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Construct-Oriented Development of a Biodata Scale of Quitting Behavior

Chris D. Fluckinger[1], Andrea F. Snell[1], and Michael A. McDaniel[2]

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Abstract

Although biographical data (biodata) has been predictive of turnover, there is no established scale designed specifically to measure attrition or quitting behaviors. The purpose of this study is to develop and test the structure of a biodata scale of quitting behaviors developed with construct-oriented scale construction. Using a large community sample (N = 702) covering different geographical regions, ethnicities, education levels, and military experience, exploratory and confirmatory factor analysis revealed five dimensions of quitting behaviors: quitting, perseverance, interdependence, commitment and coping. This basic structure was demonstrated to be invariant across different education levels and gender. We believe that this biodata scale will be a useful tool for human resource professionals and researchers interested in predicting and measuring turnover and attrition.

KEYWORDS: Biodata; Construct-Oriented Scale Construction; Quitting

Construct-Oriented Development of a Biodata Scale of Quitting Behaviors

Biodata has long been a valuable tool for researchers and human resource practitioners for its relative ease of administration, low adverse impact, and incremental validity in predicting job performance and turnover (Bobko, Roth & Potosky, 1999; Karas & West, 1999; Barrick & Zimmerman, 2005). However, one recurring criticism of biodata as it is often used is its atheoretical nature, as there is often little rational why a given item or scale predicts a certain set of behaviors (Hough & Paullin, 1994; Karas & West, 1999). This is especially true with turnover, quitting and attrition, as there exist few investigations attempting to delineate the construct of these behaviors from a biodata perspective. Hough and Paullin (1994) provide an excellent discussion of the debate over theoretical integration of biodata, and readers are referred there for in-depth discussion.

The relevant aspect of their presentation for this discussion is the description of three basic strategies to develop and key biodata inventories: 1.) the strictly criterion-referenced, empirical approach; 2.) the data-driven, factor-analytic inductive approach; and 3.) the *a priori* rational approach. Any of these strategies can be used to interpret the constructs measured by a biodata inventory; however, they differ on two key dimensions: transparency and structure. When items are deemed useful by the empirical strategy, through their correlations with other variables of interest, it is often not intuitively apparent as to the reason why. On the other hand, the rational approach would tend to only generate items that are transparent in the first place. The inductive approach lies between these two extremes, as less transparent items may be interpretable based on their factor loadings. The argument for the empirical approach is that it produces higher validities, but Hough and Paullin's (1994) qualitative and quantitative review strongly suggests that this is not always the case, particularly in cross-validation on different samples. Given our observation that much of the biodata research regarding quitting and attrition has been conducted with the empirical approach, we propose that a hybrid of the rational and inductive approaches in developing a biodata instrument will represent a meaningful new perspective of the structure of quitting and related behaviors.

Review of Relevant Research

In order to develop the biodata instrument, a thorough review of the research was conducted to determine possible dimensions of quitting behavior. The primary construct is the extent to which individuals have previously engaged in quitting behaviors in various life contexts (i.e., work, school, family commitments, etc.). However, in accordance with prominent withdrawal models, such as the unfolding model of turnover (Lee & Mitchell, 1994), a number of additional factors are associated with the ultimate behavior of quitting, such as reactions to stress, previous withdrawal behaviors (i.e., stealing and absenteeism), job/social embeddedness, and commitment.

The empirical literature describing the antecedents and correlates of turnover and other quitting behavior is used to define and explicate the main construct of interest. A cursory review of this research indicates there are at least two conceptually distinct aspects to the behavior of turnover/quitting. First, many of the correlates reflect different responses to environmentally induced stress, including maladaptive coping behaviors and deviant and/or counterproductive behaviors. Second, the extent to which individuals are engaged or embedded in, or committed to, their environment is strongly related to decisions to quit or stay. After reviewing this literature, we propose that these more subtle behaviors reflect the underpinnings of the ultimate decision to withdraw from a commitment. Thus, in addition to actual quitting and withdrawal behavior, we also propose to measure individuals' past reactions to stress and their behaviors with regards to engagement and commitment in various situations.

Another lens through which to view the organizing theme of our review is the "push/pull" nature of the various correlates. Specifically, there are some factors that push individuals to withdraw from commitments and some factors that pull individuals deeper into an environment. Research on adolescent problem behaviors such as drug use, high school dropout, teenage pregnancy, delinquency and violence typically refer to such influences as risk and protective factors (c.f., Garnier & Stein, 1998). We view behaviors that are linked to quitting as risk factors and behaviors that are linked to continuation of a commitment as protective factors.

Quitting and Job Turnover

Previous turnover research has shown that there are various job attitudes, environmental factors, cognitions, and behaviors that are associated with quitting. In a meta-analysis of the antecedents and correlates of employee turnover, Griffeth, Hom, and Gaertner, (2000) concluded that there are proximal predictors as well as more distal determinants of turnover. The proximal predictors included job satisfaction, organizational commitment, job search, comparison of alternatives, withdrawal cognitions, and quit intentions. Distal determinants included characteristics of the work environment, such as stress, job content, autonomy, and work group cohesion.

