Behavior Analysis in Practice (2020) 13:492–501
https://doi.org/10.1007/s40617-019-00399-6

DISCUSSION AND REVIEW PAPER

On Turnover in Human Services

Byron Wine[1] · **Matthew R. Osborne**[2] · **Eli T. Newcomb**[2]

Published online: 6 January 2020

Abstract
Within the field of behavior analysis, turnover can impact an organization adversely due to the loss of expertise and the required replacement expenses. Turnover in behavior analysis remains poorly understood, and few investigations have studied why employees separate and how to mitigate unwanted turnover. The purpose of this discussion article is to provide an account of turnover, as well as to make recommendations to behavior-analytic service providers regarding how to perform analyses and intervene to decrease employee turnover.

Keywords Human services · Organizational behavior management · Retention · Turnover

It has been observed that, to be effective, human services as a field require a high degree of performance from its employees (Gravina et al., 2018). Moreover, the loss of well-trained and effective employees seems to be problematic for organizations dealing with funding issues related to third-party payers and government agencies (Frederiksen & Riley, 1984). The loss of employees, or turnover, is often cited as a significant concern in human services (Hewitt & Larson, 2007). Despite findings suggesting that turnover can have a negative impact on both service delivery and remaining staff members (Sulek, Trembath, Paynter, Keen, & Simpson, 2017), little research on the topic has been conducted within the field of behavior analysis. This article reviews the literature relevant to turnover in human services in general and discusses topics related to the phenomenon in terms of definition, measurement, cost, and interventions. In addition, this article presents practice-derived recommendations to supplement the nascent state of the empirical literature.

In its simplest form, *turnover* may be defined as the permanent separation of an employee, voluntary or involuntary, from an organization (Society for Human Resource Management [SHRM], 2015). Although this is a relatively straightforward definition, there are several other variables organizations must consider when looking at turnover. For example, employees on furlough, temporary layoffs, employees on leave covered by the Family and Medical Leave Act (FMLA), promotions, transfers, and other types of separations may still be on the payroll of an organization. Because they remain on the payroll, simply counting separations exclude these employees from the turnover calculations. Therefore, this definition alone may be inadequate when agencies are assessing the impact of filling positions as a result of promotion, FMLA, employees on sabbatical, and so forth on their organization. In addition, the concept of turnover is only useful when examined relative to the number of existing and new employees in a given time period.

Calculating Turnover Rate

A standard method for calculating turnover is necessary to compare turnover across organizations and industries. Somewhat surprisingly, there does not appear to be a universal method for calculating turnover. As stated earlier, turnover may simply be measured by the number of individuals leaving an organization (Hayes et al., 2006). Strouse, Carrol-Hernandez, Sherman, and Sheldon (2004) calculated the percentage of employees departing across a time period relative to the total number of positions (e.g., employees leaving, divided by total positions, multiplied by 100).

The definitions listed to this point lead to a somewhat simplified turnover measurement procedure. For example, in defining turnover as the percentage of employees leaving over a

✉ Byron Wine
bwine@faisoncenter.org

[1] The Faison Center and Florida Institute of Technology, 1701 Byrd Ave, Richmond, VA 23230, USA

[2] The Faison Center, Richmond, VA, USA

period of time relative to the total positions in that period of time, Strouse et al. (2004) did not easily account for changes in the number of positions available. However, when discussing turnover, most people are interested in turnover over time in what is typically referred to as *turnover rate*.[1] Any given organization is likely to expand (e.g., providing services to new clients) or contract (e.g., decreasing the number of clients served possibly due to intentional downsizing or to changes in funding regulations) over time, and so the number of employees required at any one point likely varies. SHRM published guidelines on calculating turnover (SHRM, 2015). The SHRM formula has the benefit of accounting for staffing changes over time. Given the lack of empirical precedence and the likelihood that many human resource professionals are accustomed to using this formula, we will present their method.

The formula for calculating turnover percentage is the number of monthly separations divided by the average monthly employee count multiplied by 100. For example, if in June one employee separates and there was an average of 10 employees throughout the month, then the turnover rate would be $1/10 \times 100 = 10\%$. The average number of employees is obtained from taking multiple measures of the number of current employees during the month. This step is important, as the number of employees during a 1-month window may or may not be static as staffing needs expand or contract. Although no guidelines exist on how many measurements to take throughout the month, it seems that more measurements are likely better (i.e., repeated measures), as long as they do not provide too much of a hindrance to completing other important tasks. It seems reasonable that weekly measures are sufficient for many organizations.

Table 1 presents a hypothetical example of an organization with 20 employees at the beginning of January. The hypothetical organization is growing to expand services to new clients. Over the course of the month, the organization hires three new employees and one employee separates. In this example, we would first calculate the average number of employees throughout the month ($20 + 21 + 21 + 21 + 22 / 5 = 21$). One employee separated, so to determine turnover rate, we would divide 1 by 21 and multiply by 100 to get 4.8%.

