Therapist turnover in community mental health: Testing the applicability of job embeddedness and shocks

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Abstract

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Community mental health organizations experience an annual therapist turnover rate of 25-60%, which produces considerable costs to agencies, undermines implementation efforts, and threatens the long-term sustainability of evidence-based practices (EBPs). Despite substantial evidence demonstrating the negative effects of therapist turnover, there exists little empirical guidance on mitigation. To advance understanding of EBP-trained therapist turnover decisions, the current study tested the applicability of two novel concepts from the field of organizational behavior: job embeddedness and shocks. The current study implemented a prospective, longitudinal, repeated measures design to collect periodic survey data from EBP-trained therapists working in community mental health settings. Results from time-varying survival analyses revealed that job embeddedness predicted therapist turnover above and beyond a set of known risk factors of therapist turnover (i.e., job satisfaction and burnout). Although all therapists

who left their organizations reported experiencing a shock event, the number of shocks experienced was not a significant predictor of turnover. This study provides insight into factors related to therapist turnover and discusses how findings may help to inform the development of effective retention strategies.

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Introduction

The dissemination and implementation of evidence-based practices (EBPs) in mental health care is considered a national priority (IOM, 2015; US Surgeon General, 2000). Although a substantial number of EBPs for child and adolescent mental health have been developed, access to these treatments is limited and EBPs remain underutilized in community-based settings (Gotham, 2006; Lim et al., 2012). Implementation science seeks to bridge this research-to-practice gap by systematically studying factors that promote the sustainable implementation of evidence-based interventions (Proctor et al., 2015). Training community-based therapists in the delivery of EBPs is essential for expanding access to quality mental health treatments and is a major area of focus in implementation science (Beidas & Kendall, 2010). Because the majority of individuals seeking treatment do not receive EBPs, a significant expansion of a well-trained workforce is needed to meet the demand. The successful implementation and sustainment of evidence-based interventions, therefore, requires efforts to both train and retain therapists working in publicly-funded settings.

National and statewide implementation initiatives have invested considerable funds into training community therapists in EBPs (Dorsey et al., 2016; McHugh & Barlow, 2010); however, instability in the workforce has emerged as a significant barrier (Garner et al., 2012; Weisz et al., 2013; Woltmann et al., 2008). Mental health providers are currently at a critical shortage and federal projections estimate a deficit of more than 250,000 providers by the year 2025 (SAMSHA, 2013; HRSA, 2015). Additionally, community-based organizations report that annual therapist turnover rates typically range between 30 to 60 percent (Aarons et al., 2006; Mor Barak et al., 2001). These high rates mean that many community organizations experience complete workforce

turnover every four to seven years (Beidas et al., 2016; Kamis-Gould & Staines, 1986; Weisz et al., 2013). High therapist turnover impedes improvements in public health by threatening the quality and stability of services provided in publicly-funded systems. High turnover rates jeopardize EBP sustainability, which is defined as the "continued use of program components and activities for the continued achievement of desirable program and population outcomes" (p. 2060; Scheirer & Dearing, 2011; Stirman et al., 2012). Without an adequately sized, stabilized workforce well-trained in EBPs, mental health system transformations will likely fail to achieve their goals (Mendel et al., 2008).

Agency and system leaders have identified high therapist turnover rates as one of the top barriers to EBP implementation and sustainment in their organizations (Beidas et al., 2016). Frequent therapist turnover may also lead organizations to delay or avoid sending therapists to EBP trainings as trainings typically require a substantial investment in each participating therapist. High turnover rates also threaten to diminish an organization's return on investment. For example, recent estimates of training expenses suggest a cost of $2,000 to $19,000 per therapist when factoring in direct training, consultation, and certification; as well as revenue loss from unscheduled appointments (Okamura et al., 2018). Considering the already strained finances of most publicly funded mental health organizations, the costs associated with EBP implementation efforts may seem prohibitive (Stewart et al., 2016). Additionally, given the associated expenses and few 'on demand' or online training resources (most are in person, and offered only a few times a year), new hires likely treat clients for some time before receiving EBP training, if they receive any at all (e.g., Mor Barak et al., 2001). Therefore, high therapist turnover rates may also result in clients being less likely to achieve positive outcomes because they are less likely to receive EBPs (Weisz et al., 2006).

Beyond threatening implementation outcomes, high turnover rates also produce a cascade of negative effects for organizations, staff, and clients. Agencies incur both direct and indirect costs due to turnover, including financial strain, loss of EBP knowledge and leadership, and decreased organizational productivity and effectiveness (Gray et al., 1996; Jayaratne et al., 1984; Mowday et al., 1982). Additionally, high turnover places strain on remaining staff who often absorb the clinical caseload and duties of the departing therapist, adding pressure to an already demanding workload (Powell & York, 1992). In community mental health, where caseloads average 24-30 clients (e.g., Choy-Brown & Stanhope, 2018; Dorsey et al., 2017), the increased demand on remaining staff can be substantial. Turnover can be particularly detrimental in mental health care organizations as the relationship built between client and therapist is a significant mechanism for achieving positive outcomes (e.g., Hamovitch et al., 2018). The current high rates of turnover mean that nearly 50% of clients seen in a community setting will experience a change in therapist due to turnover (Babbar et al., 2018). Establishing therapeutic rapport is an important mechanism for increasing client engagement (Leach, 2005), which is a critical element for achieving successful treatment outcomes. Because rapport typically takes time to build, clinical gains may be delayed when a client is transferred to another therapist due to turnover (Strolin-Goltzman et al., 2010). Therefore, to protect clients' access to consistent, quality services, obtaining workforce stability within organizations should be a top priority.

Turnover Antecedents across the Helping Professions

Despite being a substantial threat to EBP access and sustainability, a firm understanding of the drivers of therapist turnover is obscured by mixed findings across the extant literature. For example, in a recent review of 16 studies examining turnover in

community-based behavioral health settings, Brabson and colleagues (2020) found that few variables consistently predicted turnover. When broadening the scope and including literature across the helping professions (e.g., social work, child welfare, therapists) a small number of variables emerge as relatively consistent predictors of turnover. Across the studies included in Brabson et al. (2020), and in the wider literature on individual-level factors in the helping professions, higher levels of burnout and burnout-related constructs, including emotional exhaustion, and “emotionally demanding work”, has emerged as one of the most consistent predictors of turnover (e.g., Aarons et al., 2011; Green et al., 2013; Kim & Kao, 2014; Paris & Hoge, 2010; Sheidow et al., 2007). Low job satisfaction has also been found to be a consistent predictor of turnover (e.g., Acker 2004; Ben-Dror, 1994; Kim & Stoner 2008).

When looking across turnover literature within the broader helping professions workforce, a number of organizational-level variables have also demonstrated relatively high levels of consistency in predicting turnover. Organizational culture (e.g., Aarons & Sawitzky, 2006; Beidas et al., 2016; Glisson et al 2008; Glisson et al., 2014; Kim & Kao, 2014), organizational climate (e.g., Aarons & Sawitzky, 2006; Glisson et al., 2008; Kolko et al., 2012; Sheidow et al., 2007), and leadership-related constructs (e.g., Green et al., 2013; Kim & Kao, 2014) appear to be the most consistent organizational-level predictors within the helping professions. Additionally, a small, but growing body of literature has started to examine risk factors of turnover within the context of EBP implementation efforts. Findings appear to be parallel with those found in the larger helping professions literature. Specifically, results indicate that pay, burnout, leadership-level characteristics, job satisfaction, and organizational culture and climate may be important factors related to turnover in EBP-trained therapists (e.g., Aarons et al., 2009; Brabson, 2020;

Herschell, 2020; Beidas et al., 2018; Beidas et al., 2016). Given the growing workforce shortage and continuing loss of EBP-trained providers from publicly-funded service systems, effective retention interventions are needed quickly.

Limitations in the Literature

Although expanding the scope of relevant literature to include research across the helping professions is helpful for identifying important predictors of turnover at both individual and organizational levels, there continues to be a lack of clarity regarding how and why community-based mental health therapists leave their organizations. At present, the majority of studies examining turnover have not used prospective designs, have overlooked factors associated with long-term retention, and have focused on *intention* to turnover rather than actual turnover (Holtom et al., 2006; Woltmann et al., 2008).

Reliance on secondary data analysis, the inclusion of a variety of workforce populations (e.g., child welfare workers, case workers, substance use counselors), and inconsistencies in how turnover is defined and measured (i.e., actual turnover versus turnover intention; see Fukui et al. 2020) across studies have resulted in a lack of empirical guidance for identifying and mitigating factors that contribute to therapist turnover (see Glisson et al., 2008 for additional discussion). Additionally, studies implementing different methods (e.g., qualitative versus quantitative analyses) have produced differing results. For example, quantitative studies that examined caseload size (Acker, 2004; Green et al., 2013) and licensure status (Herschell et al., 2014; Sheidow et al., 2007) found no relation with turnover, while a qualitative study found both licensure status and caseload size to be commonly reported as significant factors in therapists' turnover decisions (Beidas et al., 2016). Successful EBP sustainment likely

requires a deeper understanding of the risk factors associated with community-based therapist turnover to inform effective retention efforts. A nuanced understanding of therapist turnover factors is critical, as the lack of discretionary funds in publicly-funded settings limit organizations' ability to offer more traditional retention incentives, such as bonuses or raises (Beidas et al., 2016; Stewart et al., 2016).

Given longstanding research on employee turnover in areas *outside* the mental health field, efforts to address therapist turnover may benefit from an interdisciplinary approach. The field of Organizational Behavior (OB)—the leading discipline in research on employee turnover—has developed a theoretical model of turnover which identifies specific factors related to turnover and adds depth to understanding differences in the turnover process between individuals. In addition, these models provide information on key aspects of paths to turnover, which may help to facilitate the development of targeted, individualized turnover interventions in the future. In addition, OB scholars argue that to best understand the factors leading to turnover, a focus on turnover alone is too narrow. Attention to both *turnover* and *retention* is needed; OB scholars suggest research that examines employee turnover and retention in tandem will best inform efforts to stabilize the workforce. This position is supported by findings suggesting that predictors of turnover are not necessarily associated with retention, such that meaningful differences may exist between why people leave or stay in their jobs (Mitchell et al., 2001). Therefore, understanding the antecedents for both therapist turnover *and* retention may be critical in ensuring the sustainability of EBP implementation efforts.

The Unfolding Model of Turnover

Employee turnover has been a focus of research for more than a century and continues to be a topic of great interest given the associated costs and disruptions

incurred by employers and employees alike (Price, 1977; Hom et al., 2017). Researchers have typically distinguished between *voluntary* turnover and *involuntary* turnover. Voluntary turnover describes employee-initiated departures (e.g., quitting, resignations), while involuntary turnover describes employer-initiated departures (e.g., firings, layoffs).

The study of voluntary turnover is a complex process that has evolved considerably over the last hundred years (see Hom et al., 2017). Across this period, a number of frameworks have been developed to enhance the study and conceptualization of voluntary turnover. Although it is outside the current scope to review each of the seminal models that have shaped the study of employee turnover, it is important to highlight a few models to demonstrate how they informed the current dominant theories. Generally, theories and frameworks related to voluntary turnover can be broadly grouped into two models: *content* models and *process* models. *Content* models attempt to capture *why* employees decide to leave their organizations and *process* models attempt to capture *how* employees come to their decision to leave (see Maertz & Campion, 2004). Traditional *content* models have focused primarily on attitudinal factors such as organizational commitment and job satisfaction, while also exploring factors related to desirability and ease of job movement (e.g., perceived job alternatives). This two-part model, describing the influence of job satisfaction and perceived job alternatives on quit decisions was originally proposed by March and Simon (1958). Mobley (1977) extended the March and Simon model (1958) and specified that job satisfaction was a process and that perceived alternatives was a step within that process. In this extended model (Mobley, 1977), an employee's level of satisfaction was informed through deliberations and decisions surrounding the perceived utility of quitting.

A number of subsequent “traditional” turnover models were later developed to further refine these March and Simon (1958) and Mobley (1977) models; generally, these more *traditional* turnover models are built from the premise that individuals leave due to a gradual build-up of negative attitudes towards their work, which prompts rational decision making about whether or not to quit. In these traditional turnover models, the decision to leave is then typically weighed against the availability of suitable job alternatives with other employers (see Hom et al., 2017 for detailed discussion of turnover models). Although these traditional attitude-based models played an important role in moving employee turnover research forward, a major review of turnover predictors by Griffeth and colleagues (2000) revealed that attitudinal factors were relatively weak predictors of turnover, and generally accounted for only 4 to 5 percent of variance in turnover (Griffeth et al., 2000).

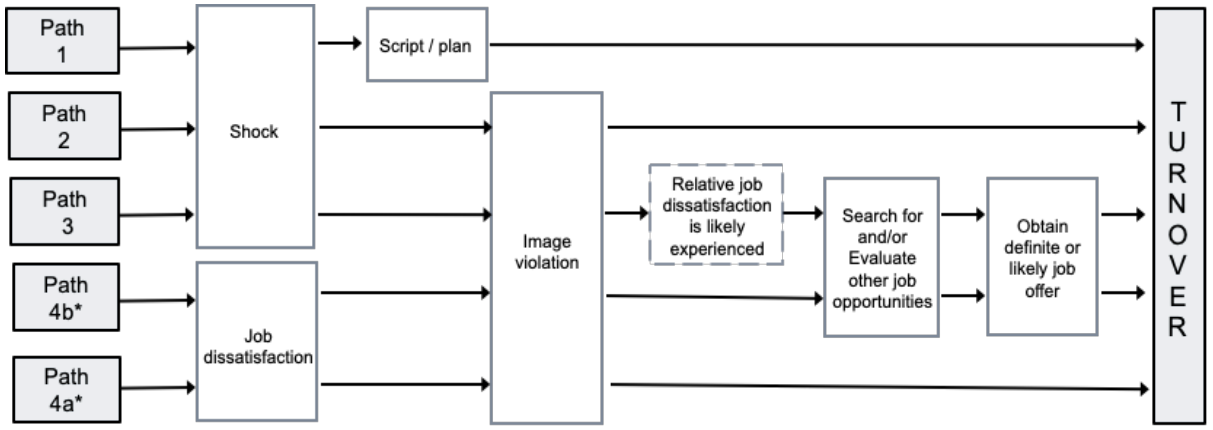
Lee and Mitchell (1994) considered the attitudinal, content-only traditional turnover models to be overly simplistic and posited that the decisions involved in the turnover process were more complex. Rather than a “one path fits all” approach to turnover, Lee and Mitchell (1994) proposed the *Unfolding Model of Turnover* as a unifying framework of five separate turnover decision pathways. The Unfolding Model of Turnover offered a way to synthesize and expand on prior theories by incorporating elements of both content and process models. The Unfolding Model of Turnover is a theoretical expansion of prior turnover theories because although it does incorporate satisfaction and perceived alternatives into the model, the primary focus is not on those traditional attitudinal variables. Furthermore, the Unfolding Model introduces a number of novel concepts (e.g., shocks, scripts, image violations) not included in traditional attitude-based content models.