The Griffeth et al. (2000) meta-analysis also revealed that there are behaviors associated with turnover. More specifically, they found that higher performing individuals tend to be less likely to quit than low performers. Findings also supported a progression of withdrawal responses in which lateness or absenteeism would be considered mild or moderate forms of withdrawal behavior whereas turnover would be considered to be the most extreme form of workplace withdrawal behavior. Previously engaging in milder forms of withdrawal behaviors, such as absenteeism, was associated with the more extreme withdrawal behavior of quitting. This supports a key tenet of biodata research that past behavior is the best predictor of future behavior (Owens & Schoenfeldt, 1979). Thus, an individual who has a habit of seeking out other jobs and therefore has short tenure in his or her previous jobs will likely repeat the same behavior of seeking out other jobs in the future (Barrick & Zimmerman, 2005). Supporting this argument, Cascio (1976) found that tenure in previous jobs, which was measured with a weighted application blank, predicted turnover. Therefore, it appears that employees who tend to rapidly quit previous jobs are likely to repeat the same quitting behavior in the future.

Barrick and Zimmerman (2005) argue that biodata inventories are generally good predictors of turnover. Similar to Cascio (1976), they found that a biodata measure regarding the number of months applicants worked in their most recent job was predictive of voluntary turnover. Another part of the biodata measure that was also predictive of voluntary turnover dealt with the number of friends and family members working at the organization. The idea is that having friends or family within the organization prior to hire will strengthen commitment to the organization and reduce the likelihood that the individual will leave. This finding regarding friends and relatives in the organization was consistent with other prior research as well (Bernardin, 1987; Breaugh & Dosset, 1989; Breaugh & Mann, 1984).

Weiss (1984) examined the determinants of quitting behavior of production workers at manufacturing facilities. One finding of this study was that workers who had quit a previous job to take the present job were less likely to quit than were the individuals who were unemployed when they applied for the job with the organization. Results of this study also indicated that job complexity is positively correlated with likelihood of quitting. Weiss argued that this finding may indicate that making jobs more complex is unlikely to increase job satisfaction, but matching better-educated workers to the more complex tasks may increase job satisfaction and decrease quitting. Finally, Weiss found that better educated workers were less likely to quit. More specifically, after controlling for alternative opportunities and demographic characteristics, individuals who were high school dropouts were approximately twice as likely to quit and had higher rates of absenteeism as compared to individuals who had completed high school. Thus, this finding provides further support to the notion that past quitting behavior, in this case quitting high school, is related to future quitting behavior.

Quitting as a Response to Stress

Stressful situations can produce intentions to quit or activate feelings toward quitting. This is similar to a basic fight or flight response, which in this case involves persevering and persisting or giving up and removing oneself from the stress-inducing situation, respectively. There are a number of individual differences in patterns of behavior that represent either effectively or ineffectively dealing with a given stressor. This section will illustrate a number of areas that are relevant to the consideration of quitting behavior.

One personal characteristic commonly discussed in the stress literature is hardiness, or also commonly referred to as resilience. This has been defined as a personal resource that includes three components: ability to perceive change as a challenge, maintaining commitment and purpose to tasks, and perceiving personal control over outcomes of events (McCalister, Dolbier, Webster, Mallon & Steinhardt, 2006). With their conception of hardiness as a resource, McCalister et al. provide evidence that people higher in hardiness experience less stress, which then has a positive impact on their job satisfaction. Thus, given equally stressful situations, those with a greater amount of this hardiness resource will demonstrate effective stress management behaviors such as suppressing negative and intrusive emotions, maintaining commitment to their focal tasks, and relying more heavily on available resources, such as supervisor and coworker support (McCalister et al., 2006). Hardiness also has an effect in situations beyond the workplace and on outcomes other than perceptual constructs such as job satisfaction and perceived stress. For example, there is evidence that hardiness is related to somatic symptoms (Bartone, Ursano, Wright & Ingraham, 1989). Research by Bartone et al. indicates that medical care workers working in the aftermath of an airline crash who possessed resources such as hardiness and social support were less likely to experience subsequent illness. Thus, hardy or resilient individuals engage in specific behaviors, such as reframing negative circumstances, utilizing available avenues of social support, and regulating emotions to buffer the effects of experienced stress. These behavioral signs of hardiness, or resilience, serve to protect individuals from engaging in thoughts of quitting or actually disengaging from environments and would therefore serve as useful indicators of maintaining a commitment.

Continuing with the previous discussion, there have been many investigations in the management and human resources literatures into the effects of perceived organizational support (POS), which involves perceptions that the organizations people are involved with value their contributions and care about their well-being. Allen, Shore and Griffeth (2003) demonstrate that high POS, in part defined by participation in decision making processes and taking advantage of growth opportunities, results in lower voluntary turnover and withdrawal. This indicates that people with high perceptions of POS will engage in behaviors such as actively debating and discussing policies as well as being involved with opportunities to learn and develop. Rhoades, Eisenberger and Armeli (2003) also found a similar result, in that high POS leads to lower voluntary turnover; however, this study showed that the effect is mediated by affective commitment. This finding shows that those with high POS will also behave in ways that demonstrate positive feelings and beliefs toward their organization. These protective patterns of behavior are especially crucial in stress-inducing situations.