Turnover is a relatively slow phenomenon (i.e., staff do not leave all at once), and trends may take some time to appear or detect. In other words, it may be necessary to aggregate turnover data into time periods that make the data more meaningful (i.e., the periods are long enough that they may demonstrate trends). For example, in most settings, yearly or quarterly turnover rates are typically of interest to business stakeholders. Given that organizations likely have monthly turnover data readily available, it will be helpful to convert this to quarterly data. To generate quarterly turnover data, simply sum the turnover percentages from the months of interest. Similarly, to generate yearly turnover, sum all 12 months. In Table 1, the rate from January was 4.8%, February was 4.4%, and so on. The turnover rate for the year was 42%. Given that the SHRM formula generates a turnover rate over time, we will reserve the term *turnover* to discuss the phenomenon of employees separating from a company for the remainder of the article. The formula provides a basic framework from which organizations can begin to evaluate turnover rate, but it is still fairly broad.

The SHRM turnover rate formula generates only one number related to turnover and does not provide insight into who is leaving and why—we will address the latter in another section of this article. When studies discuss the turnover rate in human services, they are often speaking of direct care–level employees. However, although direct-care employees are vital, so, too, are the clinicians, administrators, and support staff required to maintain operations. Organizations may want to consider evaluating and tracking direct-care staff separately from clinicians and senior administrators. Clinicians and other senior staff are often older, typically receive more compensation, and often have lower turnover rates than direct-care staff in many healthy organizations. Given that different position types may have different turnover rates, calculating turnover rate across all employees, especially in a smaller organization, may skew the turnover rates for direct-care employees. Once management decides how to best collect data on turnover rates, they can establish a baseline to evaluate both the need for and impact of an intervention to address turnover.

When considering how to calculate and evaluate turnover rate, one must pay close attention to the unit of analysis. Months are the smallest unit of time one can reasonably use to measure turnover, and so the effect of interventions may not be apparent for some time. For example, an intervention designed to decrease turnover may not yield results for several months, or longer, in many settings. This delayed effect of the intervention requires a more patient analysis of data that behavior analysts may not be accustomed to—removing an "ineffective" intervention after a few months may result in the loss of what could have been effective if evaluated over a few quarters. Additionally, because the analysis stretches over such a long period, annual fluctuations may occur that are beyond the control of the organization. It is possible that some months or quarters are more volatile than others. For example, an organization employing many young adults may find that August and May—months roughly correlated with the beginning and end of college classes—contain more separations as the student-employees return to college or graduate and move on.

[1] The term *rate*, used here, originates from the human resources literature describing turnover over time and is expressed as a percentage. As used in this context, the term *rate* does not necessarily construe a behavior-analytic definition.

Table 1 Sample turnover data for 2018

	Jan	Feb	March	April	May	June	July	Aug	Sept	Oct	Nov	Dec	Year
Week 1	20	22	24	26	28	29	28	30	31	33	34	35	
Week 2	21	23	25	26	29	29	30	30	32	34	35	36	
Week 3	21	23	25	27	28	29	30	31	32	34	35	36	
Week 4	21	23	27	27	29	29	30	31	33	34	36	37	
Week 5	22	—	—	—	29	—	30	—	—	34	—	—	
Rate	4.8	4.4	4.0	7.5	3.5	0	3.4	0	3.1	3.0	0	8.3	42%
Hires	3	2	5	2	3	0	2	1	3	2	2	4	29
Separation	1	1	1	2	1	0	1	0	1	1	0	3	12

To evaluate turnover rate in relation to yearly cyclical events, it may be helpful to view turnover rates for particular months or quarters together over time (Newcomb, Camblin, Jones, & Wine, 2019). Figure 1 presents hypothetical data from a human service organization. The *y*-axis is the percentage of turnover rate, whereas the *x*-axis contains successive years graphed by quarter. This graph allows for quarters to be compared together over successive years, which may be required to see trends over time. In Figure 1, the second- and fourth-quarter turnover rates are consistently higher than the first and third quarters. Graphing turnover data linearly over time may make cyclical patterns more difficult to identify if the changes are subtle.

Cost of Turnover

The one area related to turnover in human services that appears to have some empirical evidence is cost. However, these studies take place across a variety of human service settings, and therefore, the findings are difficult to generalize to other settings. Larson, Tolbize, Kim, and York (2016) reviewed several published articles on turnover cost and found the average cost of turnover across the studies was several thousand dollars per employee depending on how the researchers calculated the costs. When reviewing this literature, it seems difficult to derive any specific guidelines without calculating cost in each organization. For example, a private school that uses on-the-job training and loses a single teacher's assistant in a classroom may not incur significant cost. When the teacher's assistant separates, there will be some cost associated with completing paperwork, recruiting, hiring, and training, but the money may be minimal if the loss of a single employee does not interrupt the operations of the classroom. Compare this to a small in-home organization that must train a new staff member before the staff member can bill for services. In such a situation, the loss of even a single employee may result in significant lost revenue and time while the