As part of the Unfolding Model, Lee and Mitchell claimed that a concept they termed as "*shocks*" was actually responsible for the majority of employees' decisions to leave their jobs (Lee & Mitchell, 1994; Lee et al., 1999; Holtom et al., 2004). *Shocks* are distinct events that lead employees to re-evaluate their positions within their organization and are involved in the majority of the paths specified in the Unfolding Model (Lee & Mitchell, 1994; Lee et al., 1999). With the conceptualization of *shocks* in the Unfolding Model, Lee and Mitchell (1994) proposed the idea that individuals tend to stay in their job not primarily through active choice, but more as a function of habit (Kammeyer-Mueller et al., 2005). Within this framework, a shock serves as a "shock to the system," effectively pulling an employee out of their typical routine and prompting them to reexamine their status within their organization. Shocks may initiate the process of turnover through quick and sudden judgements that may ultimately result in a decision to leave. In the presence of a shock, an employee's level of job satisfaction and/or the availability of alternative job options may not matter. Although shocks can often be negative, they are broad in definition and are not limited to only overtly negative experiences. Rather, shocks may encompass any event that interrupts an employee's perception of the status quo and inspires them to consider their employment from an alternate perspective. Therefore, shocks can be positive (e.g., offered a promotion), negative (e.g., a valued supervisor quitting), or neutral (e.g., the announcement of a merger). They can also be work-related (e.g., switching to a new computerized documentation system) or non-work-related (e.g., spouse losing their job), as well as expected (e.g., reaching the end of a contract) or unexpected (e.g., death of a loved one).

Two other concepts factor into the Unfolding Model: *scripts* and *image theory* (Beach, 1990; Beach & Mitchell, 1987). A *script* can be thought of as pre-programmed behavior based on a pre-determined plan for quitting that may be enacted once certain criteria are met. These criteria may include a number of specific rules, such as “I will leave my job once I fulfill the terms of my student loan repayment contract,” or some uncertain future event such as, “ I will resign if my supervisor ever criticizes me again in front of a client.” While *scripts* are pre-programmed plans, *image theory* posits that the decision-making process may rely more on how an employee perceives certain events as they happen. Employees hold certain expectations—or *images*—for how they think their employer should respond to certain events or issues. When an event occurs and their employer responds, the employee will evaluate if their employer’s response was consistent with what they had expected. Employees may reconsider their attachment to their organization if their employer’s response was inconsistent with or *violated* their previously held image or expectation.

The Unfolding Model is the current dominant turnover model in organizational behavior research and has been applied across a variety of cultures and professions. The Unfolding Model and has generally been able to classify 77-100% of employees who leave into one of the five turnover decision paths (Lee et al., 1996; Lee et al., 1999; Holtom et al., 2008; Morrell et al., 2008). In the Unfolding Model, Lee and Mitchell (1994, 1999) describe how *shocks*, *images*, and *scripts* influence employment decisions and propose that all turnover actions may be categorized into five distinct decision paths, which are displayed in Figure 1 and detailed below:

Figure 1.
The Unfolding Model of Turnover



Note: Model adapted from Lee et al., 1999 and Eberly et al., 2009. *The above depiction of the model presents Path 4a and Path 4b in switched positions. Path 4a is typically presented between Path 3 and Path 4b.

Decision Path #1. A shock inspires an employee to activate their pre-determined *script* (Lee et al., 1999; Mitchell et al., 2001). Once the shock occurs, the script is enacted, and the employee quits. In this path, the employee does not consider other jobs, but rather chooses to follow a path that is outside of their current employment situation. They may also decide to pursue non-work-related endeavors, like parenthood, or a different professional trajectory, such as enrolling in a graduate program.

Decision Path #2. This path is activated when an employee experiences a significant negative shock and decides to leave without having another plan in place. In this instance, the shock prompts the employee to assess the fit or compatibility of the shock with their goals and/or values (Beach, 1990; Mitchell & Lee, 2001). If the employee determines that the shock or surrounding circumstances of the shock cannot be integrated with their goals or values, then the employee may choose to leave their current employment situation without exploring alternative jobs opportunities. In Decision Path #2, the employee has not determined what they will do next, which is in contrast

with Decision Path #1, where the employee responds to a shock by pursuing a pre-planned professional or personal trajectory.

Decision Path #3. An employee experiences a shock, which prompts them to begin a job search. The impact of the shock is sufficient enough for the employee to reevaluate their employment situation, prompting them to seek alternative employment. The employee evaluates job offers and leaves if they determine the alternative job to be better than their current job; the employee stays if the alternative job is not better than the current job (Lee et al., 1999; Mitchell et al., 2001).

Decision Paths #4a and 4b. Both sub-paths associated with Decision Path # 4 follow a more traditional attitude-based turnover model, which involves an accumulation of discontent leading to an employment decision. In *Decision Path #4a*, the employee experiences a gradual dissatisfaction with their job, culminating in the decision to quit without conducting a job search. In *Decision Path #4b*, the employee also experiences a growing dissatisfaction with their job, which inspires them to conduct a job search. if the alternative job is deemed better than the current job, the employee decides to leave (Lee et al., 1999; Mitchell et al., 2001).

Job Embeddedness

Another novel and potentially relevant construct in organizational behavior research that enhances the prediction of employment decisions is *job embeddedness* (Mitchell et al., 2001). Job embeddedness was developed in an attempt to answer two important questions that emerged from research on the Unfolding Model, which were, “why do shocks prompt some employees to leave and not others?” and “what are the factors that keep an employee at their job?” Job embeddedness describes the forces that keep employees attached to their organization and is unique in that it focuses on

why employees *stay*, rather than focusing on why employees *leave* (Mitchell et al., 2001).

At its broadest level, job embeddedness is a construct that considers all of the factors that may cause an individual to *remain* at their job (Mitchell et al., 2001). Mitchell and colleagues (2001) acknowledge that there are both work-related and non-work-related factors that contribute to an individual's decision to ultimately remain at a job, and the authors propose that retention can be attributed to the interplay of all of these factors. When more of these factors are present, an individual is more likely to remain at their current job, as they feel more embedded in their current situation, and it becomes less easy to arrive at a decision to leave. Mitchell et al. (2001) state that job embeddedness is influenced by an individual's connection to both their organization and their community, and they categorize these connections into three distinct aspects of embeddedness: *links*, *fit*, and *sacrifice;* each aspect is described below. Job embeddedness is a causal indicator model that is conceptualized as an aggregate multidimensional construct that is formed from each of the 6 subdimensions.

Links are relationships that an individual maintains with people or institutions in their workplace and broader community (Mitchell et al., 2001). The authors suggest that the number of links a person has is directly related to the strength of the connection they feel. Therefore, if someone has a large number of links, they will feel a stronger sense of embeddedness and will be more likely to remain at their current job. Links can be categorized as social, psychological, or financial. Examples of social links include having a friendship with a coworker or having family living in close proximity. Psychological links may include a sense of commitment to their co-workers or commitment to a club or organization within their community. Financial links can include investment of time or

money in the company, including rate of pay; they can also include personal financial links such as owning a home.

The extent to which an individual feels like they *fit* into the organization or community also factors into their level of job embeddedness (Mitchell et al., 2001). When evaluating fit, an employee considers how closely their personal goals, professional skills, and values align with their organization's. Similarly, the employee also evaluates how well they fit into their broader community. These considerations can range from tangible items, such as the availability of preferred recreational activities, to more abstract notions like the overall values of the community and the ability to contribute to their community in a meaningful way, such as through volunteer opportunities or service roles. When an individual feels a stronger sense of fit based on these factors, they are more likely to remain at their job.

Individuals also consider what they will *sacrifice* if they were to leave their job (Mitchell et al., 2001). Employees evaluate which benefits they will forfeit if they choose to leave. In relation to an individual's job, this may mean losing out on compensation such as loan repayment or high commission rates, a favorite manager or supervisor, or certain job-related benefits such as flexible hours or insurance coverage. In relation to an individual's community, this may mean forfeiting a short commute or moving out of their community to take a new job. The more elements an individual feels they may sacrifice by leaving, the less likely they are to leave. If the employee feels that the sacrifices required to leave are greater than the benefits of quitting, they will not leave the organization.

Placed within the context of previous turnover models, job embeddedness does not replace traditional attitude-based models of turnover or the Unfolding Model of

Turnover, but rather complements them (e.g. Tanova and Holtom, 2008). In support of this position, Mitchell and colleagues (2001) found job embeddedness explains a significant amount of variance above and beyond measures of job satisfaction and organizational commitment, which, as previously stated, are two primary predictors in traditional turnover models. Within the job embeddedness framework, turnover decisions are influenced by more than just job attitudes and perceived job alternatives; turnover decisions are also informed by the amount of attachment an individual has towards their job and their community (Tanova and Holtom, 2008).

Across professions, JE has been shown to lessen turnover and explain additional variance in turnover over and above that by job attitudes and perceived alternatives. Job embeddedness may also buffer the effects of shocks (Burton et al., 2010) or act as a mediator for a number of causal antecedents in the turnover process (Holtom et al., 2008). Although not yet studied within therapist populations, a similar workforce population--the nursing profession has studied job embeddedness extensively. Mitchell et al. (2001) and Holtom and O'Neil (2004) found that job embeddedness predicted the intent to leave and voluntary turnover after controlling for gender, satisfaction, commitment, job search and perceived alternatives. Job embeddedness has also been shown to predict job performance (Holtom et al., 2006).

Intersection of the Unfolding Model of Turnover and Job Embeddedness

To summarize both theories, the Unfolding Model of Turnover demonstrates how individuals participate in the act of *leaving* a job, while Job Embeddedness describes the ways in which an individual may feel compelled to *remain* in a job (Mitchell et al., 2001). These two concepts can be linked, as job embeddedness can describe the ways in which an individual considers their options when following one of the decision paths

outlined in the Unfolding Model (Holtom et al., 2006). That is, job embeddedness may potentially buffer the effects of shocks on turnover. Employees who follow a shock-initiated path in the Unfolding Model (i.e., Paths 1-3) have a statistically significant higher level of overall job embeddedness than employees who quit who do not experience a shock (Holtom et al., 2006). Among employees who remain retained (i.e., do not quit) job embeddedness levels are typically higher than for employees who quit (e.g., Mitchell et al., 2001; Holtom et al., 2006). In relation to traditional turnover models, the relation between job search and turnover has been shown to be stronger with lower levels of job embeddedness and job satisfaction, and higher levels of job alternatives (Swider et al., 2011)

Viewing the Unfolding Model through the lens of job embeddedness paints a more comprehensive depiction of turnover, as it provides insight into why a shock or dissatisfaction with a job does not always lead to turnover. This combined perspective recognizes that the steps leading to an individual deciding to leave or remain at a job are not quite as linear as the Unfolding Model suggests, but rather a more nuanced process due to employees' varying degrees of job embeddedness (Mitchell et al., 2001). Exploring the decision-making process for turnover in this way offers the opportunity to further quantify and understand the reasons that employees choose to leave and the reasons that they choose to stay. By identifying the factors that lead to turnover through the Unfolding Model and the factors that contribute to retention due to job embeddedness, it is possible to predict what may lead to each outcome. Ultimately this approach may help to inform proactive steps that can be taken to help prevent turnover and increase therapist retention in community mental health settings.

The Applicability of Job Embeddedness to Community Mental Health Therapists

An extensive search of the literature returned no empirical studies examining job embeddedness within the behavioral healthcare workforce. Even when search terms were expanded to include the social work and child welfare workforces, no empirical studies examining job embeddedness were found. Within the helping professions, the earliest mention of “embeddedness” related to Mitchell and colleagues’ (2001) concept of job embeddedness emerged in the literature in 2005 (Lawson et al., 2005). Crossley and colleagues (2007) used a combined sample of nurses and substance use counselors (*n* = 87) to conduct an initial, exploratory assessment of their global job embeddedness measure (Crossley et al., 2007). The only published conclusion related to their behavioral workforce population was that the global job embeddedness measure showed good reliability within the sample (Cronbach’s alpha was 0.88).

While no empirical studies examining job embeddedness for community therapists were found, authors examining turnover and continued EBP delivery in community settings have called attention to job embeddedness as an area for further research (Knight et al., 2012; Brookman-Frazee et al., 2018, respectively). Although measures of job embeddedness were not included in these studies, the authors’ suggestion that job embeddedness could help explain some of their results offers some evidence of the construct’s applicability to research in the behavioral healthcare workforce. In an article written for managers and leaders within social work organizations, Hernandez and colleagues (2014) provide a brief review of theories they consider to be related to employee burnout and turnover in social work and recommend job embeddedness as an important concept for organizations to consider when planning actions to reduce burnout and turnover. A 2018 study protocol (Lyon et al., 2018) focused on organizational factors affecting EBP implementation in school settings

assesses “clinician embeddedness,” which the authors defined as “the degree to which the person is visible and interacts with others in the setting” (Lyon et al., 2018, p. 4). Although not explicitly linked to the work of Mitchell and colleagues (2001), this definition does appear to capture some of the on-the-job links dimension of job embeddedness (Mitchell et al., 2001). Although a literature search for job embeddedness within the behavioral health workforce revealed few mentions of job embeddedness and no empirical studies measuring job embeddedness, references to this construct in a small number of articles provides some support for its relevance to the community-based therapist workforce.

Current Study

The current study implemented a prospective, longitudinal, repeated measures, observational design to examine factors that predict turnover in a sample of EBP-trained community mental health therapists. This study is motivated by continued calls from community stakeholders, organization leaders, and EBP implementation scholars for reductions in high therapist turnover rates. Therapist turnover has direct, negative impacts on the sustainability of EBPs in publicly-funded systems. As sustainability is best represented as a process rather than an endpoint (Shelton et al., 2018), the current study seeks to examine not only the antecedents that initiate pathways of therapist turnover, but also elements related to therapist retention.

Though a direct examination of the Unfolding Model of Turnover sits outside the scope of the present study, the applicability of the model to the mental health therapist workforce will be explored by examining two novel concepts directly related to the Unfolding Model and employee turnover in general: *job embeddedness* and *shocks*. Shocks are theorized to contribute to the majority of employee turnover decisions, while

job embeddedness is theorized to contribute directly to employee retention. The current also study incorporates variables shown to be important in traditional attitudinal models of turnover (e.g., perceived job alternatives), as well as variables shown to be consistently related to turnover in the helping professions (i.e., burnout). Gaining insight into how these constructs apply to the turnover decisions of community-based therapists will help to develop an improved understanding of why therapists leave and why they stay working in publicly-funded settings. These goals informed the development of a primary aim and an exploratory aim for the current study:

Aim 1: Examine the relation between *job embeddedness* and voluntary turnover in community-based mental health therapists.