Another area of personal characteristics likely to influence quitting behavior in the presence of stress involve the extent to which people become preoccupied or indecisive. One of these characteristics is action- vs. state-orientation. State-oriented individuals exhibit behavior that similar to quitting and failure, such as being preoccupied with thoughts of failure as well as thinking and ruminating for extended periods of time (Diefendorff, 2004). Action-oriented individuals, on the other hand, are able to maintain task-relevant thoughts (and are less likely to think about quitting in general) and are also decisive (making a decision and taking subsequent relevant actions to carry out the task). This is also similar to decision-related behaviors such as satisficing and maximizing (Schwarz, Ward, Monterosso, Lyubomirsky, White & Lehman, 2002). Satisficers are similar to action-oriented individuals, as they make decisions based on relevant information in a short amount of time and then take steps to carry out the action. Maximizers tend to consider more (often irrelevant) information, spend a great deal of time thinking or ruminating, and are more likely to experience regret, depression, lower self-esteem, and engage in social comparisons (Schwarz et al.). Decisive, task-focused, and non-ruminative behaviors therefore act as protective factors when individuals are experiencing stressful situations but work to find reasons to stay.

Finally, while most of the research presented in this section has focused around working samples or college students, there is ample evidence that the patterns of behaviors related to quitting is not specific to these samples. Fishbein, Herman-Stahl, Eldreth, Paschall, Hyde, Hubal, Hubbard, Williams and Ialongo (2006) conducted a study with at-risk urban male adolescents.

Many of these participants experienced both chronic stressors (family drug addiction) and acute stressors (legal troubles or deaths in the family). These stressors are often linked to drug and alcohol dependency—except in cases where people had what the researchers defined as high social competency skills. These skills involved using available social resources, making effective and timely decisions, and being able to inhibit aggressive or negative emotions. Similarly, Epstein, Zhou, Bang and Botvin (2007) found that alcohol use was lower among inner-city adolescents who behaved in ways consistent with the above skills, such as changing the subject when the subject of alcohol came up, taking advantage of outlets for support and information gathering, and making timely decisions and following up on them. These results further support our conclusion that the ability to utilize support structures and focus on positive reasons for staying should act as protective factors against quitting.

Embeddedness/Engagement and Quitting

People are less likely to disengage and ultimately quit when they are immersed, engaged or embedded within a given situation or organization. People may demonstrate behaviors consistent with this for a variety of reasons, including functional (preference to do more than just the bare minimum), social (having friends or family nearby or within an organization), or demographic (perceiving similarity in beliefs, ethnicity, religion, goals, etc.). This section will illustrate and discuss behaviors that are likely to occur in relation to peoples' standing on embeddedness and engagement.

Job embeddedness is the overall level at which one has become entrenched in a job. It is generally viewed as a positive, synergistic state with one's surroundings, and conceptually distinct from feeling "stuck" in one's environment. Embeddedness is not only caused by job-related factors, but also social factors, such as links to the community and family ties.

Embeddedness as is typically defined includes three key aspects: the number and strength of various links to surroundings, the extent to which these links support one's goals, and the ease with which these links can be broken (Mitchell, Holtom, Lee, Sablynski & Erez, 2001). There is evidence that a higher degree of embeddedness leads to lower voluntary turnover, as well as increased organizational citizenship behavior (OCB; Lee, Mitchell, Sablynski, Burton & Holtom, 2004). OCBs are also referred to as contextual performance, and are thought to provide the social lubrication for effective performance. Thus, these behaviors, such as helping others, showing new people around, and keeping up with and following organizational policies are indications that a given person is voluntarily putting forth valuable time and effort to create a more positive environment. People who have strong intentions to quit rarely invest this extra time and effort (Lee et al.).

Similar to the concept of embeddedness is engagement and commitment. Engagement is extent to which a person is engrossed in a given task, and has been defined as a "positive, fulfilling and work-related state of mind" (Schaufeli, Salanova, Gonzalez-Roma & Bakker, 2002). Engagement also has three dimensions: vigor, dedication, and absorption, indicating that people who are engaged will complete tasks with energy and positive affect, will find meaning and purpose through task-specific behavior, and will remain task focused until completion (Schaufeli et al., 2002). Closely related to this is the idea of commitment, which also has three dimensions: affective, continuance and normative (Meyer & Herscovitch, 2001). These are very similar to the engagement dimensions, as people with high commitment will associate the relevant target task, goal, or organization with positive feelings and pride, will feel an obligation and cost with disengagement, and perceive pressures (personal and social) to remain committed. Although the concepts of engagement and commitment are typically assessed from an attitude standpoint, there are certainly many behaviors that would be expected of people who are experiencing high levels of either construct. Rhoades et al. (2003) show that high commitment leads to lower voluntary turnover. Schaufeli et al. (2002) provide evidence that engagement is negatively related to job burnout, which is often a precursor to quitting and turnover. Behaviors demonstrated by high levels of engagement and commitment will include OCBs, tactics for framing or interpreting situations to maintain positive affect, and strategies to find purpose and meaning from working on tasks. Based on this research, we propose that prior experiences which indicate an individual has become immersed in an activity and has invested energy in making it successful will act as a protective mechanism for maintaining a commitment.