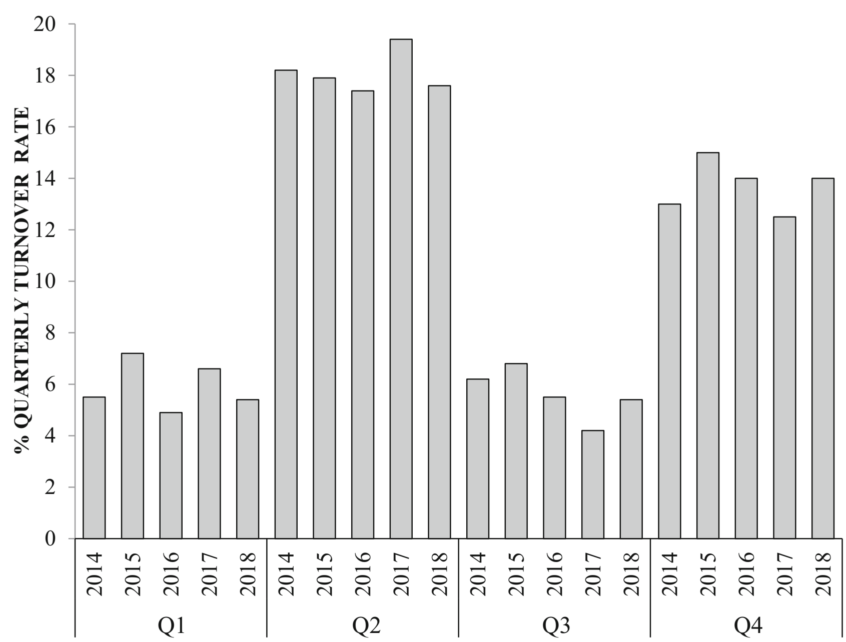

Fig. 1 Sample turnover data graphed by year and quarter

organization finds and trains the staff member's replacement. Due to the variations in services and structure found across organizations, we recommend that each organization calculate the approximate cost of turnover, instead of relying on guidelines.

Larson et al. (2016) presented general guidelines for the costs an organization needs to consider when calculating the cost of turnover. Employee separation often results in certain expenses, which can include additional human resource time directed toward termination procedures, cost of overtime, and cost of other temporary employees required to complete ongoing duties. Once the organization hires a replacement employee, it should calculate the training costs, including materials, file preparation, the time to add the employee to a network, and trainer time. The organization must identify these costs, as well as any others relevant to an organization, and track them over the course of several separations so that it can calculate an actual number related to the organization's specific context. Given the broad nature of behavior-analytic services, some organizations may have special considerations to account for that are related to things such as billing practices, certification, registration, or travel.

Predictors of Turnover

There is a large literature base on turnover outside of human services that extends across many fields. Most of this research focuses on identifying variables that predict or contribute to turnover (Allen, Weeks, & Moffitt, 2005; Dougherty, Bluedorn, & Keon, 1985; Maertz, Griffeth, Campbell, & Allen, 2007; Mitchell, Burch, & Lee, 2014; Mitchell & Zatzick, 2015; Peltokorpi, Allen, & Froese, 2015; Rubenstein, Kammeyer-Mueller, Wang, & Thundiyil, 2018). Most of the studies investigating turnover used correlational methods or regression analyses to identify variables that managers can then presumably attempt to impact. However, despite the attention turnover has received, the data are somewhat mixed, and often-noted predictors of turnover, such as absenteeism, may have inconsistent effects. Berry, Lelchook, and Clark (1985) found in a meta-analysis that there were only mild to moderate correlations between tardiness, absenteeism, and turnover. In a more recent meta-analysis, Heavey, Holwerda, and Hausknecht (2013) investigated a multitude of variables (e.g., pay structure, benefits, turnover intentions, various human resources practices, supervisory relations, alternate job availability, employee age, and employee tenure, among others) to see how they related to turnover. Although the authors identified variables that could influence turnover, they noted that definitive causes of turnover remain elusive.

In the only known analysis of predictors of turnover in behavior analysis, Kazemi, Shapiro, and Kavner (2015) examined predictors of turnover intent (e.g., the degree to which employees state they would leave if another job became available) in behavior technicians. Kazemi et al. (2015) found that self-reported satisfaction with training (i.e., not extensive enough or not relevant to the role of therapist), supervision (i.e., too infrequent, does not value staff opinion, does not care about staff well-being), pay, and different aspects of the job (e.g., lack of professional development opportunities, time spent traveling, under- or overscheduled, negative interactions with coworkers or supervisors) explained approximately 38% of the variance in turnover intentions. Researchers obtained measures of satisfaction from preestablished or adapted scales for each predictor except satisfaction with pay. In the case of training, researchers collected measures of satisfaction on both initial and ongoing training, adequateness of training materials, and training effectiveness. There were a number of measures of satisfaction with supervision, including items focused on supervisor attentiveness, interest in the employees' well-being, and level of fulfillment within their job. Although Kazemi et al. identified satisfaction with pay as a predictor of turnover intention, actual pay was not correlated with turnover (e.g., one employee was satisfied with $15 per hour, whereas another employee was not satisfied with $30 per hour, and the satisfaction, not the actual pay, predicted turnover). Moreover, their results did not reveal a significant relationship between satisfaction with pay and actual pay. In other words, a higher paid employee may have reported poorer satisfaction with pay than a lower paid employee. Finally, Kazemi et al. did not find age or level of education to be predictors of turnover intent in BTs.

For most practitioners, obtaining retrospective data about why an employee separates from the company may be difficult, as there is likely limited to no access to the employee. Furthermore, asking employees about their intent to separate might be difficult, as employees may not feel comfortable talking to their employers about plans to separate, although anonymous surveys may prove useful in this endeavor. Organizations may be able to obtain some information via brief exit interviews from employees once they provide notice of intent to separate. However, readers should view this information cautiously, as there several variables that can influence responding.