Hypothesis 1: Job Embeddedness will capture unique variance in therapist turnover beyond what is captured by job satisfaction, perceived job alternatives, and burnout.

Aim 2: Exploratory aim designed to examine the association between *shocks* and voluntary turnover in community-based mental health therapists.

Hypothesis 2: Shocks will capture meaningful variance in predicting voluntary turnover when controlling for job satisfaction, perceived job alternatives, and burnout.

Method

Participants

Participants included 71 EBP-trained therapists from 31 community mental health organizations distributed throughout diverse regions of Washington state. Participants were recruited from a pool of community-based therapists who had previously participated in at least one clinical training as part of a statewide EBP-training initiative (CBT+ Initiative; see Dorsey et al., 2016 for details).

CBT+ Initiative. Though the EBP-training initiative originally began in 2007 with a singular focus on training community clinicians in an evidence-based trauma treatment, Trauma-Focused Cognitive Behavioral Therapy (TF-CBT; Cohen et al., 2004; Cohen et al., 2016; Deblinger et al., 1996), the focus was expanded in 2009 to better serve the diverse needs of youth in the public mental health system. To provide trainings focused on treating the most common mental health problems in youth, the CBT+ initiative (pronounced "CBT *plus*") was structured to incorporate a common elements approach, as pioneered by Chorpita and Weisz (e.g., Chorpita et al., 2005a; 2005b). Since 2009, the CBT+ initiative has provided training in cognitive behavioral therapy (CBT) and parent management training (PMT) principles to target symptoms related to depression, behavioral problems, anxiety, and trauma in youth. CBT+ training includes a 3-day skills-based training delivered by expert trainers as well as 6 months of twice-a-month phone consultation to support EBP integration and delivery.

All participants in the current study had received training in the full CBT+ Initiative model prior to enrolling; 95.8% of the current sample attended a CBT+ Initiative training between 2015 and 2018. See Table 1 for additional participant characteristics.

Procedures

All study procedures were reviewed and approved by the University of Washington Institutional Review Board (IRB). Once initial IRB approval was received, a staff member at the University of Washington affiliated with the CBT+ training initiative sent an announcement to the CBT+ listserv (i.e., study participant pool) informing subscribers that research opportunities may be sent to the listserv periodically and that members could opt out of receiving invitations to participate in research activities. Individuals who did not opt out of future contact were sent an email invitation with a link

to a web-based eligibility screening survey for the current study. The email invitation also contained two attachments: 1) the IRB study information statement, which provided a detailed overview of study participation requirements as well as potential risks and benefits of participation; 2) a study flyer, which provided a condensed description of the study goals, participation procedures, and eligibility requirements.

Individuals interested in participating in the study completed a web-based survey to assess if they met study inclusion and exclusion criteria. Study inclusion criteria were as follows: a) worked at least 20 hours per week at a community mental health organization; b) viewed 'clinician' as their main role (versus 'supervisor,' 'director,' etc.); c) at least 50% of their work hours at their community organization were dedicated to providing direct clinical work. Participants were not eligible to enroll if they endorsed any of the following exclusion criteria: a) held an official job title not consistent with or equivalent to 'clinician' (for example, "clinical intern", "supervisor", "director"); b) held a caseload of fewer than 15 clients; c) had plans to retire from the field within the next 12 months; or d) more than 50% of current work hours were spent in a residential or inpatient setting. Following enrollment, eligible participants were emailed a link to complete the baseline survey. Because the IRB granted the study a waiver of written consent, eligible participants documented their consent to participate by marking on the web-based survey that they read and understood the IRB Study Information Statement and that they willingly accepted their enrollment into the study. Individuals who did not meet eligibility requirements were notified through email and thanked for their interest and time. Participants were enrolled in the current study on a rolling basis until the planned sample size minimum threshold was reached ($N \geq 70$).

Data collection. Data collection began in May of 2018 and ended in July of 2019. Participants were asked to complete online surveys five times over a 12-month period, including one baseline survey (completed at study enrollment) and four follow-up surveys administered approximately three months apart. Participants were reminded about the voluntary nature of participation at the beginning of each survey and were encouraged to contact study staff via phone or email with any questions or concerns. All survey links were sent through email and participants could complete the surveys at their convenience anywhere they had access to a computer with internet connection. Participants were asked to complete the survey within two weeks of receiving the invitation email. At each survey time point, participants were asked if they had left their job since the prior study time point. If a participant indicated that they had left their organization, they were asked to provide their job end date, whether they left voluntarily or involuntarily, and then were directed to complete an exit survey that asked about factors that contributed to their decision to leave. For these participants, the exit survey represented their final involvement with the study. Participants who indicated they had remained at their job since the last study time point completed the standard set of survey questions and remained enrolled in the study; remaining participants received survey invitations for each subsequent time point over the 12-month period.

Due to the longitudinal nature of the study and importance of participant retention at each timepoint, a participant compensation plan for the current study was developed based on a review of participant compensation and retention literature (e.g., Booker et al., 2011; Brueton et al., 2014; Wilke et al., 2017). Based on recommendations found in the literature and through correspondence with expert research advisors, participants were compensated for their time with an Amazon gift card after completing surveys at

each time point; if participants completed measures at all time points in which they were eligible, they received a 'bonus' gift card after completing the final study survey for which they were eligible. If a participant did not leave their organization and remained in the study for all 5 survey timepoints, they received a total of $70 in Amazon gift cards.

Data Storage and Security. REDCap is a secure, web-based software platform designed to support data capture for research studies. REDCap was designed with an emphasis on data security and meets HIPAA requirements for data collection and storage (Harris et al., 2009; 2019) . Additionally, participants' identities were masked using numeric codes, which were stored in a secure database separate from study data. Only study staff members had access to the key linking a participant's study code number to their name and contact information.

Measures

Participant characteristics. A series of single-item self-report questions were used to gather information related to relevant demographic-, background-, and job-specific information. Example items include questions related to age, gender identity, level of education, licensure status, work hours, and caseload size (*see Table 1*).

Organizational tenure. A single question was used to obtain participants' self-reported organizational tenure: "*How many years have you worked at your current agency*?"

Perceived Job Alternatives. A single item was adapted from the Perceived Employment Opportunities measure (Ganster, 1984; National Institute for Occupational Safety and Health) and used to measure participants' perceptions of the availability of suitable employment opportunities outside of their current organization. Participants

were asked to rate their level of agreement with the statement: "*I would have to move out of my area to find a suitable job with another employer*." Participants rated their agreement with the statement using 7-point Likert scoring, which ranged from *strongly disagree* (1) to *strongly agree* (7). In the extant turnover literature, a higher number of perceived job alternatives is thought to increase the risk of turnover; therefore, to allow for a more intuitive interpretation of the results, this item was reverse scored. Once reverse-scored, higher values of perceived alternatives would theoretically correspond with an increased risk of turnover.

Although single-item measures may raise concerns about reliability (Wanous & Hudy, 2001), support exists for the use of single-item measures if they meet certain criteria, including: 1) the meaning of the construct is sufficiently narrow, 2) the construct is unidimensional, and 3) the construct being measured is clear to the respondent (Gilbert & Kelloway, 2014; Sackett & Larson, 1990). The selection of this specific item was informed by a number of considerations intended to maximize the fit with the three criteria above. To increase the clarity of the construct being measured (criteria #3), a note was included with the item to clarify the meaning of the word "area" in the item; the note specified that "area*"* referred to the participant's neighborhood or community in which they lived. The inclusion of this note was intended to eliminate alternate interpretations of "area." Otherwise, possible erroneous interpretations of "area" could include the area or location in which the therapist worked, or a participant could interpret "area" to be in reference to populations, roles, services, modalities, or expertise in which the therapist or their current organization may have specialized in (e.g., "working with children with developmental disabilities," or "specializing in trauma treatment"). The selected item was also chosen to reduce the possibility of conflating perceived job

alternatives with other possible antecedents of turnover (criteria #1 and #2 above), as other potential measures appeared to conflate perceived alternatives with possible turnover antecedents or job embeddedness subdimensions. For example, one item on a commonly used measure of perceived alternatives states, “Given my qualifications and experience, getting a new job would not be very hard at all” (Griffeth et al., 2005). This item appears to prompt participants to not only consider the likelihood of obtaining another job, but to also consider other potential factors that may influence the likelihood of obtaining other jobs. Additionally, the selected item was particularly appealing because it specifically asks that participants answer based on jobs that would not require relocation. Therefore, this specifier seemingly also limits potential confounding with community dimensions of job embeddedness. Given these potential issues, the current item was chosen based on its fit with the three criteria above.

Job Satisfaction. The Brief Index of Affective Job Satisfaction (BIAJS; Thompson & Phua, 2012; Brayfield & Rothe 1951) was used to measure participants’ levels of *affective* job satisfaction. Affective job satisfaction can be defined as the extent of overall pleasurable emotions an employee feels towards their job (Locke, 1976). Three of the seven items in the full BIAJS measure are labeled as distractor items. To reduce participant response burden, only the four non-distractor items were included in the current study. The BIAJS uses a 5-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) with higher scores indicating higher levels of job satisfaction. The included items contained statements such as, “*I find real enjoyment in my job*” and “*Most days I am enthusiastic about my job*.” The BIAJS has demonstrated strong psychometric properties, including good internal reliability (α = .81 - .87), across countries, professions, and job-levels (Thompson & Phua, 2012; Fernández-Muñoz &

Topa, 2018). In the current study, the four-item version of the BIAJS demonstrated high internal consistency (α = .87), which is consistent with studies conducted in other healthcare settings (α = .92; e.g., Scarlet et al., 2017).

Burnout. Two subscales of the Copenhagen Burnout Inventory (CBI; Kristensen et al., 2005)—work-related burnout and client-related burnout—were used to assess the extent to which participants experienced prolonged psychological and physical exhaustion, negative job attitudes, and a loss of concern and feeling for patients. Broadly, the CBI is designed to capture employees' perceived sources of burnout. All items are rated on a 5-point Likert scale associated with one of two response sets; one response set captures frequency of occurrence (1, *never/almost never*; 2, *seldom*; 3, *sometimes*; 4, *often*; 5 *always)*, the other captures level of agreement (1, *to a very low degree*; 2, *to a low degree*; 3, *somewhat*; 4, *to a high degree*; 5, *to a very high degree*). One example from the 7-item work-related subscale includes, "*Are you exhausted in the morning at the thought of another day at work?*". An example from the 6-item client-related subscale includes, "*Do you feel that you give more than you get back when you work with clients?*". As higher scores on the CBI indicate higher levels of burnout, one item on the work-related subscale is reverse scored—*"Do you have enough energy for family and friends during leisure time?".* For the current study, separate scores were calculated for each subscale and then combined to create a total score. The CBI work-related and client-related subscales have demonstrated good construct validity for employees working in helping professions (Walters et al., 2018; Leake et al., 2017). The internal reliability of the CBI is commonly reported above 0.80 (α = 0.85–0.87; see Dev et al., 2018) and reported to have high face, convergent, divergent, and predictive validity (Campos et al., 2011; Kristensen et al., 2005; Milfont et al., 2008) across

countries and professions. The current study demonstrated high internal consistency for the total burnout score (α = .91) as well as each subscale (work-related α =.85; client-related α = .86).

Embeddedness. The Job Embeddedness-short form (Felps et al., 2009; Holtom et al., 2006; Mitchell et al., 2001) was used to capture both *on-the-job* and *off-the-job* forces that influence employee retention. The short form contains 21 items designed to measure the constructs of *fit*, *links*, and *sacrifice* as they relate to the two context-specific domains of job embeddedness: community embeddedness (i.e., *off-the-job* forces) and organizational embeddedness (i.e., *on-the-job* forces). The Job Embeddedness measure is typically used to generate an overall aggregate score, though is often disaggregated to the level of its two context-specific domains to produce a separate community embeddedness score and an organizational embeddedness score. Each domain may be further disaggregated to produce separate subdomain scores (i.e., a set of community *fit*, community *links*, and community *sacrifice* scores; and a set of organization *fit*, organization *links*, and organization *sacrifice* scores).

Five of the six subdimensional scales include three items each, which are measured on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Higher scores indicate higher levels of embeddedness. The *off-the-job Links* subdimensional scale includes six items measured using either the aforementioned 5-point Likert scale or a binary yes/no scale. Example items from the *community* embeddedness subdomains include: 1a) Community fit: *The place where I live is a good match for me;* 1b) Community links: *I am active in one or more community organizations (e.g., churches, sports teams, schools, etc.);* 1c) Community sacrifice: *Leaving the community where I live would be very hard.* Example items from the *organizational*

embeddedness subdomains include: 2a) Organizational fit: *My job utilizes my skills and talents well;* 2b) Organizational links: *I am active in one or more community organizations (e.g., churches, sports teams, schools, etc.);* 2c) Organizational sacrifice: *Leaving the community where I live would be very hard.*

The Job Embeddedness measure can yield three levels of scoring: 1) six subdimension scores (e.g., *organizational fit*; *community links*) 2) two dimension scores (i.e., *organizational embeddedness* and *community embeddedness*), and 3) an overall job embeddedness score (i.e., aggregate score of all items). Given the differing response scales, all items are standardized (i.e., converted to Z-scores) and subdomain scores are first generated by averaging the standardized items relevant to each subdomain (e.g., community sacrifice). Dimensional (e.g., organizational embeddedness) scores can then be calculated by averaging the averages of the relevant subdomain scales. To calculate the overall or aggregate job embeddedness score, the two dimensional scores are averaged. The current study uses the aggregate job embeddedness score for the primary analyses. Note, the measure developers emphasize that job embeddedness is a causal indicator formative model, which means that the construct is created using the scores of the included items. Items do not have to be correlated, and if an item is dropped, the construct's meaning will likely change (Fleuren et al, 2018). Because job embeddedness is conceptualized as a causal indicator formative model, standard tests of reliability are not applicable

Shocks. Shocks was measured using the Distinct Events Checklist (DEC; see Appendix A for the full measure). The DEC is a measure developed by the study author in collaboration with members of her NRSA committee. The DEC contains 40 items total, with 39 items each representing a category of shocks; the 40th item provides the option

for participants to add their own Distinct Event. A definition of Distinct Events was provided at the start of the measure to orient participants to the purpose of the checklist. Participants were instructed to read through the 40 items and mark each item they had experienced in the last 3-month period; internal consistency measures for the DEC were high (KR-20 = .83). The current study used the DEC to generate a sum score for the total number of items each participant endorsed.