Although this section's discussion thus far has included the positive behaviors associated with embeddedness and engagement, there are also negative behaviors associated with these constructs that should predict quitting behavior. One such construct is anti-citizenship behaviors (ACB), which are the opposite of OCBs. These types of behaviors include sabotaging others' work, intentionally making others look bad, and framing situations to maintain negative affect and perceptions, such as always finding fault in others or continually focusing on negative aspects of the immediate environment (Ball, Trevino & Sims, 1994). Similar to ACB is the concept of organizational deviance, which involves behaviors that are clearly detrimental to individual work performance (drug and alcohol use while on the job) as well as damaging to the organization (stealing equipment and damaging company property; Bennett & Robinson, 2000). Negative and detrimental behaviors such as ACB and organizational deviance have been linked to turnover (Robinson & Bennett, 1995) and clearly show that a person is unengaged, uncommitted and unwilling to put forth extra time and effort to be successful. These types of behaviors would therefore be viewed as risk factors for actual quitting behavior.

Hypothesized Taxonomy of Quitting Behaviors

Based on our review of the relevant literature, we propose to measure three main categories of quitting behavior. The most obvious is prior quitting behaviors across a variety of situations. The more subtle behaviors that we believe underlie the actual decisions to withdraw from a commitment are reactions to stress and engagement or embeddedness. A full outline of these dimensions can be found in Table 1. Consistent with the contruct-oriented scale development approach (Hough & Paullin, 1994), target situations and behaviors were developed for each of the proposed subscales (see Table 1). These behavioral statements were then directly used to generate items for the biodata instrument. We hypothesized that the biodata items would group as meaningful factors that capture our three main dimensions of quitting behavior: past quitting, quitting as a stress response, and engagement/embeddedness.

Method

Participants and Procedure

This project was part of a larger project. The biodata quitting scale was placed within a larger survey containing personality, situational judgment, and cognitive ability items. Only the biodata instrument is relevant to the current study. All surveys were proctored and took between 30 and 90 minutes to complete.

A community sample was recruited to provide a diverse range of ethnicity, socioeconomic status, education level, military experience, prior work experience, and geographic locations. A diverse sample was deemed important to cover the range of life and work experiences that are thought to be relevant in decisions to quit or disengage. Participants were recruited in college campuses, soup kitchens, flyers placed in labor union shops, and ROTC offices. The final sample consisted of 702 participants, with representation from the US midwest

(*N* = 383), the northeast (*N* = 66) and the south (*N* = 253). The sample had a relatively equal balance between males (*N* = 383) and females (*N* = 319). The majority of the sample was Caucasian (*N* = 510), in addition to Black (*N* = 111), Asian (*N* = 9), and Hispanic (*N* = 45) participants. The sample was moderately educated, as the majority possessed a high school diploma (*N* = 450), although a substantial number had a GED or lower (*N* = 252). A number of participants had prior military experience (*N* = 79), and of those, the majority had completed their tour of duty before leaving (*N* = 53).

Measure

Based on the content areas and target behaviors and situations listed in Table 1, a total of 48 biodata items were generated. Of these items, those which referred to illegal acts (i.e., theft, cheating and property damage) came under heavy scrutiny by human participant review boards and were subsequently removed. Due to space constraints on the survey, other items were removed based on question length and redundancy with other items in a given content area. Twenty-four items were included on the final survey, and the scale demonstrated an acceptable internal consistency reliability ($\alpha = .76$). Responses were recorded on a 1 (*strongly disagree*) to 5 (*strongly agree*) scale with respect to the extent to which each statement reflected the respondent's behavior.

Analysis

The analysis proceeded in three primary steps: exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and tests of measurement invariance across different groups. The decision to use both an EFA and CFA as opposed to simply an EFA approach was based on consistent recommendations from the factor analytic literature that the results of EFAs be tested in confirmatory analyses in separate samples to prevent capitalization on chance and the idiosyncrasies of one particular dataset (Fabrigar, Wegener, MacCollum & Strahan, 1999; Henson & Roberts, 2006). Given these strong recommendations, the total sample was randomly divided into an EFA sample (N = 335) and a CFA sample (N = 367). These sample sizes are large enough to ensure adequate power to interpret loadings and structure (Fabrigar et al, 1999; Hu & Bentler, 1999). After the EFA was conducted, the structure was then applied in a CFA framework. Following model revisions, a multiple groups CFA was conducted with the full sample to test for sources of measurement invariance between different demographic groups.

Results

Exploratory Factor Analysis

A principal axis factoring extraction (PAF) using SPSS software was deemed appropriate given our *a priori* expectations that the behavioral items would be best represented as latent factors. The extraction choice is often based more on theoretical expectations than actual differences in results (Henson & Roberts, 2006), but in situations with items that have low communalities, as is often the case with biodata and behaviorally-based instruments, larger differences between principal components analysis (PCA) and PAF extractions are expected, and the choice of extraction should be backed by solid rationale (Fabrigar et al, 1999). As recommended by Fabrigar et al. (1999), an oblique rotation (Promax) was also applied to determine if the extracted factors were highly correlated.