Administration of exit interviews is a fairly common practice in organizations, but it is unclear how effective the practice is at identifying variables that allow management to impact turnover (Pace & Kisamore, 2017). Despite the popularity of such tools, many published articles only present case studies or anecdotal accounts of exit interview efficacy (e.g., Harris, 2000). Flint and Webster (2013) reviewed over 1,500 citations and were unable to find empirical evidence of exit interviews being used to objectively decrease turnover. Therefore, organizations may be best served by asking employees for discrete information, such as where they will work next. Asking employees where they intended to go after working with us allowed us to categorize the turnover (described next). The categories allowed us to more specifically focus on types of turnover that we could directly influence such that we developed goals for the both overall turnover rate and the specific type of turnover that was occurring.

Separation Assessment

To obtain specific, potentially useful information, we recently implemented a system whereby we administered an anonymous survey to employees after they provide notice of resignation (Table 2). The main goal of the assessment was to ask what they were going to do next, what they liked most about working in the organization, and what they liked least about working in the organization. The first question, related to where employees were going, allowed for a more nuanced examination of voluntary turnover. The latter two questions required a narrative answer and were analyzed for common themes.

After collecting data on the turnover rate, we created a taxonomy of turnover variations. We decided that an outgoing employee's separation could be categorized as good for the company or the employee (e.g., going back to school, retiring, deciding to be a stay-at-home parent, moving to a new location), neutral for the company or the employee (e.g., family or personal needs, career outside of human services, moving from a part-time to a full-time position in another organization), or bad for the organization or the employee (e.g., promotion or lateral move to another company, termination). We do recognize the inherent problem with terms like *good*, *neutral*, and *bad* as they are value-laden terms. However, these terms seemed easy to use and intuitive to human resources personnel, and we have provided a meaningful definition for each category.

In our taxonomy, *good* turnover was seen as somewhat healthy for our employees in that we provided training and a meaningful experience, and the employees, most of whom were young adults, were making a move that was best for their life goals—that is, we recognize the reality that this type of turnover will happen, and even though we may be losing a high-quality employee, we still plan for it. Although losing employees is difficult, we hope that they speak well of their experience and can use the skills they learned from us in other positions throughout their careers. Although good turnover could be problematic if it occurs at a high rate, it is to be expected and planned for in this industry. One of the most common forms of good turnover we encountered is employees separating to attend school.

Neutral refers to a category that describes events generally attributable to variables outside of the organization's control. This category describes situations in which employees separate for a legitimate reason that may or may not be good for them (e.g., physical or mental health conditions, taking care of ill family members, deciding to leave the human services field). This category, which is neither clearly beneficial for the organization or for the employee, is also to be expected and planned for, and there is not much an organization can do to control this type of turnover.

The final category of *bad* turnover represents employees leaving for reasons that could be, at least partially, attributed to organizational factors. Anytime an employee separates to take a similar job in a new organization, it is typically bad for the old organization (i.e., the employee may be working for a direct competitor). Also, some may consider an employee who separates from an organization for a promotion in another organization to be neutral, but it does suggest that the employee may not have seen a career path in the current organization. We also consider it bad turnover when an organization terminates an employee, and therefore the organization is unable to conduct an exit interview. It is our opinion that, in addition to decreasing turnover overall, an employee retention intervention should more strongly influence the bad category.

We should note that our taxonomy is unique, in that some might say losing a talented employee (e.g., the employee moves across the country) is a bad form of turnover, whereas in our taxonomy we categorize it as good. Due to the characteristics of many employees in our organization (i.e., young men and women, most of whom possess bachelor's degrees), we expect them to occasionally move on to new opportunities—we are accustomed to this as long as they are not leaving to do the same job for a competitor. If we were in another industry, we might consider the loss of talented workers, who might be older and more educated, to be bad. We do acknowledge that the loss of employees in leadership roles for any reason may be considered bad by an organization, and that perhaps our taxonomy is best reserved for direct-care and other entry-level positions. We found that approximately half of our voluntary turnover fell into the bad category. This information was helpful in setting a turnover goal that

Table 2 Sample exit interview

Date: Supervisor:
What did you like most about working for _____?
What did like least about working for_____?
Why are you leaving (select one)?
__New career outside of human services
__Moving away from the area
__Going back to school
__Family/personal
__Promotion at another agency in the same field
__A job at another agency in the same field
__Accepted a full-time position (part-time employees only)
__Other:

included both the turnover rate and the type of turnover. Future research is required to evaluate our categorizations, or any categorization system used in this manner. It could be that decreasing bad turnover, relative to the other two categories, improves some aspect of the organization, but we are unable to make any definitive statements.

Mitigating Predictors Associated With Turnover

As noted earlier, most of the literature on turnover focuses on identifying predictors. In one of the few studies using an experimental design, Aarons, Sommerfeld, Hecht, Silovsky, and Chaffin (2009) demonstrated that turnover was lowest in a group of mental health social service employees when evidence-based practice (EBP) and fidelity monitoring of staff was implemented. Interestingly, the turnover in the EBP plus monitoring groups was lower than in the EBP without monitoring and practice as usual, either with or without monitoring, groups. Although this study has interesting implications, it may not be especially relevant for behavior analysis organizations given that the Behavior Analyst Certification Board® *Professional and Ethical Compliance Code* mandates all certified practitioners rely on empirically validated procedures to inform practice. Presumably, most behavior analysts have already created what amounts to the EBP and fidelity-monitoring condition found to be most effective in the study by Aarons et al.

