and increase turnover). Further, building a richer and more connected data set (e.g., life cycle surveys) about employees could facilitate understanding of contextual factors surrounding the pre-entry influences most strongly associated with employee turnover. Such information, when connected with post-exit data (from surveys or third-party sources such as LinkedIn) could facilitate understanding of post-exit destinations (Hom et al., 2012). Such connected data sets, with pre-hire through post-exit information, are virtually unheard of in the turnover literature, but could become a reality as part of big data efforts. It is our sense that many of these data points exist in various pockets of organizations, but are fragmented and not easily integrated.

Enhancing causal inference through experiments. Big data also perhaps opens up greater opportunities for experimentation, an approach not often associated with turnover research. Allen et al. (2014) reported that only 12% of turnover studies have used quasi-experimental or true experimental designs (86% were correlational). They also note that the use of quasi-experiments has actually declined over time. This is unfortunate given that both researchers and practitioners often care most about determining turnover *causes* rather than correlates. In many ways, the advent of big data has the promise to revive interest in, and facilitate the use of, experimental approaches. With more companies investing in their internal analytics capabilities (e.g., better systems, more analysts), practitioner-generated interest in carefully designed evaluation studies that help document the impact of various interventions on employee retention should rise. As one rare example at the collective level, Peterson and Luthans (2006) manipulated characteristics of incentive practices across different business units and tracked the effects on turnover rates both across time (multiple measures pre- and post-

intervention) and relative to a control group. Similar studies that track the effects of changes in HR policies or practices on turnover (e.g., Trevor & Nyberg, 2008), could be conducted to understand short- and long-term organizational consequences.

Building global understanding of employee turnover. Anecdotally, we have heard of numerous U.S. companies who are more or less content with turnover levels domestically, but struggle to attract and retain talent in emerging markets. The challenge is that nearly all of the employee turnover literature is U.S.-based, raising questions about its usefulness in studying turnover dynamics abroad. As Hom (2011) summarized, “Unfortunately, prevailing theory and research on turnover offer little guidance to U.S. multinationals on ways to retain host-country nationals” (p. 345). As companies invest in big data technology, researchers may begin to gain access to larger, more reliable, multinational company data sets that could be leveraged to conduct large-scale studies of turnover antecedents and consequences across regions. To date, such multi-country (or multi-culture) comparative work has been sparse to non-existent (see Ramesh & Gelfand, 2010, for an exception).

One obvious place to launch such investigations is within large, multinational corporations that have sizable employee populations in regions beyond the U.S. As one example, IBM employed over 430,000 employees in more than 170 different countries in 2012. Qualitative fieldwork is needed to establish the relevance of traditional turnover theories in emerging and established markets outside of the U.S. given variations in labor supply/demand as well as cultural values. Another possibility, successfully employed in other literatures, is to form research teams from multiple universities across the globe to assemble large-scale data sets that offer the opportunity to conduct comparative model tests across regions and cultures.

Summary: Envisioning Possibilities for Turnover Research

In Table 2, we recap our views on the potential of big data to influence turnover research and practice. Drawing from our review of recent turnover research, as well as the comprehensive analysis by Allen et al. (2014), the dominant or “traditional” paradigm for studying employee turnover involves individual-level, survey-based studies where predictors are measured at a single point and from one or a few sources to forecast voluntary exit from the firm. Without question, this literature has been vast and informative in clarifying relevant influences on decisions to quit. However, opportunities lie ahead to supplement this understanding with more ambitious investigations that capitalize on the hallmarks of big data. In particular, we expect to see researchers’ broadening the focus to include pre-entry as well as post-exit destinations, using more innovative approaches to data collection (e.g., social, mobile) from a variety of sources (e.g., peers, external sources), with multiple waves of measurements, and across multiple levels of analysis. From a theoretical standpoint, we suggest that researchers begin by providing more appropriate tests of existing theories, many of which involve reasoning that calls for exactly these types of dynamic, multisource, and multilevel investigations. This said, we encourage the development of novel, inductively-developed theories as researchers’ discover patterns and profiles that explain employee turnover but that do not neatly fit within existing frameworks.

[Insert Table 2 about here]

To conclude, research on employee turnover has a long and rich history. Substantial progress has been made in outlining and testing prominent conceptual frameworks, but many opportunities for further evaluation remain. As we have found, the characteristics typically associated with big data have generally been slow to arrive in the turnover domain (and, in HR,

more generally), but offer promise in helping explain how and why employees choose to leave organizations, as well as how these aggregate decisions impact organizations more broadly.