The majority of shocks research in the larger employee turnover literature has been conducted using retrospective study designs. In these studies, shocks are measured by identifying employees who have recently quit and either administering a survey or conducting semi-structured interviews with them to obtain information on whether a shock event had occurred prior to quitting (e.g., Morrell et al., 2008; Mitchell et al., 2001). Therefore, as few shock measures have been developed for use in prospective study designs, the current version of the DEC was designed to be used in an exploratory capacity. The items included in the DEC were informed by qualitative interviews conducted by the lead author with a sample of EBP-trained community mental health therapists who had been recruited from the same listserv as the current sample. Items were designed to be specific enough to prompt participants to recall possible occurrences of specific events, while also remaining broad enough to be applicable to the majority of participants. To enhance the validity of the DEC, the measure was designed to align with measurement recommendations for event inventory measures (e.g., Epel et al., 2018). Additionally, efforts to maximize construct validity included giving the measure the more neutrally-valanced name of “Distinct Events” rather than “shocks” in an effort to avoid priming participants to consider only negative events. This was done because the term *shock* itself may hold a negative connotation, and the theory

behind shocks claims that shocks can be positive, negative, or neutral in valence (Lee et al., 1999). Although outside the scope of the current study, it should be noted that the DEC asked an additional 2-3 follow-up questions for each Distinct Event endorsed by a participant; see Appendix A for additional information. The DEC also contains a comment box, which is labeled as “optional”, and provided as a free-text space in the measure where participants can add additional detail or clarify their responses.

Turnover. Turnover is coded as a binary variable (0 = no turnover occurred/censored; 1 = turnover occurred). At the start of each quarterly survey, participants completed a set of brief screening questions to indicate whether they left their organization within the last three to four months (i.e., since the last survey). When participants indicated “yes” they were asked to specify whether their leaving was voluntary or involuntary. Participants who indicated that they had left their organization were also asked to provide their specific job end date. Results only include individuals who voluntarily resigned from their original agency. Original agency is defined as the organization the therapist was employed at when they entered the study. See the Data Analytic Plan for additional information on how the Turnover variable was coded and used in the analyses.

Data Analytic Plan

Survival Analysis. Survival analysis, or time-to-event analysis, refers to a set of statistical methods that can be used to estimate both the likelihood of an event occurring (e.g., death, employee turnover) and the time it will take until that event occurs. Researchers in the field of organizational behavior have pioneered the application of survival analyses to the study of employee turnover (e.g., Morita et al., 1989; Morita et al., 1993; Somers & Birnbaum, 1999; Hom & Kinicki, 2001). Although survival analysis

can be viewed as an analogue to logistic regression, it offers analytic capabilities beyond standard regression models. The properties typical of turnover data would invalidate the core assumptions of many standard statistical techniques which require normally distributed data and equal follow-up periods across participants. Thus, a significant strength of survival techniques is the ability to account for the unique nature of employee turnover data, which is typically highly skewed due to the distribution of survival times and participant censoring. Instead of dropping a case and treating it as missing, in survival analysis, a participant who experiences turnover can continue to contribute data up until the time just before their study participation ends. Overall, survival analysis offers analytical techniques that generally fit longitudinal data well and have the capacity to utilize and account for data that are often ignored or discarded in other analytical methods. For the current study, a specialized survival analysis technique—an Extended Cox Regression which can incorporate time-varying predictor variables—was used as the primary method for testing the study hypotheses. Specifically, a multivariable, time-varying covariate, non-repeatable event hazard analysis was used to assess how job embeddedness and shocks perform as predictors of therapist turnover. Analyses were conducted using SPSS and R.

Missing data. Another benefit of survival analysis is the ability to account for censoring in the data, which makes it particularly useful for longitudinal study designs (Singer & Willett, 2003; Tabachnick & Fidell, 2013). Censoring is a special type of missing data which occurs when the exact survival time is unknown for one or more participants (Mills, 2011). Two common types of censoring are left censoring and right censoring. Left censoring can occur when a participant's *start time* is not observed within a study's period of observation. Right censoring can occur when a participant's *end time*

is not observed. Right censoring may occur due to study dropout or the study observation period ending before all participants have experienced the event of interest (e.g., turnover). Censoring is a common limitation encountered in longitudinal studies due to difficulties with participant retention as well as practical limitations that restrict data collection to finite periods of time. The current study contains both left- and right-censored data. Our data can be considered left censored because participants were not all enrolled as new hires and, instead, reported a wide-range of organizational tenures. We attempt to reduce possible bias from left-censoring by including organizational tenure as a control variable in our model. Our data is also right-censored because the majority of participants were still working at their organizations when the study observation period ended. Although all employees will eventually discontinue their employment at their organizations, because the study ended before all participants had left their jobs, we are missing the exact job end dates for the participants who were still working at the end of the study period. Right-censored data is common in longitudinal time series studies and survival analysis is a robust analytic method that can typically account for right censored data. Additionally,

Measurement of Time. One potential issue that can occur with time-dependent variables in survival analyses is that the frequency with which they are measured may not correspond to the precision with which event times (i.e., turnover) are measured (Allison, 2014). For the current study, the event times (turnover) were measured in more precise units than the predictors. In the current study, participants who voluntarily left their organizations were asked to provide the exact date they left their job, which allowed for the event to be observed on a daily, continuous scale. Ideally, the time-dependent predictor variables, such as shocks, would also be measured on a daily basis, however,

the study was designed to collect predictor variables on a quarterly schedule. The timescale is typically matched to unit of measurement used for the event indicator. Since turnover events were measured in daily units, we converted the predictor variables to mimic a daily timescale by implementing the commonly used imputation method of "last value carried forward" (Allison, 2014). This method allowed for the study timescale to be continuous. This conversion to a continuous timescale was helpful for reducing the occurrence of *ties* in event times. Ties in event times should be minimized when possible as they can significantly bias results, particularly in small samples (Mills, 2011).

Another aspect of time in survival analyses that warrants consideration is how to define the "time of origin" (see Fieberg & DelGuidice, 2009 for detailed discussion). In survival analyses, time of origin is used as the start time when calculating the length of time until the event of interest occurs. In turnover research time of origin is often defined as the date an employee started working at their current organization. Because the current study is observational in nature and enrolled participants who reported a range of organizational tenures, the time of origin was defined as the study start time. Given that study entry represents the time origin and the study timescale is measured as continuous, outcomes were measured in reference to the number of days since study entry. As noted in the "missing data" section above, an organizational tenure variable was included in the first step of the model as a control variable to reduce the bias that may occur from left censoring. Because exact employment start dates were not collected, tenure was treated as a time-invariant variable, meaning that its values remained the same for all time intervals across the study period.

Given the longitudinal design of the study and the variable nature of our predictors, we would expect the values of our predictors to vary across the observation

period. Fixed variables are variables with values that are recorded in the database with identical values across all the across the time period, whereas the values of time-varying variables are allowed to change at each new interval. Failure to account for this variation over time can produce biased estimates in the results (Kammeyer-Mueller et al., 2005). All predictor variables aside from organizational tenure were included as time-varying variables in the analyses. By treating our predictors as time-varying, we were able to update their values throughout the study period to reflect changes in scores when new survey data was completed by a participant. Participant scores were updated at the beginning of each of the four time intervals as long as the participant was still enrolled and used to calculate the daily turnover hazard until the end of that time interval.

Model variables. All model variables were selected *a priori*, during the study design phase; the selection of the variables was informed by a review of employee turnover literature within the helping professions as well as within the broader organizational behavior literature. The outcome variable is the binary voluntary turnover variable, which indicates whether a participant did or did not quit their job during the study observation period. To indicate whether a participant quit their organization, a dummy variable, *turnover status*, was computed. A value of “0” indicated that a particular participant did not experience the event (turnover) and a value of “1” was used to indicate that a participant had experienced the event during the study period (aka quit their organization). The predictor variables used to test study hypotheses were job tenure, perceived job alternatives, burnout, job satisfaction, a shocks sum score, and job embeddedness.

Data Preparation. The association between time-varying predictors and the risk of turnover can be studied using an extension of the standard Cox Proportional Hazard Model. A time-varying Cox model, also called an Extended Cox Regression, was fit by structuring the data in a "counting process" style. Also known as a *person-period* or *long-form* data structure, this method creates multiple rows of data for each participant by separating their total length of study time into intervals (Andersen & Gill, 1982). Each interval is defined by a start and stop time, allowing the values of predictor variables to vary from one interval to the next. All participants who did not quit their organization by the end of an interval were marked as censored and included in the risk set for the subsequent interval. In contrast, any participant who did quit during a particular interval was marked as having experienced the event of interest and was removed from the risk set for all subsequent intervals. Interval lengths in person-period data structures can vary by participant and by interval. Structuring the data in this format allows us to enter our predictors in a lagged form so that they precede turnover events and avoid issues with reverse causal ordering (Box-Steffensmeier & Jones, 2004).

Model building. An Extended Cox Regression was run in a series of steps to determine significant predictors of turnover. To ensure adequate power, the number of variables recommended for inclusion in a cox regression model range from 1:5 to 1:15 based on the number of events (i.e., instances of turnover) in your sample (Vittinghoff et al., 2007; Harrell, 2015). Therefore, no additional variables beyond the model variables we chose *a priori* could be included in the model given our smaller sample size and relatively few number of participants who experienced turnover. The full model was built across four steps. The first two steps were used to create a base model that included all control variables. The first step added the organizational tenure variable to the model

and the second step added the three attitudinal variables (perceived alternatives, burnout, job satisfaction) to the model. The third and fourth steps were used to evaluate whether the variables of interest— shocks and job embeddedness—captured additional variance beyond the control variables. Shocks was included in the third step, and job embeddedness was added to the model in the fourth and final step. Each step in the model produced an estimate of the daily hazard function, or daily likelihood of a participant quitting, given that they had survived up to the current day. The coefficients for each variable included in the model calculate hazard rates. Hazard rates represent a change in the likelihood of turnover for each 1-unit increase in the predictor variable (e.g., job embeddedness) when all other variables in the model are held constant. Hazard rates with a value greater than 1 indicate an increased likelihood of turnover occurring, while hazard rates less than 1 indicate a decreased likelihood for turnover. To test the global null hypothesis (that all predictor effects on turnover = 0), the likelihood ratio test will be used as it performs well with small samples. A significant result for the model likelihood ratio test would indicate whether the model as a whole can predict changes in the hazard rate in the event of interest (i.e., turnover).

Assumptions. Cox proportional hazard analyses are based on the assumption that the magnitude of the effect that each predictor has on the outcome variable (i.e., turnover) remains constant across time (Allison, 2014). To assess whether our data met this assumption, we computed statistical analyses to test the relationship between Schoenfeld residuals and time for each predictor variable (Grambsch & Therneau, 1994; Schoenfeld, 1982). Individual and global omnibus proportional hazard tests were computed to determine violations of the proportionality assumption.

Model interpretation. For the current data, the event predicted is turnover (i.e., voluntary resignation) and the censored data are those participants where the outcome is 'survived' at the end of the study period (i.e., therapists who remained employed at their organization). In Cox regression, the dependent variable is the hazard rate, which for this study indicates the likelihood that a participant who has 'survived' through a given time point will resign during the next observation period (i.e., before the next time point) (Hosmer and Lemeshow, 2000). The resulting coefficients yield hazard ratios, which represent the change in the likelihood of turnover for each 1-unit increase in the predictor variable. Hazard ratios greater than 1 indicate increased risk of an event occurring (i.e., turnover); hazard ratios less than 1 indicate decreased risk of an event occurring. The confidence intervals presented in the tables are the confidence intervals for the hazard ratios of each variable included in the models. Confidence intervals that do not include the value of 1 can be interpreted to mean that the hazard ratio is statistically significantly different from 1, which means the log hazard rate change is significantly different from 0.To test our hypotheses, we performed an extended Cox regression with time-varying covariates to assess the impact of each covariate on the baseline hazard rate.

Results

Descriptive Statistics

Sample characteristics. Table 2 contains demographic information for study participants. Out of the 71 participants enrolled at baseline, one participant dropped out of the study, and two left their organizations involuntarily. The two participants who experienced involuntary turnover did not meet criteria to be considered *noninformative* censoring and so were excluded from the analyses. Given our small sample size and

relatively few turnover events, a conservative approach was taken to reduce the likelihood of bias affecting our findings and case wise deletion was used to exclude participant who dropped out of the study from the analyses. Therefore, 68 participants were included in the final analyses. Nineteen of the 68 therapists voluntarily left their organization within the 12-month data collection period, resulting in a 27.9% employee turnover rate for the study sample. The majority of study participants were licensed (64.7%), Masters-level (98.5%), white (75%) females (88.2%) who worked full-time (91.2%) and primarily provided clinical services in outpatient settings (69.1%). On average, participants were 34.9 (*SD* = 8.9) years old, had worked at their organization for 3.0 (*SD* = 2.7) years, had worked in the field for 4.3 (*SD* = 4.5) years, and had been licensed for 3.1 (*SD* = 3.6) years. The average caseload size for participants was 37.5 (*SD* = 16.8) and the typical ratio of caseload size to number of work hours was 1:1.

Table 1.