Strolin-Goltzman et al. (2009) demonstrated how unique interventions to decrease turnover could be developed by gathering groups of employees from all levels of a child welfare organization into work teams. These teams developed interventions that did indeed impact turnover to some degree, but the interventions were not presented in sufficient detail to allow for replication and were noted to be idiosyncratic to each work group. However, one component known as a shadowing program for new employees in the Strolin-Goltzman et al. study does seem to have support in the field of nursing. Fox (2010) detailed a mentoring program wherein new nurses were matched with high-performing veteran nurses for a year. Mentors received a small monetary bonus (25% initially and the remaining 75% when their mentees reached a year on the job). A formal meeting took place to introduce the two matched nurses, and checkups occurred at 4 and 6 weeks to ensure the two were getting along and that regular meetings were taking place. Formal luncheons were held around six months to celebrate progress. Prior to the mentoring program, the hospital setting experienced a turnover rate of 31% of nurses within the first year of employment. There was no turnover in the pilot group, which prompted the hospital to rapidly expand the program. After 2 years, the turnover rate among new nurses dropped from the preintervention rate of 31% to 10%. These programs are reportedly gaining popularity for retaining nurses in hospital settings (Mottet, 2006). We know of no studies that have used this method to decrease turnover in applied behavior analysis (ABA) settings with behavior analysts or behavior technicians.

In the ABA literature, research designed to impact turnover is limited. Strouse et al. (2004) developed an intervention to decrease turnover in residential settings. After conducting an assessment, the authors found that part-time workers separated more than full-time workers. Also, employee schedules varied depending on supervisors. Lastly, the authors found that consistently working Saturdays and Sundays was correlated with increased separations. Using the results from the assessment, the authors implemented an intervention that involved switching from 8-hr shifts to a 12-hr shift across 3.5 days. Shifts were restructured so that employees consistently worked one day, but not both days, of the weekend. Employees also received a small raise, and part-time positions were effectively eliminated. This intervention decreased turnover, demonstrating that practitioners can develop interventions to address specific problems found within an organization (i.e., creating function-matched interventions to address the barriers identified from an assessment).

As referenced previously, Kazemi et al. (2015) identified key predictors of turnover through an examination of turnover intentions within a group of behavior technicians. Findings indicated that 38% of the response variance of surveyed technicians' intentions to separate could be accounted for by four combined variables: satisfaction with (a) training, (b) supervision, (c) pay, and (d) different aspects of their job. Although it may not surprise readers to learn that satisfaction with training, supervision, pay, and various aspects of one's job are, at a minimum, influential on retention, proactively addressing them either independently from one another or through a cohesive system is easier said than done. These findings suggest that behavior-analytic service providers should develop new systems or transplant established systems into their onboarding, oversight, compensation, and professional development systems—whether those be independent or tandem systems.

Newcomb et al. (2019) recently reported on a gamified model of professional development for direct-care staff, whereby they incorporated elements of game design into a system of employee professional development activities and related behaviors. Construction and creation involved several steps, including, but not limited to, identifying (a) skills and competencies that were most valuable to the organization (a private school for individuals diagnosed with disabilities), (b) an efficient delivery system for the development of activities and training for manager and administrator roles, (c) response effort for employees, and (d) appropriate compensation.

The resulting product was a badge-based system whereby direct-care staff acquired and demonstrated a new competency through a personalized system of instruction and demonstration. Following successful completion, employees earned the badge associated with that specific area of development, of which there were eight. Areas of focus included demonstrating high levels of competence with (a) instructional fidelity, (b) the basic visual inspection of data, (c) the use of technical vocabulary, (d) treatment plan description and implementation, (e) the ability to generate equal-interval line graphs using computer software, (f) the preparation and implementation of stimulus preference assessments, (g) the preparation and implementation of skill-based assessments, and (h) the preparation and descriptive data collection for use with functional assessment. Earned badges translated to increases in pay and were associated with widespread organizational recognition, as we publicly posted the badges and displayed them on employee key cards. Though preliminary in scope, a modest decrease in turnover was observed from a preintervention rate of 55.9% per year to 42.5% after the intervention.

Organizations could develop other interventions to address the factors identified by Kazemi et al. (2015). For example, an organization could create a point system for behavior analysts where small performance bonuses are tied to earning points that are awarded for completion of behavior-analytic tasks. Supervisors could award points for presenting at conferences, leading journal club groups, presenting at peer review groups, and so on. Supervisors could provide feedback on performance as the employees complete these tasks and then deliver earned points in a monthly public forum. Tasks could also be anchored so that more difficult tasks are worth more points and only available after employees have succeeded at easier tasks.