The results of multiple tests to determine the number of factors to retain are presented in Table 2. Inspection of eigenvalues-greater-than-one criteria indicated the presence of up to seven factors, but the scree plot indicated five factors. Given the tendency of these criteria to overfactor (Fabrigar et al, 1999; Henson & Roberts, 2006; Hayton, Allen & Scarpello, 2004) a parallel analysis was also conducted. Parallel analysis generates random datasets based on the sample data and presents averages of the extracted eigenvalues as well as the 95% confidence interval of the random eigenvalues. The point at which the random values become larger than the raw extracted eigenvalues indicates the point at which subsequent factors do not explain additional meaningful variance. The parallel analysis indicated that no more than six factors could be reliably interpreted. Though important, the parallel analysis also has a slight tendency to overfactor (Hayton et al., 2004). A factor analysis was also run with M*plus* software using maximum likelihood extraction to obtain fit statistics to guide the decision of how many factors to extract. The point at which the RMSEA and CFI indicate moderate-to-good fit is between five and six factors.

The PAF was run again, this time forcing a six factor solution. Two problems became apparent. First, one item demonstrated a very low extracted communality (.136; all other items were > .2) and was removed. Second, the sixth factor was a doublet factor, consisting of two items (the first two items of the scale). Given the limited ability of a two-item factor to represent a stable latent construct, the difficulty in confirmatory model specification for two-item factors, and the probable spuriousness of their relation, one item was removed (the item with the lower communality, an acceptable criterion in dealing with doublet factors (Klein, 1993). Given the interpretational difficulties of the six-factor solution, the EFA was run for a final time forcing a five factor solution. This solution was readily interpretable, and the five factors were labeled quitting, perseverance, interdependence, commitment and coping.

Descriptive statistics, alpha reliabilities and factor correlations can be viewed in Table 3.Given the moderate to large pattern of intercorrelations, the oblique solution was retained. Although perhaps a bit more difficult to interpret than the orthogonal solution, forcing zero correlations between factors does not seem to be a reasonable constraint with this data (Fabrigar et al., 1999). Note that the quitting scale is coded so that higher quitting behaviors are related to lower effective coping behaviors. Also noteworthy are the relatively low alpha reliabilities (ranging from $\alpha = .52$ to $\alpha = .69$). From a classical test theory perspective, these low reliabilities are potentially problematic, but behaviorally-based, biodata items often demonstrate lower internal consistency reliabilities than attitudinal scales (Hough & Paullin, 1994), and low reliabilities often have little impact on the actual structure of a model (Little, Lindenberger & Nesselroade, 1999). Thus, even though the low reliabilities should be interpreted with caution, we believe that given the conceptual fit of the model, and the nature of biodata in general, that the model is still meaningful.

For ease of interpretation, the final scale is presented in Table 4 (note that one item was moved based on the CFA results, as described below). Overall, the EFA-generated five-factor solution did not fit exactly with our *a priori* three-factor model, but the dimensions did emerge in a manner consistent with our rational approach.

Confirmatory Factor Analysis

A series of CFA models were specified to determine whether the EFA model fit the CFA sample, and the results are presented in Table 5. The first model tested the structure specified by the EFA on the CFA sample. All loadings and correlations between latent factors were significant. The fit statistics indicated relatively poor fit to the data, as the CFI (.80) was much lower than cutoffs recommended by Hu and Bentler (1999; propose that CFI values > .95 indicate good fit), and the RMSEA (.055) was short of Hu and Bentler's standards (values < .05 indicate good fit). Thus, modification indices were inspected to determine potential causes for the low level of fit. The largest involved recommending an item to be moved from the perseverance to the quitting factor. This made conceptual sense, as the item involved the behavior of quitting an activity that wasn't going one's way. Fit after moving this item was tested in the Revised 1 model in Table 5, and did improve slightly over the EFA model, but the CFI (.83) was still considerably lower than desirable. An additional model was specified based on modification indices that used a correlated uniquenesses strategy. This strategy is somewhat controversial, and some researchers argue that it should not be used without strong *a priori* reasons for doing so (Cortina, 2002). However, correlated uniquenesses can be justified if there are legitimate reasons that items are related other than their shared cause through a latent factor (Kline, 1998). In this case, uniquenesses were allowed to correlate only if they used similar wordings or described similar situations and resided within the same subscale. In all, four uniquenesses were permitted to correlate, and fit was assessed in the Revised 2 model. This model produced a better fit that is close to acceptable fit by the CFI index (.89) and good fit as indicated by the RMSEA (.041). Overall, the revised model was deemed to produce acceptable fit, and that with a few modifications, the results from the EFA sample generalized to the CFA sample (although the use of correlated uniquenesses should be noted with any interpretation).

An interesting question regarding the five factors of quitting behaviors is whether they are all caused by a second-order factor. Evidence of a higher order factor is provided by a nested model comparison, as the correlations between the five latent factors are removed and modeled through the second-order factor, as demonstrated by Ryan, Chan, Ployhart and Slade (1999). Although the presence of a higher order factor was not specifically hypothesized, it would present evidence that the five factors are caused by one general quitting construct. As presented in Table 5, constraining the relations between factors through a higher order factor resulted in a significant reduction in model fit, as shown by the chi-square difference test. The CFI (.84) and RMSEA (.05) also dropped, providing evidence that a second-order factor structure does not fit the data well. This finding means that the factors represent distinct and somewhat non-overlapping areas of quitting behavior. Given that the revised model fit the CFA sample best, the model was applied to the entire sample. The fit statistics were largely similar and are interpreted as acceptable (though possibly not "good") fit to the data.