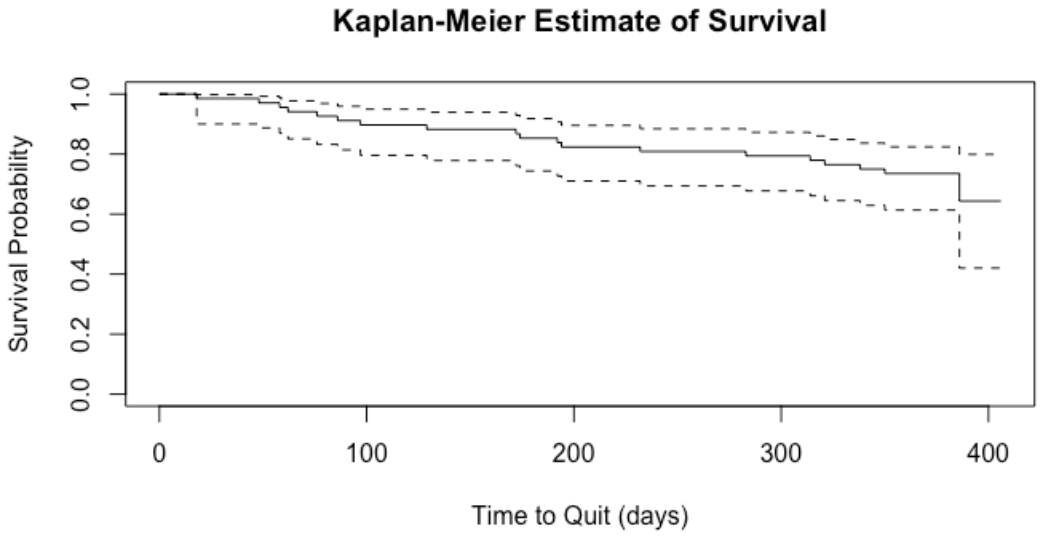
Participant Demographics (N=68)

Measure	*N*	Frequency (%)
Gender identity		
Female	60	88.2
Male	6	8.8
Genderqueer/gender non-conforming	2	2.9
Education level		
Masters	67	98.5
Race/ethnic identity		
White or Caucasian	51	75.0
Multiracial	5	7.4
American Indian or Alaska Native	4	5.8
Asian American or Asian	4	5.8
Hispanic or Latino	3	4.4
Pacific Islander	1	1.5
Work hours		
Full-time	62	91.2
Part-time	6	8.8
Licensed		
Yes	44	64.7
No	24	35.3
Primary clinical setting		
Outpatient	47	69.1
School-based	17	25.0
Bx rehab/Wraparound	3	4.5
Inpatient	1	1.5
	M	*SD*
Age	34.9	8.9
Years in field	4.3	4.5
Years licensed	3.1	3.6
Organizational tenure (in years)	3.0	2.7
Average caseload size	37.5	16.8
Ratio of caseload size to work hours	1.0	0.4

Note. Bx rehab = behavioral rehabilitation

Kaplan Meier Estimates to visualize the sample survival distribution. The Kaplan Meier method was utilized to generate a visual display of the distribution of survival time across the sample and study observation period. Kaplan-Meier (KM) estimates are non-parametric statistics meaning there is no assumption about the shapes of hazard functions, or the influence of predictor variables (Mills, 2011). The KM estimator gives the probability that survival time is greater than a pre-specified time. For this analysis, time periods of 100 days were entered to create a total of 4 intervals that captured each of the start stop periods within the four time intervals of the study. The cumulative proportion surviving was plotted for each of the 4 intervals. This model is advantageous for simplistic questions that concern the timing of events. It can help to answer questions concerning the timing of turnover for individuals and has minimum data requirements; however, a primary disadvantage of KM models is that they rely on predetermined time intervals that are both discrete and arbitrary (Mills, 2011). In Figure 2, the solid black line represents the survival probability estimate plotted over the span of 400 days; the dotted lines around the solid black line represent the 95% confidence bands.

Figure 2.
Kaplan-Meier Survival Distribution



Preliminary analyses of model variables. See Table 2 for means, standard deviations, and correlations for all model variables. Means and correlations for predictor variables were computed using only baseline data. Pearson's correlation coefficients were calculated to check for multicollinearity among model variables. A number of correlations were statistically significant at the .05 alpha level. Job embeddedness was positively correlated with job satisfaction, $r(68) = .64$, p = < .01 and negatively correlated with the shocks sum score $r(68) = -.29$, $p = < .05$ and burnout $r(68) = -.46$, $p = < .01$. The shocks sum score was positively correlated with burnout $r(68) = .27$, $p = < .05$ and negatively correlated with job satisfaction $r(68) = -.43$, $p = < .05$. Job satisfaction had a negative association with burnout $r(68) = -.63$, $p = < .01$. Burnout had a negative association with organizational tenure $r(68) = -.31$, p = < .05. To assess for any issues with multicollinearity across time, variance inflation factors (VIF) and tolerance statistics were calculated to measure the strength of interrelationships among model variables within each study time interval. VIF and tolerance statistics indicated that no concerning levels of multicollinearity were present among any of the six predictor variables across any of the four study time intervals (*VIF* < 2.7 and Tolerance > .37 for all variables across time intervals; Allison, 1999).

To determine the strength of association between each model variable and a binary *overall turnover status* variable, point-biserial correlations were calculated and can be viewed in Table 2 (Tate, 1954). Baseline data was used for all predictor variables for this set of correlational tests; however, the overall turnover status variable was calculated using data collected across the full 12-month study period. Overall turnover status was created as a dummy variable; values were coded as "0" if a participant remained employed at their organization across the full study observation period or were

coded as “1” if a participant had voluntarily left their organization during the study period. Within the current study sample, the baseline measure of job embeddedness was the only model variable significantly associated with *overall turnover status*; the point-biserial correlation between job embeddedness and voluntary turnover was $r_{pb}(68) = -.31$ $p = <$ .05. These results provide initial evidence of a significant relationship between job embeddedness and voluntary turnover, and may suggest that higher levels of job embeddedness are be related to a lower risk of turnover (Cohen, 1988).

Table 2.

Means, standard deviations, and correlations for model variables using baseline data[^]

	Variable	*M*	*SD*	1	2	3	4	5	6
1	Organizational Tenure	2.52	1.27						
2	Perceived Job Alternatives	5.04	1.73	.06 [-.18, .30]					
3	Burnout	2.70	0.72	-.31* [-.51, -.07]	-.02 [-.26, .22]				
4	Job Satisfaction	3.55	0.97	.19 [-.05, .41]	-.07 [-.30, .17]	-.63** [-.76, -.46]			
5	Job Embeddness[&]	0.02	0.51	.22 [-.02, .43]	.18 [-.06, .40]	-.46** [-.63, -.25]	.64** [.48, .77]		
6	Shocks (sum score)	7.18	5.21	-.02 [-.25, .22]	.02 [-.22, .25]	.27* [.04, .48]	-.43** [-.61, -.21]	-.29* [-.49, -.06]	
7	Overall Turnover Status[^#]	--	--	-.10 [-.33, .14]	-.14 [-.37, .10]	.13 [-.12, .35]	-.22 [-.44, .02]	-.31* [-.51, -.07]	.13 [-.11, .36]

Note. M and *SD* are used to represent mean and standard deviation, respectively. Values in brackets indicate the 95% confidence interval for each correlation; * indicates $p < .05$; ** indicates $p < .01$; ^ = Variables 1 through 6 were collected at baseline; variable 7 (*overall turnover status*) was collected at the end of the 12-month study observation period; [&]Job Embeddedness is a standardized variable; # Because *overall turnover status* is a binary variable, all correlations computed with this variable were calculated using point-biserial correlations

Time-varying bivariate analyses. Bivariate analyses were computed for descriptive purposes for all model variables using time-varying data, see Table 3. These analyses allowed us to observe each explanatory variable predicting turnover without controlling for any other variable. Out of the six model variables tested, two variables—job satisfaction (*ß* = -0.84, *p* = < .001) and job embeddedness (*ß* = -1.30, *p* = < .001)—were shown to be statistically significant in predicting turnover at the bivariate level. Additionally, the regression coefficients for both predictors were negative, which suggests that higher job satisfaction and higher job embeddedness are associated with a decreased risk of turnover. Although job satisfaction and job embeddedness were the only statistically significant predictors in these analyses, the p-values of all six predictor variables met the suggested .25 p-value threshold (Bursac et al., 2007; Hosmer & Lemeshow, 2000) which justifies their inclusion in the primary analysis multivariable model. Note that these analyses were performed primarily for descriptive purposes. Results should be interpreted with caution as bivariate analyses do not take into account possible relations between predictor values or potential interactions.

Table 3.

Separate time-varying bivariate cox regressions for each model predictor

Predictor	Estimate (b)	*p*	HR (e^b)	95% CI for HR
Tenure	-0.27	.18	0.76	[0.51-1.10]
Perceived Alternatives	-0.15	.20	0.86	[0.68-1.10]
Burnout	0.45	.15	1.60	[0.85-2.90]
Job Satisfaction	-0.84	< .001***	0.43	[0.26-0.70]
Shocks	0.06	.13	1.10	[0.98-1.20]
Job Embeddedness	-1.30	< .001***	0.27	[0.14-0.51]

Note. HR = hazard ratio; CI = confidence interval of HR; Perceived Alternatives = Perceived Job Alternatives

Primary Analyses

Extended Cox Regression with time-varying predictors. A multivariable Extended Cox Regression with time-dependent predictor variables was used to determine the variance explained by shocks and job embeddedness in predicting therapist turnover while controlling for tenure and the three attitudinal variables (perceived job alternatives, burnout, and job satisfaction). Tenure, perceived job alternatives, burnout, and job satisfaction were entered as controls into the model; tenure was entered in the first block of the model and the three attitudinal turnover variables were entered into the second block. To observe whether the shocks sum score or job embeddedness variable accounted for any additional variance beyond the variables already entered into the model, the shocks variable was included in the third block and job embeddedness was included in the fourth block, see Table 5. Model comparisons were computed to determine the best fitting model; proportionality assumptions were tested as described in the Data Analytic section.

The first model in the Extended Cox Regression included organizational tenure as a single predictor. Results suggest that organizational tenure (*ß* = -0.27, *p* = .19) did not have a significant impact on the hazard rate for turnover. Additionally, the overall model significance test was not significant ($X^{2=}$ 1.93; df = 1; *p* = .20), and so the null hypothesis cannot be rejected for Model 1. In Model 2, when perceived alternatives, burnout and job satisfaction were added as predictors, the overall model was shown to be significant ($X^{2=}$ 15.35; df = 4; *p* = .004). When holding all other variables constant, job satisfaction (*ß* = -1.04, *p* = < .001) was the only predictor in Model 2 that significantly improved the model's predictive capability. Organizational tenure, perceived alternatives, and burnout did not appear to have a significant influence on the likelihood of turnover.

When the shocks sum score was added to the third step of the model (Model 3), although the overall model was significant ($X^{2=}$ 15.7; df = 5; p = .008), the shocks sum variable itself was not a significant predictor of therapist turnover (ß = -0.03, p = 0.55). The control variables included in Model 3 showed similar results to Model 2, where job satisfaction was shown to be the only independent predictor of turnover (ß = -0.99, p = *.001*).

In Model 4, job embeddedness is introduced as the final variable. The overall model was significant (χ2 = 19.68, df = 6, p =.003). Additionally, after accounting for the effects of all other variables in the model, job embeddedness was the only independent predictor of turnover (ß = -0.99, p = .04). These results suggest that for every one unit increase job embeddedness scores, the daily risk of turnover is reduced by 64%. The inclusion of job embeddedness in the model appeared to better capture a portion of the variance that job satisfaction had previously accounted for in predicting turnover. Although job satisfaction had appeared to be independently significant in Model 2 and Model 3, it did not meet the .05 level of significance in Model 4, though it approached significance (ß = -0.09, p = .06). In summary, when job embeddedness was added to the model*,* it was a significant predictor of turnover with all other variables held constant *(p = .04*). The inclusion of job embeddedness in the model appeared to better capture a portion of the variance that job satisfaction had previously accounted for, with job satisfaction's significance level reduced (to p = .06).

Model Fit Statistics and Assumptions. Model fit statistics (including pseudo R^2 change scores and AIC scores) were compared between models. Methods for model selection can be thought of as choosing ß to maximize a penalized log(partial) likelihood. Model 4 appeared to be the best fit for the data, as it had the lowest AIC value across all

models (*AIC* = 143.4) [(Model 2 *AIC* = 143.76); (Model 3 *AIC* = 145.42)]. Pseudo R^2 change scores were also calculated to determine if the additional variables included in each step had a significant impact on the prediction capabilities of the previous model [(pseudo R^2 change score between Model 1 & Model 2 = .05, p = .004); (pseudo R^2 change score between Model 2 & Model 3 = .001, p = .55); (pseudo R^2 change score between Model 3 & Model 4 = .016, $p < .05$)]. Proportionality assumptions were tested for each predictor variable and model. Individual and omnibus model tests indicated that no predictors or models violated the proportionality assumption, though did reveal that the p-value for Job Satisfaction approached significance (p = .053). Schoenfeld residuals were also plotted against time and visually inspected for any violations of proportional hazards. The plots did not reveal any violations of the proportional hazard assumption. See Appendix B for the plotted Schoenfeld residuals.

Table 4.

Extended Cox Regression models with time-varying covariates (N=68)

Predictor	Estimate (b)	*SE* (b)	*p*	HR (e^b)	95% CI for HR
Model 1:					
Tenure	-0.27	0.21	.19	0.76	[0.51-1.14]
Model 2					
Tenure	-0.30	0.22	.17	0.74	[0.48-1.14]
Job Alternatives	-0.17	0.12	.15	0.85	[0.67-1.06]
Burnout	-0.40	0.40	.32	0.66	[0.30-1.47]
Job Satisfaction	-1.04	0.30	.0005**	0.35	[0.20-0.63]
Model 3					
Tenure	-0.31	0.22	.16	0.74	[0.48-1.13]
Job Alternatives	-0.27	0.12	.14	0.84	[0.67-1.06]
Burnout	-0.24	0.40	.29	0.65	[0.30-1.44]
Job Satisfaction	-0.99	0.30	.001**	0.37	[0.20-0.67]
Shocks	-0.03	0.49	.55	1.03	[0.93-1.13]
Model 4					
Tenure	-0.33	0.22	.14	0.72	[0.46-1.11]
Job Alternatives	-0.09	0.12	.46	0.91	[0.72-1.16]
Burnout	-0.62	0.43	.15	0.54	[0.23-1.24]
Job Satisfaction	-0.65	0.34	.06.	0.52	[0.27-1.01]
Shocks	0.06	0.05	.25	1.06	[0.96-1.16]
Job Embeddedness	-1.02	0.49	.04*	0.36	[0.14-0.94]

Note. HR = hazard ratio; CI = confidence interval; Job Alternatives = Perceived Job Alternatives

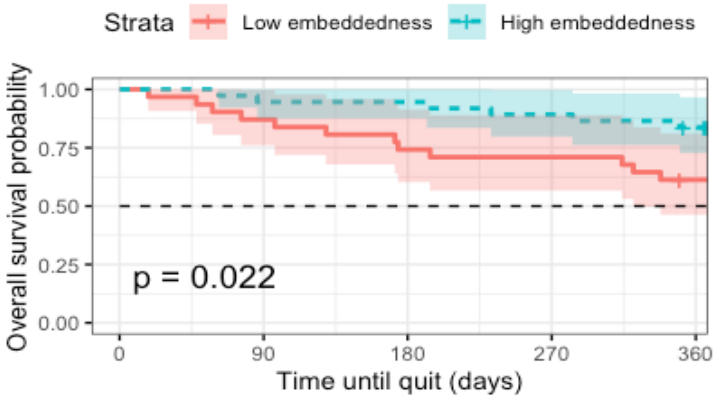
Post-hoc Analyses

Comparing survival distributions for varying levels of embeddedness. To further explore the effects of job embeddedness on therapist turnover, results from a log-rank test were plotted to compare the survival distributions for highly embedded participants versus participants with low or average levels of embeddedness. To facilitate the comparison of survival probabilities, job embeddedness was dichotomized at its mean score and a dummy variable was created to identify a *high embeddedness* group and a *low embeddedness* group within the participant sample. The dichotomy values for the log-rank test were derived by defining individual scores above the sample mean score as *high embeddedness* (coded as "1" in the log-rank analyses), and measure scores at or below the mean as *low embeddedness* (coded as "0" in the log-rank analyses). Note that for standard log-rank analyses, time is defined as a longevity variable representing the total length of time a participant remains in the study until they experience an event (e.g., turnover) or are censored. Therefore, as standard log-rank tests cannot accommodate time-varying covariates, only baseline job embeddedness data is used for these analyses.