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Table 1
Key Elements of Turnover and Retention Research, 2009-2014

Authors	Year	Journal	Sample Size and Type	Level of Analysis	Turnover Type	Role of Turnover	Data Sources	Analytic Methods
Ballinger, Lehman, & Schoorman	2010	OBHDP	807 employees in 45 firms	Individual	Total	DV	Self, HR record	OLS, survival analysis
Becker, Connolly, & Slaughter	2010	PP	3012 employees in 1 firm	Individual	Total	DV	Manager, HR record	Logistic regression, t-test
Becker & Cropanzano	2011	JAP	1755 employees	Individual	Voluntary	DV	HR record	Cox proportional hazard regression
Bidwell & Briscoe	2010	OS	2823 employees	Individual	Total	DV	Self	Cox proportional hazard regression
Burris, Detert, & Romney	2012	OS	7578 employees in 335 groups of 1 firm	Individual, group	Involuntary	DV	Self, manager, HR record	HLM, multilevel logit regression
Carnahan & Somaya	2013	AMJ	163 employees in 232 groups	Individual, group	Total	IV	HR record	Dyadic fixed-effects Poisson estimates
Felps, Mitchell, Hekman, Lee, Holtom, & Harman	2009	AMJ	8663 employees in 1037 groups	Individual, group	Voluntary	DV	Self	OLS, HLM
Fugate, Prussia, & Kinicki	2012	JOM	153 employees in 1 firm	Individual	Voluntary	DV	Self	SEM
Gardner, Wright, & Moynihan	2011	PP	1748 employees in 93 groups	Individual	Voluntary	DV	Self, manager, HR record	OLS, MANOVA
Godart, Shipilov, & Claes	2013	OS	349 employees in 356 firms	Firm	Total	IV	Public data	Cross-sectional time-series panel regressions
Hausknecht., Trevor, & Howard	2009	JAP	5631 employees in 75 groups of 19 firms	Individual, group	Voluntary, involuntary, total	IV	Self, customer, HR record, public data	HLM
Hom & Xiao	2011	OBHDP	417 employees in 4 firms	Individual	Voluntary	DV	Self	HLM
Kraimer, Seibert, Wayne, Liden, & Bravo	2011	JAP	264 employees	Individual	Voluntary, involuntary	DV	Self, manager	OLS
Kraimer, Shaffer, Harrison, & Ren	2012	AMJ	112 employees	Individual	Voluntary	DV	Self	OLS, logistic regression
Liu, Zhang, Wang, & Lee	2011	JAP	817 employees in 115 groups	Individual, group	Total	DV	Self, HR record	HLM, Mediated moderation

Mackenzie, Podsakoff, & Podsakoff	2011	PP	150 groups	Group	Total	DV	Self, manager, HR record	SEM
Maltarich, Nyberg, & Reilly	2010	JAP	5310 employees	Individual	Voluntary	DV	Self, public data	Survival analysis, mediation
McClellan, Burris, & Detert	2013	AMJ	5200 employees in 136 groups of 1 firm	Group	Total	DV	Self, manager, HR record	HLM
Messersmith, Guthrie, Ji, & Lee	2011	JAP	2570 employees in 528 firms	Firm	Total	DV	Public data	HLM
Nishii	2013	AMJ	1324 employees in 100 groups	Group	Voluntary	DV	Self	SEM
Nyberg	2010	JAP	12545 employees in 884 groups	Individual	Voluntary	DV	Self, HR record, public data	Survival analysis, mediation
Owens, Johnson, & Mitchell	2013	OS	704 employees in 218 groups	Individual, group	Voluntary	DV	Self, HR record	HLM
Ployhart, Weekley, & Ramsey	2009	AMJ	114198 employees in 1255 groups	Individual, group	Total	IV	Self, HR record	Random coefficient growth model
Rafferty, & Restubog	2010	JOM	115 employees in 1 firm	Individual	Voluntary	DV	Self, HR record	SEM
Ramesh & Gelfand	2010	JAP	797 employees	Individual	Voluntary	DV	Self, HR record	Logistic regression
Russell & Sell	2012	OBHDP	525 employees	Individual	Voluntary	DV	Self	Logistic regression
Shaw, Dineen, Fang, & Vellella	2009	AMJ	209 firms	Firm	Involuntary, total	DV	HR record, public data	OLS
Shin, Taylor, & Seo	2012	AMJ	242 employees in 45 groups in 1 firm	Individual, group	Voluntary	DV	Self, manager	HLM
Siebert & Zubanov	2009	AMJ	1625 employees in 325 groups in 1 firm	Group	Total	IV, moderator	HR record	OLS
Swider, Boswell, & Zimmerman	2011	JAP	895 employees in 1 firm	Individual	Voluntary	DV	Self, public data	Logistic regression
Van Iddekinge, Ferris, Perrewé, Perryman, Blass, & Heetderks	2009	JAP	861 groups in 1 firm	Group	Total	DV	HR record	Latent growth model, cross-lagged panel analyses

Note. Search limited to six journals (see text for full list of inclusion criteria); AMJ=Academy of Management Journal, JAP=Journal of Applied Psychology, JOM=Journal of Management, OS=Organization Science, OBHDP=Organizational Behavior and Human Decision Processes, and PP=Personnel Psychology.

Table 2

Big Data's Potential Influence on Turnover Research

	Traditional Approach	Influence of Big Data
Period of interest	Entry to exit	Pre-entry, entry, exit, and post-exit
Level of analysis	Individual	Individual, collective, and multilevel
Research design	Static cohort or cross-sectional	Longitudinal and repeated-measures; experimental
Measurement strategies	Traditional (e.g., formal opinion surveys, HR records)	Innovative (embedded surveys; use of mobile devices, sensor networks, social media)
Frequency of predictor measurement	Static (single-wave)	Dynamic (three or more waves)
Source of predictor data	Mostly single-source self-reports	Multisource to include self-reports, coworker, community, and "ambient" data
Data analysis techniques	OLS, logistic regression, survival analysis	Survival analysis, repeated-measures/longitudinal/time series analyses; network analysis, HLM