Tests of Measurement Invariance

A series of restricted model tests were run to determine whether the model was invariant across different demographic groups. This analysis can provide evidence that the model is measuring the underlying constructs similarly for different groups. Failure to obtain invariance can limit generalizeability of results across demographic groups. As demonstrated by Chen, Sousa and West (2005), the test of invariance (for a first-order model tested here) is a sequential process that first estimates loadings and intercepts for each group (configural invariance), then constrains the loadings to be equal across groups (loading invariance), then constrains the intercepts to be equal across groups (intercept invariance), and finally constrains error variances to be equal across groups (error invariance). A significant chi-square difference test at any step is taken as evidence of noninvariance and the process then ends. The results for education, gender and ethnicity are presented in Table 6 (other demographic variables did not have large enough sample sizes within-group to test for invariance).

Education. High school and non-high school graduates were compared in the first test of invariance. The configural model produced similar, but slightly lower, fit to the model that did not estimate loadings for the groups separately (CFI = .86, RMSEA = .49). Constraining the factor loadings to be equal across the educational groups resulted in nearly identical fit statistics and a non-significant chi-square difference. This indicates that the pattern and magnitude of loadings on the latent factors is equal between those with and without a high school education.

The next step involved fixing the intercepts, or means, of the items to be equal across groups. This model resulted in a significant chi-square difference value, indicating that constraining the item means to be equal reduces is untenable. This result is probably due to the fact that those with a high school education may have higher levels resistance to pressure to quit. Separate correlations between gender and the factors show that those with a high school education have higher levels of perseverance (r = .27, p < .01) and commitment (r = .16, p < .01).

Gender. The configural model fit did not show substantial decrease in fit (CFI = .88, RMSEA = .045), thus allowing the test for factor loading invariance. This model showed nearly identical fit (CFI = .87, RMSEA = .044) to the configural model, and the chi-square difference test was not significant, indicating that the measurement structure was similar for males and females. Constraining the intercepts to be equal did cause a slight reduction in model fit (CFI = .86, RMSEA = .046) and a significant chi-square difference value. This is likely due to the fact that females in this sample were less likely to quit (r = .19, p < .01), are more likely to persevere when faced with difficulty (r = .19, p < .01), are more likely to commit to challenges (r = .09, p < .05), but have less effective coping behaviors (r = -.16, p < .01).

Ethnicity. Caucasians and African Americans were compared in this test of invariance. The configural model did not fit the data well (CFI = .84, RMSEA = .051), indicating that estimating the model for both groups reduced model fit, and preventing further tests of invariance. This is a potential area for concern, because the factor structure and loadings patterns may differ substantially between Caucasians and African Americans. However, the sample size for African Americans was too small in the current sample to fully investigate an alternative factor structure for this group.

Discussion

This study applied the construct-oriented scale development approach, as suggested by Hough and Paullin (1994) to create a biodata scale to measure the construct of quitting behavior. This represents a meaningful contribution to the literature, as no published studies (to our knowledge) have used this strategy to develop a biodata measure for quitting behavior. Biodata can be a valuable predictor of many future job-related behaviors (Bobko et al., 1999), but the reliance on criterion-related scale construction often raises questions regarding the constructs that are measured with various biodata instruments (Karas & West, 1999).

Dimensions of Quitting Behavior

Based on our literature review, we identified a number of categories of behaviors (i.e., absenteeism, theft, reactions to stress, OCBs, etc.) that have been theoretically and empirically linked to quitting and turnover behaviors. This represented the rational component of our rational/inductive hybrid of Hough and Paullin's (1994) construct-oriented scale development protocol. We grouped these categories of antecedents to quitting behavior into 3 groups: prior quitting behavior, protective factors (behaviors resultant of embeddedness, commitment, etc.) and risk factors (avoidant coping, absenteeism, etc.). Although grouping constructs by protective and risk factors is relatively rare in work and organizational psychology, it is often found in stress research (Bartone et al, 1989; McCalister et al., 2006) and substance abuse treatment research (Fishbein et al., 2006; Epstein et al, 2005), which both involve maintaining a course of action in the face of adversity or intense desires to quit or disengage.

The inductive strategy, based on confirmatory and exploratory factor analyses, did not exactly match our *a priori* rational structure. Specifically, instead of arriving at 3 overall factors (quitting, protective factors, and risk factors), both the EFA and CFA supported a 5 factor solution (See Table 1 for placement of items). Interestingly, behaviors originally conceived as protective factors were divided into interdependence and commitment factors, as having others to support and pressure continuation is somewhat distinct from the behavioral tendency to follow through with promises and commitments. Similarly, risk factors were generally divided into perseverance and coping, as engaging in maladaptive behaviors in response to stress and adversity is somewhat distinct from the behavioral tendency of engaging in smaller withdrawal behaviors (i.e., cutting class). These results indicate that a more fine-grained classification of quitting-related behaviors might be more appropriate than protective and risk factors.