The model presented in Newcomb et al. (2019) and the hypothetical point system model previously described both address each of the predictors outlined by Kazemi et al. (2015). First, by devising ongoing training opportunities, they account for employees who are interested in developing additional skills and competencies. Second, the models' interface and mechanics occasion additional and more targeted employee-supervisor interactions. Because the models focus exclusively on professional development, the interactions are abundant with components commonly associated with effective supervision: clear expectations, positive and constructive feedback, and generalized conditioned reinforcement. Third, the gamified model described by Newcomb et al. (2019) exemplifies one way in which to account for satisfaction with pay, by arranging ample opportunities for obtaining increases in pay. The second model provides access to smaller, more immediate pay bonuses for achievement. Both systems are designed to be effective, regardless of whether employees are seeking eventual promotion or desire to remain at their current level and make ongoing contributions by excelling and further developing skills. In both models, entry is elective on the part of the employees, pay is related to acquiring new job-related competencies, and opportunities are available over a continuum of time and at varying degrees of response effort. Finally, several elements of these models overlap with the "job aspect" factors used by Kazemi et al. (2015). To briefly list a few examples of these factors, both systems offer multiple opportunities for ability utilization (i.e., the company makes use of employees' talents) and recognition for their work and contributions, and the badge system provides elevated status through the visual badge stimuli.

Suggestions for Organizations

There is limited literature on turnover in both scope and depth. However, the importance of the topic necessitates evaluation and intervention while the field awaits more empirical investigations. Figure 2 presents the following recommendations, which are based on the available data and clinical practice that the authors have found helpful.

An analysis of turnover begins before employees are hired by an organization. Hiring practices are the first step in influencing turnover. Technicians are typically considered entry-level employees, and so there may be a temptation to hire any potential employee who meets the minimum qualifications. However, some measure of fit (i.e., whether applicants are adequately informed and willing to do the type of work found in human service organizations) with the organization is advisable. Minimally, the person responsible for hiring should include realistic job previews in the interview process. A realistic job preview allows potential employees to sample some aspects of the job and observe others while they complete the job's tasks. This technique has been shown to decrease turnover by presumably allowing employees to weigh the benefits and costs of the job firsthand and decide whether such a position is acceptable (Kupperschmidt, 2002; Premack & Wanous, 1985). Another consideration related to hiring is that there are some data that suggest full-time employees are likely to stay longer than part-time employees (Strouse et al., 2004).

The second step of the taxonomy follows a realistic job preview and functions to ensure EBPs are in place. The techniques for managing small groups of employees are often referred to collectively as performance management (PM). PM techniques include, but are not limited to, objective data collection on employee performance, the implementation of objective goals, and feedback on performance related to the stated goals (Daniels & Bailey, 2014). Although these techniques are beyond the scope of this article to describe in detail, organizations should strive to use these, as well as other established procedures from organizational behavior management (OBM). For a review of OBM studies in human services settings, readers are directed to Gravina et al. (2018).

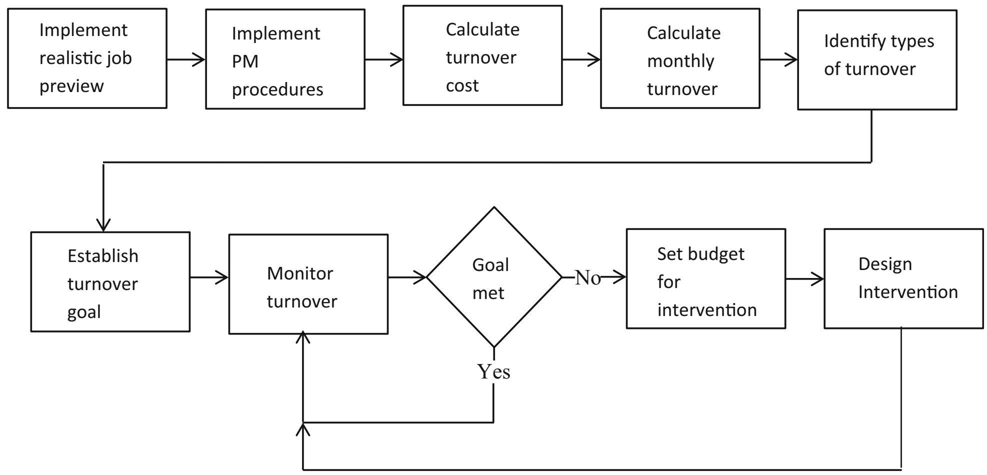

Fig. 2 Flowchart for turnover practices

While implementing and monitoring basic PM practices, employers should generate a detailed analysis of what employee turnover costs their organization at each level. The potential costs presented earlier in the article should be considered, in addition to other idiosyncratic variables (e.g., whether training is automated, the type of background checks required, recruiting costs) related to the organization. Generating an estimate of cost per individual separating from the organization will allow the responsible party to begin to budget for employee loss. Additionally, it is likely that an organization will need to adjust turnover cost over time given that some costs may not be readily quantifiable (e.g., quality of clinical services, availability of senior staff to train).

Employers must calculate turnover rate each month using weekly measures of separations, per the SHRM formula. If management suspects that there may be cyclical patterns (e.g., the beginning and end of academic semesters), they may consider using the graphing conventions presented in Figure 1. When employees provide notice of separation, employers should attempt to gather information related to why they are leaving and develop categories of turnover. Management can use the ongoing turnover data, and the information related to cost, to establish turnover goals unique to the organization.