The results of the log-rank test suggest a significant difference in the likelihood of survival (i.e., retention) between the high and low embeddedness groups ($X^2 = 5.2$, $p = .02$). Figure 3 displays the survival curves for the *high embeddedness* and *low embeddedness* groups plotted with their respective 95% confidence bands. Since too few participants in the high-embeddedness group had experienced turnover by the end of the study period, statistical comparisons of median survival times between the groups could not be calculated. However, a visual examination of the two slopes in Figure 3

appears to reveal a relative *survival* advantage for highly embedded participants compared to participants with low or average levels of embeddedness.

Figure 3.
Log-rank analyses for high-embeddedness and low-embeddedness groups



Bivariate analyses for job embeddedness subscales. To gain additional insight into how job embeddedness relates to therapist turnover, we computed exploratory, bivariate extended cox regressions for each job embeddedness dimension- and subdimension-scale. Bivariate analyses for the two dimension scales—organization embeddedness (i.e., on-the-job embeddedness) and community embeddedness (i.e., off-the-job embeddedness)—were calculated first. As seen in Table 5, results indicate that the organization embeddedness dimension score significantly predicts turnover (*ß* = - 1.10, *p* <.001). The presence of a negative coefficient and significant p-value suggests that as levels of organization embeddedness increase the risk of turnover decreases. The regression coefficient for the community embeddedness dimension was also negative; however, the association was not significant (*ß* = - 0.65, *p* = .06). Although the p-value of the community embeddedness score approached significance, it did not pass the .05 threshold. Bivariate analyses were also computed for the six sub-dimension embeddedness scales; results mirrored findings from the higher-order dimension analyses. All three organization embeddedness subdimension scales were shown to be significant predictors of turnover, with all relationships in the expected direction [organization fit (*ß* = - 0.62, *p* = .009), organization links (*ß* = - 0.63, *p* = .001), and organization sacrifice (*ß* = - 1.00, *p* < .001)]. These findings indicate that as scores in each organization subdimension increased risk of turnover decreased. None of the three community embeddedness subdimension scales were significant predictors of turnover when measured at the bivariate level; though all regression coefficients were in the expected direction [community fit (*ß* = - 0.39, *p* = .09), community links (*ß* = - 0.50, *p* = .26), and community sacrifice (*ß* = - .39, *p* = .11)]. Findings should be interpreted with caution as analyses were underpowered and exploratory in nature.

Table 5.
Bivariate time-varying Cox Regression for job embeddedness subdimensions

Predictor	Estimate (b)	*p*	HR (e^b)	95% CI for HR
JE Composite (total)	-1.30	< .001***	0.27	[0.14-0.51]
JE Organization (total)	-1.10	< .001***	0.33	[0.19-0.55]
JE Community (total)	-0.65	.06	0.52	[0.26-1.00]
JE Organization Fit	-0.62	.009**	0.54	[0.34-0.86]
JE Organization Links	-0.63	.001**	0.53	[0.36-0.78]
JE Organization Sacrifice	-1.00	< .001***	0.37	[0.21-0.64]
JE Community Fit	-0.39	.09	0.67	[0.43-1.10]
JE Community Links	-0.50	.26	0.61	[0.25-1.50]
JE Community Sacrifice	-0.39	.11	0.68	[0.42-1.10]

Note. HR = hazard ratio; CI = confidence interval of HR; JE = Job Embeddedness

Time-invariant Cox Regression. We conducted an exploratory time-invariant Cox Proportional Hazards analysis to assess whether using time-varying data methods for our primary analyses provided any benefit over a standard time-invariant technique (see Table 6). The person-period data structure used for time-varying analyses is inappropriate for a time-invariant model. While a time-varying method is able to link participants with each of their associated time intervals, a time-invariant method would treat each time interval as a unique participant. As an example, the 68 participants in our study sample contributed a total of 240 observation points across the study period (i.e., Time interval 1 = 68 observations/surveys completed; Time interval 2 = 60 observations; Time interval 3 = 58 observations; Time interval 4 = 54 observations (68 + 60 + 58 + 54 = 240)). An extended cox regression analyzing time-varying predictors would calculate analyses using a correctly estimated sample size of 68 participants. Alternatively, a time-invariant Cox Proportional Hazard method would incorrectly estimate the sample size of the person-period dataset to be 240 participants. Therefore, before computing the time-invariant Cox analyses, the data was restructured so that only the baseline predictor data, the turnover status variable (did they quit or not), and the longevity time variable were included in the time-invariant dataset. In these analyses, predictor baseline values were used to predict therapist turnover status at the end of the 12-moth observation period.

To facilitate comparisons between the time-invariant and time-varying models, the same stepped model building approach from the time-varying primary analyses was used. Tenure was added to Model 1 and perceived alternatives, burnout, and job satisfaction were added in Model 2 The shocks sum score was added to Model 3 and the aggregate job embeddedness score was added to Model 4. The overall models for

Model 2 ($X^{2=}$ 11.57; df = 4; p = .02) and Model 3 ($X^{2=}$ 11.59; df = 5; p = .04) were significant in predicting turnover. Model 4 approached significance ($X^{2=}$ 12.55; df = 6; p = .05); [Model 1 overall test ($X^{2=}$ 1.94; df = 1; p = .16)]. Across all four time-invariant models, only Job satisfaction demonstrated some ability to independently predict turnover, as seen in Model 2 ($ß$ = - 0.77, p = .002) and Model 3 ($ß$ = - 0.77, p = .003). None of the other predictor variables were independently significant in the final model. These non-time varying models were then compared with the time-varying analyses. While a direct statistical comparison cannot be made given that the models cannot be considered as nested models, model comparisons using the AIC statistic may provide some indication of the goodness of fit across the models. Comparing AIC scores from the full time-invariant model (*AIC* = 150.56) to the full time-varying model (*AIC* = 143.33) revealed that the AIC for the time-varying analyses were lower, which may suggest that time-varying models better fit our turnover data. These results, although underpowered and exploratory in nature, provide some support to suggest an advantage to measuring turnover more frequently across time.

Table 6.
Cox Proportional Hazard Regression models with time-invariant covariates

Predictor	Estimate (b)	*SE* (b)	*p*	HR (e^b)	95% CI for HR
Model 1: Time-invariant					
Tenure	-0.28	0.21	.18	0.76	[0.51-1.14]
Model 2: Time-invariant					
Tenure	-0.27	0.23	.24	0.76	[0.49-1.20]
Job Alternatives	-0.09	0.14	.50	0.91	[0.70-1.19]
Burnout	-0.25	0.41	.55	0.78	[0.35-1.74]
Job Satisfaction	-0.78	0.25	.002**	0.46	[0.28-0.76]
Model 3: Time-invariant					
Tenure	-0.27	0.23	.24	0.77	[0.49-1.20]
Job Alternatives	-0.09	0.14	.51	0.91	[0.70-1.19]
Burnout	-0.25	0.41	.54	0.78	[0.35-1.73]
Job Satisfaction	-0.77	0.26	.003**	0.47	[0.28-0.77]
Shocks	0.01	0.04	.87	1.01	[0.93-1.10]
Model 4: Time-invariant					
Tenure	-0.28	0.23	.22	0.76	[0.48-1.18]
Job Alternatives	-0.05	0.14	.74	0.95	[0.72-1.26]
Burnout	-0.33	0.43	.43	0.72	[0.31-1.65]
Job Satisfaction	-0.56	0.34	.10	0.57	[0.29-1.12]
Shocks	0.02	0.04	.74	1.02	[0.93-1.10]
Job Embeddedness	-0.64	0.65	.32	0.53	[0.15-1.88]

Note. HR = hazard ratio; CI = confidence interval; Job Alternatives = Perceived Job Alternatives

Exploratory Analyses

Shocks descriptive summary. Note that the shocks variable included in these exploratory analyses differ from the shocks sum score variable included in all prior analyses. For example, the shocks sum score variable included in the prior analyses represents a within-person variable measured at the individual level; the value of the individual-level shocks sum score is a simple sum score created by summing all shock categories that a participant endorsed on the Distinct Events Checklist (DEC). In comparison, the shocks variable included in these exploratory analyses represents a group-level variable that is computed at the level of the shock category. The values of this exploratory shocks variable represent the number of individuals who endorsed each specific shock category on the DEC.

As discussed in the Data Analytic Plan, survey measures, including the shocks measure, were completed at the start of each time interval; only turnover status was collected at the end of each time interval. As displayed in Table 7, for each time interval, participants were separated into two groups, a *turnover* group and a *stayer* group. Participants were placed in the "turnover" group if they left within that time interval, while participants were included in the "stayer" group if they had *not* left their organization by the end of each time interval. Count scores and relative risk scores were calculated between the two groups.

For ease of comparison, only the baseline exploratory shocks scores are presented in Table 7 below; however, see Appendix C (Tables C1-C3) for exploratory shock scores across each of the four time intervals. The total sample size at baseline (i.e., time interval 1) was $N = 68$. Eight participants voluntarily left their organizations by the end of time interval, and so the size of the turnover group for time interval 1 in Table

7 was *n* = 8; the stayer group for time interval 1 was n=60. As can be observed in Table 7, the overall study sample generally appeared to endorse a large number of shocks, with more than half of the total sample (57.4%) reporting that they had experienced the same shock event—*high turnover within a short period*–within the last three months. This same shock was also endorsed as the most frequently experienced shock across both the turnover (75%) and the stayer (48.5%) sub-samples. The next four most frequently endorsed shocks in the turnover subsample included *high turnover within a short period (75%), learned about a job opening (75%), recruited for another job (62.5%),* and *friend at work quit (62.5%).*

Relative risk scores are ratio scores that represent the probability of an event occurring in the turnover group compared to the probability of the event occurring in the stayer group. In considering relative risk scores for time interval 1, it appears that therapists are 7.5 times more likely to quit within a 3-month period if they have *recently returned to work after being on extended leave*. Additionally, therapists are more than 3 times more likely to quit if they had realized they could not accomplish their career goals at their current job or if they had recently experienced the death of a loved one. Therapists were also more than 2 times more likely to quit if they: *learned about a job opening, experienced an* i*ncrease in barriers to accessing trainings and/or benefits, had a friend(s) at work quit, experienced a major change in their job without adequate notice or support, observed that* m*ajor decisions were made by their organization without therapist input, they experienced* a m*ajor change(s) in physical work setting, and/or* they were *recruited for another job.*

Because Table 7 presents only the time interval 1 data and because our small sample size for the turnover group limits the strength of claims that can be made,

differences between the most frequently endorsed shocks for the turnover group and the stayer group are considered exploratory. They may offer some insight into the distinct events that may increase a therapist's likelihood of turnover.

Table 7.

Shocks endorsed by participants (Time interval 1 data only)

	Turnover Sample *n=8*		Stayer Sample *n=60*		RR
Shock description	n	%	n	%	
Recently returned from extended leave	2	25	2	3.3	7.58
Realized could not accomplish career goals at current job	3	37.5	8	11.8	3.18
Death of a loved one	2	25	5	8.3	3.01
Learned about a job opening	6	75.9	16	26.7	2.84
Increase in barriers to accessing trainings and/or benefits	2	25	7	10.3	2.43
Friend(s) at work quit	5	62.5	18	26.5	2.36
Major change occurred without adequate notice or support	3	37.5	11	16.2	2.31
Major decisions were made without therapist input	4	50	15	22.1	2.26
Major change(s) in physical work setting	1	12.5	4	5.9	2.12
Recruited for another job	5	62.5	18	30	2.08
Increase in workload without increase in pay	4	50	19	27.9	1.79
High turnover in a short period	6	75	33	48.5	1.55
Major reorganization/merge	2	25	11	16.2	1.54
Positive change in major relationship	1	12.5	5	8.3	1.51
Important request(s) denied or not prioritized	1	12.5	6	8.8	1.42
Change in supervisor or director	3	37.5	18	26.5	1.42
When requested support, received none/inadequate	2	25	13	19.1	1.31
Own health concerns emerged	3	50	24	40	1.25
Realized more valuable than currently paid	3	37.5	21	30.9	1.21
Became licensed	1	12.5	8	11.8	1.06
Major or frequent policy and/or procedural changes	1	12.5	8	11.8	1.06
Encouraged to apply for a new position	1	12.5	8	11.8	1.06
Experienced a major shift in job tasks	1	12.5	10	14.7	0.85
Loved one experienced a decline in health	2	25	18	30	0.83
Conflict or negative interaction occurred	1	12.5	11	16.2	0.77
Sudden change in work climate	2	25	23	33.8	0.74
Increase in client crises	2	25	24	35.3	0.71
Realized personal goals necessitate more money or flexibility	1	12.5	21	35	0.36

Note. The table is sorted in descending order based on the RR column; RR = relative risk.

Discussion

The current study implemented a prospective, longitudinal, repeated measures design to examine factors related to turnover in a sample of EBP-trained community mental health therapists. To our knowledge, this study is the first to apply the Unfolding Model of Turnover (UMT) to the therapist workforce by assessing two core constructs related to this theory: job embeddedness and shock events. Specifically, we tested whether job embeddedness (Hypothesis 1) and shock events (Hypothesis 2) enhanced prediction of voluntary therapist turnover beyond traditionally studied turnover constructs, including tenure, perceived job alternatives, burnout, and job satisfaction. Findings revealed job embeddedness significantly predicted therapist turnover and captured unique variance when added to the full model. Although all therapists who left their organizations reported experiencing a shock event, the number of shocks experienced was not a significant predictor of turnover. These findings have several important implications that warrant further discussion.

Findings from the current study suggest that job embeddedness may operate as a protective factor against therapist turnover. In the current sample of community mental health therapists, higher levels of job embeddedness predicted a lower probability of turnover when all other model variables were held constant. More specifically, every 1-unit increase in job embeddedness was associated with a 64% reduction in the daily likelihood of therapist turnover. Additionally, findings revealed that job embeddedness captured unique variance in turnover even after controlling for commonly included, typically significant predictors of turnover, such as job satisfaction and burnout. These findings provide compelling support for the applicability of job embeddedness to the study of therapist turnover, as satisfaction is one of the most frequently used measures

when studying turnover across the helping professions (Crossley et al., 2007; Eby & Rothrauff-Laschober, 2012; Garner et al., 2012; Knight et al., 2011, 2012) and within the wider turnover literature (Griffeth, et al., 2000; Harman et al., 2007, Rubenstein et al., 2018). The suggested utility of incorporating job embeddedness into the study of therapist turnover is further strengthened by findings across other helping professions, which have demonstrated that job embeddedness is able to predict turnover beyond job satisfaction and perceived job alternatives (Crossley et al., 2007; Holtom & O'Neill, 2004; Jiang et al., 2012). Additionally, the significance of job embeddedness in the prediction of therapist turnover is further supported by the findings of the log-rank analyses. These analyses suggest that therapists with high levels of embeddedness had a relatively higher likelihood of survival compared to therapists with medium and low levels of embeddedness.