Unlike many turnover/withdrawal models, which are conceptualized primarily for work settings, this particular structure of quitting behaviors may apply to numerous settings that are important for selection and assessment with respect to quitting and turnover. Because our rational model was developed based on a broad range of research areas (i.e., work, military, substance abuse and stress) and was tested using a large community sample consisting of a wide range of educational backgrounds, geographical locations, and military experience, these 5 quitting-related factors may be useful in a wide range of contexts, from evaluating the impact of a substance abuse intervention (Fishbein et al., 2006) to understanding employee turnover (Lee & Mitchell, 1994). This rationale is indirectly supported by the tests for structural invariance, which despite mean differences for gender and educational variables, show that the basic structure of the model fits relatively equally for each of the groups.

Limitations and Future Research

Even though the biodata instrument developed here may be valuable to researchers and practitioners, and the quitting structure may be useful for generating additional items, it is also necessary for the scale to demonstrate criterion-related validity. Although beyond the scope of the current study, a key property for instruments to possess applied utility is evidence that they can predict outcomes of interest. Hough and Paullin (1994) note that construct-oriented scales are not likely to display higher or lower criterion-related validities. However, the advantage of beginning from an emphasis on the construct is having confidence in what is actually measured—something that is often lost when biodata items are keyed only with reference to criterion-related validity (Karas & West, 1999).

Also of key interest for future research will be the impact of faking. When used in the context of high stakes testing, such as for selection or job placement, noncognitive measures (biodata included) often show evidence of being faked, in terms of mean differences, changes in factor structure, or reduction in criterion-related validity (Hough & Oswald, 2005). Future research is needed to investigate the effectiveness of the quitting scale in different applied contexts (i.e., military, academic, and work settings) and for different purposes (selection, placement, etc.).

Another related issue for future research might be the response scale used. This study included an agree/disagree scale, although many biodata instruments rely on response scales of discreet behavioral episodes (i.e., number of jobs voluntarily quit). Although items were written to represent specific behaviors (and not abstract behavioral tendencies), it might be the case that more subjectivity could be included in the process of reporting whether behaviors are descriptive of oneself as opposed to traditional counts of past behavior (Nisbett & Wilson, 1977), or compared with *"not at all"/"very often"* anchors (Karas & West, 1999). Additional research could shed light on whether the response choice has a positive, negative, or negligible effect on various psychometric properties of this particular biodata instrument.Finally, more research will need to be undertaken to determine the causes for—and potential solutions to—the generally low internal consistency reliabilities of the five scales (α.= .52-.69). A logical explanation for this finding would be a low number of items per factor, as 4 out of the 5 scales contained 4 items. One solution would be to generate similar items to boost alpha reliability, but that could reduce one of the main reasons to use construct-oriented scales: parsimony. One of the key advantages of construct-oriented biodata scales, in addition to the ease-of-interpretation advantage, is that they generally cross-validate strongly with fewer items required than empirical approaches (Reiter-Palmon & Connelly, 2000). Although relatively low alpha reliability is often found with biodata measures (Reiter-Palmon & Connolly, 2000), this can reduce inferences of construct validity. Efforts to compensate through multi-trait multi-method (MTMM) matrices of similar constructs (such as organizational commitment, job embeddedness and counterproductive work behaviors) might provide additional insight into the construct validity of our quitting dimensions.

Summary

Using the construct-oriented method, we conducted a thorough review of the quitting, turnover, and withdrawal literature to identify key behavioral antecedents of actual quitting behavior, which led to the creation of behavioral items. Based on exploratory and confirmatory factor analyses on a large community sample, this study indicates that quitting behaviors and antecedents of quitting behavior group into five primary dimensions: past quitting behavior, perseverance, interdependence, commitment and coping. This structure, in addition to the finding that the quitting dimensions are not directly caused by a higher-order latent quitting factor, leads to the conclusion that there possibly exists a range of social and work-related behaviors that may be valuable in addition to previous quitting behavior in predicting future quitting behavior. In short, the act of quitting or disengaging from a given situation is related to a rather complex combination of factors such that push or pull individuals.

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Table 1. *Table to guide item generation*

Content Area	*A priori* Group	Target Situations and Behaviors
Quitting	Quitting behavior	Quit a job because of being tired Quit school project or assignments because are too difficult or take too long Quit school because it has nothing to offer me Quit a job because it didn't go as expected Quit activities because they don't go as desired Quit a job before having another job lined up
Not following through	Risk factor	Agree to help friends with something (i.e., give them a ride, help them move) but then didn't show up Sign up for school activities (i.e., clubs, sports teams, committees) but don't go because they aren't interesting
Personal goals	Protective factor	Start saving for something but then quit Make personal goals (i.e., work out more, give up a bad habit) but then give up because it is too difficult Make educational goals (i.e., get a diploma or certificate) and stick to it
Reactions to stress	Risk factor	Dwelt on negative situations that interfered with daily life Denied that bad things were happening Did other things to avoid thinking about problems Put less effort into a situation when facing difficulty
Active coping	Protective factor	Came up with a plan to solve a problem when it came up Focused attention and effort on solving a problem Sought help from other resources to solve a conflict or problem Had someone to talk to when I had a problem
Avoidant coping	Risk factor	Made first priority to get out of the situation (i.e., boss, girlfriend/boyfriend, family) when there was conflict
OCB	Protective factor	Helped coworkers/schoolmates Encouraged others to stick to the task when things got difficult Saw a problem as a challenge to be overcome Did more than what is needed for a project
Dedication	Protective factor	Stuck to task/project until completion
Commitment	Protective factor	Followed through on projects to prevent letting others down Worked on tasks/activities even when they were not enjoyable Completed a goal even if others thought it was okay to quit
Theft/cheating	Risk factor	Cheated because a test was too difficult Took property from work or school and didn't return it
Property damage	Risk factor	Didn't take care of things that weren't personally owned
Absenteeism	Risk factor	Didn't go to work because felt like deserved a day off Cut class to do something more fun with time