Setting turnover goals can be difficult but should be based primarily on the cost analysis and turnover rates in the geographic region. If you have relationships with other providers, consider asking for them to share their turnover data—although be prepared to share your turnover data if you ask it of others. As an example, a small organization with 20 direct-care staff members would apply the recommended taxonomy by first implementing sound interviewing and PM procedures. Next, the organization would calculate what turnover costs them. Let us suppose that after conducting a careful cost analysis, they discover that each direct-care staff member lost costs them approximately $3,000. If the organization experiences an annual direct-care turnover rate of 40%, with half of the turnover falling into the bad category, management would know that turnover is costing the organization approximately $24,000 (i.e., about eight employees turning over per year) and that four of the employees are leaving for reasons that may be at least in part under the control of the organization. To implement targeted goal setting, the owner would select a target that is meaningful but achievable. For example, the owner might elect to focus on decreasing the number of bad separations to two employees per year and, correspondingly, overall turnover to 30%.

Having calculated a turnover cost, established a goal, and evaluated ongoing data, management can then budget an intervention, if needed. In the example provided previously, management stands to save $6,000 annually if the organization can reduce turnover to 30%; therefore, management may elect to budget up to that amount (or more if discretionary funds are available) for an intervention. Newcomb et al. (2019) presented one method to address the factors that account for turnover according to Kazemi et al. (2015): training, supervision, pay, increasing job aspects related to making use of employee talents, recognizing skill development, and increasing status. The gamified model presented by Newcomb et al. (2019) is one option to address these aspects in one intervention, but that intervention may not be appropriate in all circumstances, and certainly other interventions could be crafted. For example, the mentorship model presented by Fox (2010) warrants further investigation.

There are many challenges related to human services: the high needs of clients, the stressful job conditions, limited funding, and burdensome regulations, among others. It is likely turnover will always be a concern for employers in human services. The methods of analysis, assessment, and intervention synthesized here through a review of empirical research, recommendations from professional organizations, and clinical practice represent a beginning for behavior analysts. This topic deserves attention from researchers and practitioners to further develop and refine techniques to impact turnover. Although difficult, there are avenues for future research. First, researchers must conduct more thorough research to replicate Newcomb et al. (2019) and other systems designed to address the factors identified by Kazemi et al. (2015). Additionally, researchers have yet to carefully examine the effects of implementing established PM techniques, relative to traditional management techniques, on turnover. Future researchers could also study the proposed taxonomy (e.g., whether the types of turnover warrant tracking, or whether it is possible to decrease bad turnover relative to the other categories and the effect, if any, this has on organizations). Previous studies have begun to evaluate long-term exposure to burnout in the field of behavior analysis, but unlike other fields, researchers have yet to link burnout to turnover (Hurt, Grist, Malesky, & McCord, 2013; Plantiveau, Dounavi, & Virues-Ortega, 2018). Burnout warrants additional evaluation in the behavior-analytic research given the stressful nature of human services. In sum, through careful analysis and planning, it may be possible to impact turnover in a meaningful way in human services organizations.

Author Note Byron Wine, the Faison Center and Florida Institute of Technology; Matthew R. Osborne, The Faison Center; Eli T. Newcomb, The Faison Center.

Compliance with Ethical Standards

Conflict of Interest Byron Wine has no conflict of interest. Matthew R. Osborne has no conflict of interest. Eli T. Newcomb has no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

References

Aarons, G. A., Sommerfeld, D. H., Hecht, D. B., Silovsky, J. F., & Chaffin, M. J. (2009). The impact of evidence-based practice implementation and fidelity monitoring on staff turnover: Evidence for a protective effect. *Journal of Consulting and Clinical Psychology, 77*, 270–280. https://doi.org/10.1037/a0013223.

Allen, D. G., Weeks, K. P., & Moffitt, K. R. (2005). Turnover intentions and voluntary turnover: The moderating roles of self-monitoring, locus of control, proactive personality, and risk aversion. *Journal of Applied Psychology, 90*, 980–990. https://doi.org/10.1037/0021-9010.90.5.980.

Daniels, A. C., & Bailey, J. S. (2014). *Performance management: Changing behavior that drives organizational effectiveness* (5th ed.). Atlanta, GA: Performance Management Publications.

Dougherty, T. W., Bluedorn, A. C., & Keon, T. L. (1985). Precursors of employee turnover: A multiple sample causal analysis. *Journal of Organizational Behavior, 6*, 259–271. https://doi.org/10.1002/job.4030060404.

Flint, A., & Webster, J. (2013). Exit interviews to reduce turnover amongst healthcare professionals [Review]. *Cochrane Systematic Reviews, 28*, 1–27. https://doi.org/10.1002/14651858.CD006620.pub3.

Fox, K. C. (2010). Mentor program boosts new nurses' satisfaction and lowers turnover rate. *Journal of Continuing Education in Nursing, 7*, 311–316. https://doi.org/10.3928/00220124-20100401-04.

Frederiksen, L. W., & Riley, A. W. (Eds.). (1984). *Improving staff effectiveness in human service settings: Organizational behavior management approaches*. New York, NY: Routledge.

Gravina, N., Villacorta, J., Albert, K., Clark, R., Curry, S., & Wilder, D. A. (2018). A literature review of organizational behavior management interventions in human service settings from 1990 to 2016. *Journal of Organizational Behavior Management, 38*, 191–224. https://doi.org/10.1080/01608061.2018.1454872.

Harris, D. H. (2000). The benefits of exit interviews. *Information Systems Management, 17*, 17–20. https://doi.org/10.1201/1078/43192.17.3.20000601/31236.3.