An examination of the job embeddedness subscales provided further insight into the mechanisms that may underlie the construct's possible protective effects against turnover. The organization embeddedness dimension score and each of the three organization subdimension scores—links, fit, and sacrifice—were strong independent predictors of turnover and will be discussed in greater detail in the subsequent paragraphs. Although the broader employee turnover literature has found evidence for community, or *off-the-job*, factors of job embeddedness to be related to turnover, none of the three community embeddedness subscales in the current sample were significant predictors in our sample. This result is somewhat surprising, given that the community embeddedness subscales measure non-work elements not typically captured by the attitudinal variables most commonly included in turnover studies (i.e., job satisfaction, organizational commitment). Therefore, community embeddedness may offer greater

potential to capture unique variance above more traditional predictors of turnover (Holtom & O'Neill, 2004; Mitchell et al., 2001). Recent reviews in the broader turnover literature may help to explain these results (e.g., Holtom, 2017; Rubenstein, 2018). Recently conducted recent scoping reviews have suggested that the relative strength of community embeddedness versus organizational embeddedness as a predictor of turnover may be influenced by the *context* in which participants are answering the survey questions. Generally, organizational embeddedness appears to be the stronger predictor of turnover in studies focused mostly on job-related constructs. In contrast, community embeddedness appears to be the stronger predictor in studies that are more heavily focused on off-the-job factors (see Rubenstein et al., 2018 and Holtom et al. 2017 for further discussion). Given that the current study was focused primarily on on-the-job factors, our findings are in-line with the broad patterns reported in these reviews.

In reference to the significant findings related to all three organizational embeddedness subdimension scores, some interesting overlap emerges when these sub dimensions are compared to literature conducted in the context of turnover in the helping professions. Starting with fit, the embeddedness subdimension of organizational fit can be defined as the fit between an employee's values, career goals, and their organizational culture (Mitchell et al., 2001). The element of organizational fit that has received the most support in the literature on turnover in the helping professions is the connection between organizational culture and turnover.

Comprehensive reviews that have reported findings associated with organizational culture across a variety of professions have established a strong link between organizational culture and organizational performance, including the effects of organizational culture on turnover (Hartnell et al., 2011; Sackmann, 2011). A number of

studies establishing the importance of organizational culture to organizational outcomes have also been conducted specifically within child welfare and the mental health field (e.g., Glisson & Green, 2006; Glisson et al., 2012; Glisson, et al., 2013; Olin et al., 2013; Yoo & Brooks, 2005). Within the helping professions, the influence of proficient organizational cultures on turnover has recently emerged in the literature. A proficient culture is defined as "agency expectations and norms for [provider] competence, up-to-date knowledge, and prioritization of client well-being" (Glisson et al., 2013). In child welfare agencies, proficient cultures have been shown to moderate the relationship between turnover and client outcomes Additionally, findings from a recent study examining turnover of EBP-trained therapists indicated that the enhancement of a proficient culture may serve as a possible mechanism for increasing therapist retention (Beidas et al., 2016). The definition of a proficient culture indicates that it may map on well to the definition of the organization fit subdimension of job embeddedness. Most obviously, both constructs emphasize the importance of culture, and the "competency" and "up-to-date knowledge" aspects of proficient culture may overlap with the career goals element of organizational fit. Additionally, the "prioritization of client well-being" seems like it may align closely with the "values" aspect of organizational fit.

Additionally, the strategies the authors suggested for developing a proficient culture appear to generally map on well to the organization dimension of job embeddedness (Beidas et al., 2016; Mitchell et al., 2001). Suggestions included increasing recognition for therapists' use of EBPs in verbal and monetary ways, which appears to align well with embeddedness *fit* dimensions related to therapists' goals and values. Additionally, the study suggested increasing training, supervision, and peer consultation, which would serve to increase organization *links* by strengthening and

increasing the number of connections a therapist creates within their organization. Support for the applicability of the organizational links embeddedness subdimension in retaining therapists may be found across a number of constructs including studies that have looked at leadership variables in relation to turnover including constructs such as leader member exchange, and transformational leadership (e.g., Aarons et al., 2006). Effective supervision may mediate or provide protection from the negative impact of stressful work demands by offering both emotional and social support (Kadushin & Harkness, 2002; Mor Barak et al., 2001; Sterner, 2009). The crossover between organizational sacrifice and constructs studied within the mental health workforce is less clear however, as the job embeddedness sacrifice items are non-specific. Therefore, it is likely that the sacrifice dimension is one that may be more context and career specific than the fit and links dimension of job embeddedness. Therefore, additional research is likely needed to identify the specific factors that contribute to the organizational sacrifice subdimension for community therapists. Qualitative research in particular may be a helpful next step for gathering this information. Qualitative research may serve to enhance both the breadth and depth of understanding the elements that contribute to the sacrifice dimension for community-based therapists.

Although we did not find support for a shocks sum score as a direct predictor of turnover, a descriptive examination of shocks and enriched our understanding of shocks as they relate to community-based therapists and revealed important areas for future study. For example, one of the most frequently endorsed shocks in the turnover group was "a high amount of turnover in a short period of time." This shock overlaps with the idea of turnover contagion (Felps et al. 2008) where a series of prior turnovers may produce a cumulative effect on remaining employees by increasing the salience of

quitting decisions. Another frequently reported shock in the turnover group was "a friend at work quit." The frequency with which the job embeddedness links subdimension appeared in the turnover group raises questions about whether certain shocks may be more potent than others given that the shock may directly affect levels of job embeddedness by reducing the number of links. Interestingly, when looking at the relative risks between turnover and stayer groups, risks appeared higher for shocks related to fit and values, such as not being involved in important decisions or access to trainings being made more difficult. These shocks analyses are preliminary examinations of this construct, and more research is needed to understand which shocks are most impactful on therapist turnover as well as the best way to analyze shocks and their impact to better understand turnover.

In addition to expanding current knowledge of therapist turnover predictors, findings from this study support the advantages of measuring turnover antecedents over time. The majority of turnover studies in the extant literature has relied on cross-sectional designs to study the antecedents of turnover. Organizational behavior (OB) scholars have noted the limitations of cross-sectional designs and claimed that an overreliance on designs that provide only a snapshot of the turnover process stalls scientific advancement. Prominent researchers in OB have made calls for research that considers time as a factor in the turnover process (e.g., Holtom et al., 2008; Rubenstein et al., 2018). As suggested in the Unfolding Model, studying turnover variables across time is key to capturing the dynamic nature of turnover decisions. The turnover process involves “an evolutionary confluence of personal, situational, and accidental forces on the decision to leave an organization” (Lee & Mitchell, 1991, p. 118). The current study built upon recommendations in the broader turnover literature to study temporal

components of the employee turnover process (e.g., Rubenstein, 2018; Nyberg & Ployhart, 2013). This study examined the temporal relationship between time-lagged scores of shocks, job embeddedness, work attitudes, and therapist turnover. The current study also compared time-varying survival models to time-invariant survival models to assess for any relative advantage of one model over the other. The comparison indicated an advantage to using time-varying methods, as the time-varying model was shown to be a better fit for our turnover data. Overall, utilizing time-varying methods appeared to increase our understanding of predictors of therapist turnover. Results from the time-varying model supported the applicability of job embeddedness to the EBP-trained workforce. Our findings suggest that researchers may benefit from adopting a longitudinal, repeated measures approach to understanding turnover. As the extant literature suggests and the current findings support, implementing such an approach would better capture the underlying processes of turnover as they evolve over time. By capturing the dynamic nature of these variables and the turnover process in general, understanding of context-specific risk and protective factors of therapist turnover would improve and thereby help to facilitate the development of effective retention strategies.

Strengths and Limitations

The current study provided an opportunity to contribute unique findings to the literature on therapist turnover. Strengths of this study include the use of a prospective, longitudinal, multi-wave research design that allowed us to better capture the dynamic and time-varying unfolding process of employee turnover. These design characteristics and the use of advanced time-to-event survival analyses allowed us to examine the impact of turnover and retention variables on therapist employment decisions across

time. The current study built upon recommendations in the literature to consider and incorporate the role of time when studying turnover (e.g., Hom et al., 2017; Nyberg & Ployhart, 2013; Rubenstein et al, 2018), which may have provided a more accurate understanding of how and why turnover may occur for therapists working in community-based settings. Another strength is that the length of the study allowed for the use of actual turnover as an outcome. The longitudinal design and measurement of *actual* turnover status sets this study apart from the majority of employee turnover studies—in the helping professions and within the broader turnover literature—as the majority of turnover studies use cross-sectional designs and rely on turnover *intention* as a proxy for turnover. Although longitudinal studies often encounter higher rates of missing data due to loss to follow-up, the current study was able to maintain a high participant retention rate (98.5%). Additionally, our longitudinal, multi-wave study design allowed for use of time lag techniques when structuring the data, which reduces the risk that reverse causality could bias results.

Several limitations should also be considered when interpreting the results from this study. We did not recruit participants using random sampling methods, instead, our sample represents individuals who responded to a call to participate in a study focused on therapist turnover and retention. Additionally, participants were not drawn from a nationally representative sample, which may limit generalizability beyond publicly-funded service systems in Washington State. Because we did not include a comparison group of non-EBP-trained therapists, we cannot draw conclusions as to whether findings are unique to EBP-trained therapists. All study data relied on surveys that were self-reported, and so findings are subject to the inherent limitations of self-report data (e.g., Podsakoff et al., 1986; 2012). Additionally, it is possible that some of our selected

measures were not suitable for adequately capturing the intended constructs. For example, we originally selected our single-item measure of perceived job alternatives for the purpose of minimizing possible confounds. However, single-item measures, especially when used in smaller sample sizes, may negatively affect the validity of the measure, and have increased vulnerability to response bias and context effects (Kopalle & Lehmann, 1997). Additionally, our shocks measure and the way in which we operationalized shocks as a sum score may also have been inadequate or inaccurate in capturing the shocks construct. Additional testing (e.g., cognitive interviewing; factor analyses) is needed to refine the shocks measure and enhance its usefulness. Our limited sample size and number of observed turnover events also restricted the number of variables we could include in our analyses. In survival analysis, to obtain adequate analytic power, recommendations for the minimum number of events per variable range from 5 to 15 (Vittinghoff et al., 2007; Harrell, 2015). Therefore, we had to be selective in which variables to include, and so other potentially important variables, such as organizational climate, were excluded from analyses. These power-related restrictions also prevented us from being able to conduct multi-level analyses. The relatively small number of observed events (i.e., 19 turnover events) also meant that we were underpowered to include interaction terms in models or test for mediation, limiting ability to understand the possible interrelationships between predictor variables. Compared to the large sample sizes typically seen in studies using survival analysis, the relatively small sample size may also at least partly account for the nonsignificant findings related to tenure, perceived alternatives, and burnout. Despite these limitations, findings from the current study have important implications for future research.

Implications

This study adds to the literature by highlighting factors associated with turnover for EBP-trained therapists. If therapists are at an increased risk of turnover when they have low levels of job embeddedness, then organizations may benefit from regularly assessing these variables. Although similar in concept, turnover and retention are separate constructs suggested to have their own unique set of antecedents. While the current study measured job embeddedness in relation to turnover, job embeddedness is emphasized in the literature as a framework related to employee retention. In addition, given that job embeddedness is measured as a causal indicator model that captures the forces that contribute to employees staying at their jobs, the measure itself can be used to facilitate the development of targeted retention strategies (Mitchell, et al., 1999). In light of the critical workforce shortages of mental health providers, job embeddedness may be a helpful tool to utilize in attempts to decrease the current high rates of turnover and increase therapist retention. Incorporating periodic assessments of job embeddedness may help to inform the development of retention strategies that can help organizations to stabilize their therapist workforce.

Thus, successful EBP implementation likely requires effective strategies to enhance both the training and retention of skilled therapists (Garner et al., 2012). Since high turnover rates of EBP-trained therapists threaten EBP sustainment within organizations, measuring an organization's average levels of job embeddedness may serve as useful pre-implementation metric for assessing the likelihood of that organization being able to achieve and maintain EBP sustainment. If an assessment reveals low levels of job embeddedness at an organization, retention interventions may need to occur before EBP training efforts are initiated to ensure a higher likelihood of EBP sustainability. Assessing job embeddedness in the early stages of the

implementation process may help to inform the judicious use of resources (e.g., time, money) when planning EBP implementation efforts.

Conclusions

This study adds to the current knowledge of factors related to EBP-trained therapist turnover by using advanced methodology and time-varying analytical techniques to test the applicability of two novel constructs from the field of organizational behavior: job embeddedness and shocks. Job embeddedness independently predicted turnover even when entered into a model containing variables that are known to be consistent predictors of therapist turnover (i.e., job satisfaction and burnout). In the current study, for every 1-unit increase in job embeddedness, the risk of turnover decreased by 64%. When job embeddedness was disaggregated to its dimension and subdimension forms, the community dimension of job embeddedness was not a significant predictor of turnover; however, the organizational dimension of job embeddedness and each affiliated subdimension (organizational links, fit, and sacrifice) were strong predictors of turnover. Shocks, when treated as a sum score, did not predict therapist turnover in the current study, though each therapist who experienced turnover had reported experiencing a shock at some point during the study period. Additional research is needed to refine the measurement of shocks and to further assess the role they play in therapist turnover decisions. Findings from the current study suggest that it may be beneficial for organizations and implementation researchers to measure therapists' levels of job embeddedness. Routinely assessing job embeddedness may enhance turnover prediction and may help to facilitate a proactive approach to reducing turnover rates and increasing therapist retention.

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Appendix A: Distinct Events Checklist

Distinct Events Checklist

With this measure, we are trying to capture how often certain events occur and the strength of their effects. More specifically, we want to know about *jarring events*, which are events that disrupt the "status quo" or general pattern of your typical day-to-day routine and may prompt thoughts related to leaving your job. These events can be expected or unexpected; positive, negative, or neutral; and can occur at work or in one's personal life.

Instructions: As you read through the list of events below, please mark all events that have occurred in your life in the last **3 months**. You will be asked follow-up questions for the events you marked. If you have not experienced a listed event, then leave that item blank and move to the next item.