Table 2. *Exploratory factor analysis*

	EFA		Parallel Analysis			EFA	
Factor	Initial Eigenvalue	% Variance Explained	Raw Extracted Eigenvalue	Mean Eigenvalue	95^{th} Percentile (PA)	RMSEA	CFI
1	4.20	17.49	3.48	.60	.69	.082	.54
2	2.34	27.19	1.63	.51	.58	.063	.75
3	1.73	34.39	.98	.45	.50	.053	.84
4	1.33	39.92	.60	.39	.44	.048	.88
5	1.28	45.27	.54	.34	.39	.042	.92
6	1.16	50.09	.45	.29	.34	.032	.96
7	1.04	54.43	.29	.25	.29	.026	.98

Notes: Extraction method was Principle Axis Factoring (PAF). RMSEA and CFI values obtained from a supplemental maximum likelihood extraction. RMSEA = root mean square error of approximation. CFI = comparative fit index. PA = parallel analysis.

Table 3. *Factor correlations, alpha reliabilities and descriptive statistics*

Factor	*M*	*SD*	1	2	3	4	5
1. Quitting	2.61	.87	(.69)	-.45**	-.15**	-.23**	-.24**
2. Perseverance	3.48	.75	-.17	(.52)	.16**	.23**	.23**
3. Interdependence	4.03	.46	-.51**	.29**	(.60)	.43**	.19**
4. Commitment	4.06	.50	-.21*	.28**	.31**	(.61)	.15**
5. Coping	3.00	.67	-.25**	.46**	.30**	.24*	(.55)

Notes: Correlations in the upper diagonal and reliabilities based on full sample ($N = 702$). Correlations in the lower diagonal based on the EFA sample ($N = 335$).
*$p < .05$, **$p < .01$

Table 4. *Final quitting biodata scale*

Factor	Item
Quitting	I have left a job because it wasn't what I expected.
	I have quit a job in the past because I didn't feel like doing it anymore.
	I have quit a job before having another job lined up.
	I have quit an activity (i.e., playing a game) because it wasn't going my way.[a]
Perseverance	I have left school because I felt like it didn't have enough to offer me.
	In school, I sometimes cut class because there was something more fun to do with my time.
	In my life, I have known how to stay out of trouble.
	I have started saving money for something (i.e., car, school, electronics) but I spent the money on something else.
Interdependence	When something bad has happened in the past, I saw the problem as a challenge to be overcome.
	I have people who push me to succeed (i.e., parents, siblings, church members).
	I have completed goals even when others around me thought it was okay to quit.
	When I have had a problem I couldn't solve, I tried to get help or information from family, friends or teachers.
	When I have worked with others, I enjoyed being part of a team.
	I have encouraged others to stick to a task when things got difficult.
Commitment	I have followed through with commitments even if I didn't enjoy doing so.
	When I have told someone I would help them with something (i.e., give them a ride, help them move) I always show up.
	In the past, I have followed through on promises because I didn't want to let others down.
	I have gone out of my way to help coworkers or schoolmates.
Coping	When something bad has happened in the past, I refused to believe it was happening.
	I have gotten frustrated in the past when things have not gone as expected.
	In the past, when I had a problem I felt like I was not in control.
	In the past, when things got really difficult, I decided to put less effort into working on the problem.

Note: [a]Item 24 initially loaded on the perseverance scale in the EFA.

Table 5. *Goodness-of-fit summary for confirmatory factor analysis*

Model	χ^2	*df*	CFI	RMSEA	SRMR	$\Delta\chi^2$	Δdf
EFA	432.67	199	.80	.055	.064		
Revised 1	387.76	199	.83	.051	.057		
Revised 2	316.10	195	.89	.041	.05		
Higher order	385.01	200	.84	.050	.06	68.9**	5
Final (full sample)	448.78	195	.88	.043	.05		

Notes: Revised model 1 moved one item to another factor. Revised model 2 allowed four correlated uniquenesses. The final model tested the revised model 2 on the full sample.
*$p < .05$, **$p < .01$

Table 6. *Tests of measurement invariance for education, gender and ethnicity*

Model	χ^2	*df*	CFI	RMSEA	SRMR	$\Delta\chi^2$	Δdf
Education							
Configural	702.44	390	.86	.049	.057		
Loading invariance	718.05	407	.86	.048	.059	24.3	17
Intercept invariance	773.30	424	.84	.050	.063	54.8**	17
Gender							
Configural	661.81	390	.88	.045	.053		
Loading invariance	686.13	407	.87	.044	.058	24.3	17
Intercept invariance	773.37	424	.86	.046	.061	54.8**	17
Ethnicity							
Configural	1009.78	624	.84	.051	.067		

Notes: CFI = comparative fit index. RMSEA = root mean square error of approximation. SRMR = standardized root mean square residual.
*p < .05, **p < .01