Hayes, L. J., O'Brien-Pallas, L., Duffield, C., Shamian, J., Buchan, J., Hughes, F., et al. (2006). Nurse turnover: A literature review. *International Journal of Nursing Studies, 43*, 237–263. https://doi.org/10.1016/j.ijnurstu.2005.02.007.

Heavey, A. L., Holwerda, J. A., & Hausknecht, J. P. (2013). Causes and consequences of collective turnover: A meta-analytic review. *Journal of Applied Psychology, 98*, 412–453. https://doi.org/10.1037/a0032380.

Hewitt, A., & Larson, S. (2007). The direct support workforce in community supports to individuals with developmental disabilities: Issues, implications, and promising practices. *Mental Retardation and Developmental Disabilities, 13*, 178–187. https://doi.org/10.1002/mrdd.20151.

Hurt, A. A., Grist, C. L., Malesky Jr., L. A., & McCord, D. M. (2013). Personality traits associated with occupational "burnout" in ABA therapists. *Journal of Applied Research in Intellectual Disabilities, 26*, 299–308. https://doi.org/10.1111/jar.12043.

Kazemi, E., Shapiro, M., & Kavner, A. (2015). Predictors of intention to turnover in behavior technicians working with individuals with autism spectrum disorder. *Research in Autism Spectrum Disorders, 17*, 106–115.

Kupperschmidt, B. R. (2002). Unlicensed assistive personnel retention and realistic job previews. *Nursing Economics, 20*, 279–283.

Larson, S. A., Tolbize, M. S. A., Kim, O., & York, B. (2016). *Direct support professional turnover costs in small group homes: A case study*. Minneapolis: University of Minnesota, Research and Training Center on Community Living.

Maertz Jr., C. P., Griffeth, R. W., Campbell, N. S., & Allen, D. G. (2007). The effects of perceived organizational support and perceived supervisor support on employee turnover. *Journal of Organizational Behavior, 28*, 1059–1075. https://doi.org/10.1002/job.472.

Mitchell, M., & Zatzick, C. D. (2015). Skill underutilization and collective turnover in a professional service firm. *Journal of Management Development, 7*, 787–802.

Mitchell, T. R., Burch, T. C., & Lee, T. W. (2014). The need to consider time, level, and trends: A turnover perspective. *Journal of Organizational Behavior, 35*, 296–300.

Mottet, L. M. (2006). *Nurse mentor magic: Training for nurses*. Dubuque, IA: Simon & Kolz.

Newcomb, E. T., Camblin, J. G., Jones, F. D., & Wine, B. (2019). On the implementation of a gamified professional development system for direct care staff. *Journal of Organizational Behavior Management. Advance online publication.* https://doi.org/10.1080/01608061.2019.1632243.

Pace, V. L., & Kisamore, J. L. (2017). Strategic exit interviewing: Encouraging voice, enhancing alignment and examining process. *Journal of Organizational Effectiveness: People and Performance, 4*, 59–75. https://doi.org/10.1108/JOEPP-03-2016-0023.

Peltokorpi, V., Allen, D. G., & Froese, F. (2015). Organizational embeddedness, turnover intentions, and voluntary turnover: The moderating effects of employee demographic characteristics and value orientations. *Journal of Organizational Behavior, 36*, 292–312. https://doi.org/10.1002/job.1981.

Plantiveau, C., Dounavi, K., & Virues-Ortega, J. (2018). High levels of burnout among early-career board-certified behavior analysts with low collegial support in the work environment. *European Journal of Behavior Analysis, 19*, 195–207. https://doi.org/10.1080/15021149.2018.1438339.

Premack, S. L., & Wanous, J. P. (1985). A meta-analysis of realistic job preview experiments. *Journal of Applied Psychology, 70*, 706–719. https://doi.org/10.1037/0021-9010.70.4.706.

Rubenstein, A. L., Kammeyer-Mueller, J. D., Wang, M., & Thundiyil, T. G. (2018). "Embedded" at hire? Predicting the voluntary and involuntary turnover of new employees. *Journal of Organizational Behavior, 40*, 342–359. https://doi.org/10.1002/job.2335.

Society for Human Resource Management. (2015). How to determine turnover rate. Retrieved from https://www.shrm.org/resourcesandtools/tools-and-samples/how-to-guides/pages/determineturnoverrate.aspx

Strolin-Goltzman, J., Lawrence, C., Auerbach, C., Caringi, J., Claiborne, N., Lawson, H., et al. (2009). Design teams: A promising organizational intervention for improving turnover rates in the child welfare workforce. *Child Welfare, 88*, 149–168.

Strouse, M. C., Carroll-Hernandez, T. A., Sherman, J. A., & Sheldon, J. B. (2004). Turning over turnover: The evaluation of a staff scheduling system in a community-based program for adults with developmental disabilities. *Journal of Organizational Behavior Management, 23*, 45–63. https://doi.org/10.1300/J075v23n0204.

Sulek, R., Trembath, D., Paynter, J., Keen, D., & Simpson, K. (2017). Inconsistent staffing and its impact on service delivery in ASD early-intervention. *Research in Developmental Disabilities, 63*, 18–27. https://doi.org/10.1016/j.ridd.2017.02.007.

Weiss, D. J., Davis, R. V., England, G. W., & Lofquist, L. H. (1967). *Manual for the Minneapolis satisfaction questionnaire*. Minneapolis: University of Minnesota, Industrial Relations Center.