***Note:** The examples listed for some of the items below are provided to help demonstrate how broadly event categories can be interpreted.

Personal life events:

1. Moved to a new residence (can be temporary or permanent)
   Examples: Moved into a house you just bought, moved to a different apartment, moved in with a relative while your home is under construction
2. About to have a baby/adopt a child or just learned were pregnant/approved for adoption
3. Loved one's health declined, and/or they needed a greater level of care
   Examples: more frequent doctor/hospital visits, parent moving in with you
4. Own health concerns emerged and/or someone who cares for you acknowledged/pointed out your stress, exhaustion, health, etc.
   Examples: started getting frequent migraines, a friend said they were worried about how stressed you seemed
5. Advised to/decided you will need to take extended time off in the near future to address own health issues/needs
   Examples: surgery, illness
6. Recently returned to work after being on leave/taking extended time off
   Examples: maternity/paternity/family leave, taking time off to focus on health issues/needs, recovery from surgery
7. Change in personal or family goals/plans (and needing more money and/or flexibility to meet those goals)

Examples: decided wanted to save up to buy a house, planning to go back to school, decided to start a family/add a new member to the family

8. Death of close friend or family member
9. Threat to your personal safety/wellbeing
   Examples: car accident, mugged, apartment robbed
10. Change in or loss of support at home or in the community
    Examples: family moved out of state, partner deployed, longtime nanny/babysitter moved away
11. Major shift in finances (financial loss and/or taking on major additional financial burden)
    Examples: partner lost job, major rent increase, started daycare/switched to higher cost daycare, started paying college tuition for child or partner
12. Major separation of relationship with a significant other
    Examples: separation, divorce, break up
13. Major positive change in relationship with a significant other
    Examples: reconciliation, moving in together, got engaged, got married)

Work-related events:

Instructions: Below, please select "Yes, occurred" for all work-related events that you have experienced in the last **3 months**. If you have not experienced a listed event, leave that item blank and move to the next item.

14. A sudden change in the work climate at your site and/or organization as a whole
15. A change in supervisor or director
    Examples: your supervisor left, your director moved to a different site, a new director was hired
16. A close friend at work quit
17. High turnover at your site in a short period of time (Can be across or within groups (such as peers, support staff, supervisor, upper management, etc.))
18. A major reorganization or merge
19. A major change to physical work setting
    Examples: moved buildings, major renovations/upgrades to work space, change in quality or availability of equipment, heat/cooling systems malfunctioning
20. Became licensed
21. Realized you couldn't accomplish job/career goals at current organization
    Examples: hours for licensure, specialized training, working with certain client population, told that your goals are not a priority to the agency
22. Realized you are more valuable than what you are getting paid

Examples: learning of pay discrepancies, learning of others with fewer trainings/qualifications being paid more to do the same or less

23. Learned about a job opening (outside of current organization) that seemed like an attractive option
24. Approached about/recruited for another job outside of current organization (formally or informally)
25. An increase in difficulty around trying to access trainings, specialized learning, benefits, rewards, etc.
26. An increase in workload, duties, or hours without corresponding increase in pay, benefits, direction, and/or support

    Examples: being assigned to a committee, pressure to "donate" hours
27. Noticeable shift in job tasks

    Examples: major change in client population, increased number of assigned intakes, more case management than therapy
28. Reached out for help/support and received none or the support you received was inadequate
29. A major (or period of frequent) policy or procedural level change

    Examples: change to open access, change to EMR, RSN requirements, paperwork requirements, productivity, shift from salary to hourly
30. Higher ups made a major decision without consulting clinicians and/or didn't follow through on advice/feedback etc. provided by clinicians
31. Major change made without adequate notice and/or without enough support or information to properly adhere to the change in a timely manner
32. An increase in (or period of frequent) subpoenas and/or court appearances
33. An increase in the number of clients on your caseload who are court mandated to attend treatment and/or clients required to attend treatment to be able to access psychiatric care/prescription medication
34. An increase in the number of crises clients assigned, or multiple clients going into crisis during the same period (this could also include increase in mandated reporting events).
35. Experienced discrimination at work
36. Conflict or negative interaction with someone at work

    Examples: treated unfairly, invalidated, excluded, or accused of something you didn’t do, publicly criticized or felt publicly embarrassed, someone broke trust and shared something you told them privately/in confidence
37. Were encouraged to apply and/or applied for a promotion or different position within the organization
38. Had a request denied and/or did not get something you were promised but that you felt was very valuable/needed

    Examples: denied a pay increase, denied a promotion/shift to another role, denied a switch in your work schedule, denied a training or important learning opportunity

39. Safety incident occurred, or safety concerns not validated or taken seriously
40. Other personal-life or work-related events: _____
    [*You will have the option to enter & complete responses for up to 5 "other" events]
    40a. Please provide a brief description of the event:
    _____

**If you have read through all of the events above, and none of the listed events have occurred in your life in the last 3 months please mark the following box to indicate that you read through the survey but have not experienced any of the listed events:*

[ ] No distinct or jarring events occurred in my life in the last 3 months

Comments:

_____
_____
_____
_____
_____

Supplemental material for the Distinct Events Checklist.

The current study did not analyze data obtained from the follow-up questions included in the Distinct Events Checklist. The follow-up questions are listed below for informational purposes only.

The Distinct Events Checklist was designed to populate up to three follow-up questions for each event item a participant endorsed. *The three questions are listed below as "A", "B", and "C". Questions "A" and "B" populated for every event item endorsed; question "C" also populated for every event item endorsed, unless a participant marked "None" for their response to question "B".*

Details:

- *The follow-up questions "A" and "B"* appeared for each event item a participant endorsed.
- *The appearance of follow-up question "C" was contingent on a participant's response to question "B":*
  - *Question "C" did not appear if a participant marked **"None"** as their response for question B*
  - *Question "C" did appear if a participant marked any response option other than "None" for question "B" (i.e., if **1, 2, 3, 4, 5 to 10,** or **More than 10** was marked)*

Distinct Events Follow-up questions (populated for each event item endorsed):

A. How many events in this category occurred in your life in the last 3 months?
Response options: **1 | 2 | 3 | 4 | 5 to 10 | More than 10**

B. How many of these events prompted you to question whether you could or would want to stay working at your organization*? **even if only briefly*
Response options: **None | 1 | 2 | 3 | 4 | 5 to 10 | More than 10**

C. Among the event(s) in this category that prompted you to question if you should stay at your organization, please choose the event that has affected you the most and use the sliding scale to indicate how much it has affected you*:
Response options: **Mark a number on the sliding scale [ranging from 1 (a very small extent) to 100 (a very great extent)] to indicate how much the event has affected you**

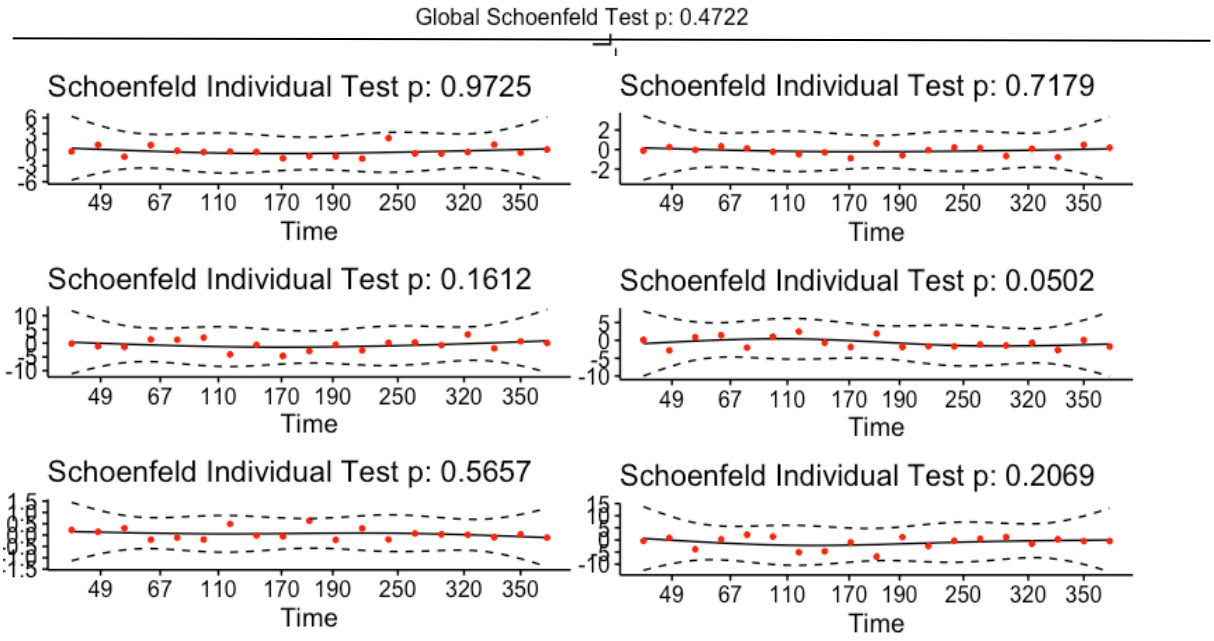
**In thinking about how much an event has affected you, you can consider any of the following: (1) the overall level of disruptiveness it has had on your life, (2) the emotional impact it has had on you, (3) how much you've needed to shift your behavior in response to the event, (4) how much or how long it will continue to affect you/your life moving forward*

|1|----------|100|

Appendix B: Plotted Schoenfeld Residuals

Figure B1

Visual plot of Schoenfeld Residuals to investigate proportional hazards assumptions



Note: Top left: Organizational tenure; Middle left: Burnout; Bottom left: Shock sum score; Top right: Perceived Alternatives (reverse scored); Middle right: job satisfaction; Bottom right: job embeddedness (aggregate score)

Appendix C: Shocks Count Scores

Table C1.

Personal shocks endorsed by therapists across four time intervals

	Time 1[a]		Time 2[b]		Time 3[c]		Time 4[d]	
	TO	STAY	TO	STAY	TO	STAY	TO	STAY
	n=8	*n*=60	*n*=2	*n*=58	*n*=4	*n=54*	*n*=5	*n=49*
Shock description	*COUNT SCORES[#]*							
Own health concerns emerged	4	24	1	23	2	17	1	8
Realized personal goals necessitate more money and/or flexibility	1	21	1	23	1	14	1	8
Loved one experienced a decline in health	2	18	-	16	-	10	1	19
Major financial change	-	9	-	12	-	5	-	5
Death of a loved one	2	5	-	5	-	3	-	3
Positive change in a major relationship	1	5	-	2	-	3	1	3
Moved residences	-	5	-	4	-	1	-	-
Recently returned from extended leave	2	2	-	-	1	1	2	0
Loss of a major support	-	3	-	4	-	2	-	-
Separation in a major relationship	-	3	-	3	-	1	-	-
Welcomed a new child/baby	-	2	-	4	-	3	1	1
Scheduled upcoming extended leave	-	2	-	3	1	1	-	1
Experienced a threat to safety	-	2	-	1	-	2	-	-

Note. TO = Turnover subsample; STAY = Stayer subsample, or sample of participants who had not turned over before or within the listed time interval; a = the total sample size(stayers and leavers combined) for Time Interval 1: 68; b = total sample size for Time Interval 2: 60; c = total sample size for Time Interval 3=58; d = total sample size for Time Interval 4=54; # = Count Scores refer to the number of therapists who endorsed each shock

Table C2.
Work-related shocks endorsed by therapists across four time intervals

	Time 1[a]		Time 2[b]		Time 3[c]		Time 4[d]	
	TO	STAY	TO	STAY	TO	STAY	TO	STAY
	n=8	*n*=60	*n*=2	*n*=58	*n*=4	*n=54*	*n*=5	*n=49*
Shock description	*COUNT SCORES[#]*							
High turnover in a short period	6	33	1	29	1	20	1	15
Recruited for another job	5	18	1	13	1	16	1	12
Increase in client crises	2	24	1	16	2	17	2	13
Sudden change in work climate	2	23	1	27	2	9	1	9
Realized more valuable than currently paid	3	21	1	25	1	14	1	10
Friend(s) at work quit	5	18	2	18	1	11	1	6
Increase in workload without increase in pay	4	19	1	8	-	15	1	12
Learned about a job opening	6	16	1	23	4	14	3	17
Change in supervisor or director	3	18	1	16	2	13	-	14
Major decisions were made without therapist input	4	15	1	13	1	9	-	12
When requested support, received none/inadequate	2	13	-	12	-	7	-	6
Major change occurred without adequate notice or support	3	11	1	8	1	6	-	7
Major reorganization/merge	2	11	-	12	-	7	-	3
Conflict or negative interaction occurred	1	11	1	13	-	11	3	6
Realized could not accomplish career goals at current job	3	8	-	7	1	8	-	5
Experienced a major shift in job tasks	1	10	1	6	-	5	-	5
Became licensed	1	8	-	4	-	3	2	2
Increase in barriers to accessing trainings and/or benefits	2	7	-	9	-	5	-	4
Major or frequent policy and/or procedural changes	1	8	1	5	1	5	-	9
Encouraged to apply for a new position	1	8	1	9	-	7	1	6
Important request(s) denied or not prioritized	1	6	1	4	-	4	-	2
Experienced discrimination	-	3	-	5	-	3	1	2
Scheduled an extended leave	-	2	-	3	1	1	-	1
Major change(s) in physical work setting	1	4	-	3	-	2	-	1
Increase in court- or medication-mandated clients	-	3	1	1	-	2	-	4

Note. TO = Turnover subsample; STAY = Stayer subsample; a = the total sample size(stayers and leavers combined) for Time Interval 1: 68; b = total sample size for Time Interval 2: 60; c = total sample size for Time Interval 3=58; d = total sample size for Time Interval 4=54; # = Count Scores refer to the number of therapists who endorsed each shock

Table C3.

Subset of work-related shocks not endorsed by the turnover group

	Time 1[a]		Time 2[b]		Time 3[c]		Time 4[d]	
	TO	STAY	TO	STAY	TO	STAY	TO	STAY
	n=8	*n*=60	*n*=2	*n*=58	*n*=4	*n=54*	*n*=5	*n=49*
Shock description	*COUNT SCORES*[#]							
Safety incident occurred or concerns not taken seriously	-	7	-	3	-	4	-	3
Increase in subpoenas or court appearances	-	1	-	1	-	2	-	2

Note. TO = Turnover subsample; STAY = Stayer subsample; a = the total sample size(stayers and leavers combined) for Time Interval 1: 68; b = total sample size for Time Interval 2: 60; c = total sample size for Time Interval 3=58; d = total sample size for Time Interval 4=54; # = Count Scores refer to the number of therapists who endorsed each shock