Article

Public Personnel Management
2021, Vol. 50(4) 538–558

DOI: 10.1177/0091026020977562
journals.sagepub.com/home/ppm
SAGE

Predictors of Turnover Intention in U.S. Federal Government Workforce: Machine Learning Evidence That Perceived Comprehensive HR Practices Predict Turnover Intention

In Gu Kang[1], Ben Croft[1], and Barbara A. Bichelmeyer[2]

Abstract
This study aims to identify important predictors of turnover intention and to characterize subgroups of U.S. federal employees at high risk for turnover intention. Data were drawn from the 2018 Federal Employee Viewpoint Survey (FEVS, unweighted $N = 598{,}003$), a nationally representative sample of U.S. federal employees. Machine learning Classification and Regression Tree (CART) analyses were conducted to predict turnover intention and accounted for sample weights. CART analyses identified six at-risk subgroups. Predictor importance scores showed job satisfaction was the strongest predictor of turnover intention, followed by satisfaction with organization, loyalty, accomplishment, involvement in decisions, likeness to job, satisfaction with promotion opportunities, skill development opportunities, organizational tenure, and pay satisfaction. Consequently, Human Resource (HR) departments should seek to implement comprehensive HR practices to enhance employees' perceptions on job satisfaction, workplace environments and systems, and favorable organizational policies and supports and make tailored interventions for the at-risk subgroups.

[1]Boise State University, ID, USA
[2]University of Kansas, Lawrence, USA

Corresponding Author:
In Gu Kang, Assistant Professor, Department of Organizational Performance and Workplace Learning, College of Engineering, Boise State University, 1910 University Drive ENGR 329, Boise, ID 83725-2070, USA.
Email: ingukang@boisestate.edu

Keywords
federal government, organizational behavior, public management, turnover, CART analysis

Turnover among U.S. federal government workforces has been of great concern for the last several decades (Pitts et al., 2011). Turnover intention has been widely accepted as a proxy of actual turnover in public administration research (Bertelli, 2007; S. Kim, 2005). There are two rationales for justifying why turnover intention is commonly used by researchers. First, according to the Reasoned Action Approach (RAA; Fishbein & Ajzen, 2010), it is assumed that a person's behavior is determined by their intention to perform the behavior. From this theoretical standpoint, turnover intention is assumed to be the strongest predictor of actual turnover. Empirical evidence supports this claim in the public sector (S. Kim, 2005; Pitts et al., 2011). Second, from a practical perspective, self-reported intention on turnover tends to be more favorable than direct observation on actual turnover by researchers due to some reasons. For instance, turnover intention is ease of use and more cost-effective by measuring employees' self-reported perceptions via surveys than actual turnover with a longitudinal approach. In addition, while observing actual turnover may cause an ethical issue of revealing personal information on leaving their organizations, measuring turnover intention can avoid this kind of ethical consideration by administering surveys anonymously (Dalton et al., 1999).

Cumulative research evidence on turnover intention consistently shows that job satisfaction is significantly and negatively associated with turnover intention (Chiu et al., 2005). According to a 2018 government-wide management report, 68% of federal employees "strongly agree" or "agree" with the statement that they are satisfied with their jobs (United States Office of Personnel Management, 2018). Despite a high level of job satisfaction among federal employees, 33% of federal employees stated they intend to leave their organization in the next year. Thus, given the importance of job satisfaction, other individual and organizational/workplace environmental factors should be examined to better understand why federal employees still intend to leave when they have high job satisfaction.

Many scholars have investigated various antecedents of turnover intentions in federal agencies, including diverse individual characteristics, job characteristics, organizational policies, and workplace environments (i.e., Ertas, 2015; S. Kim, 2012; S. Y. Kim & Fernandez, 2017; Ko & Hur, 2013; Liss-Levinson et al., 2015; Pink-Harper & Rauhaus, 2017; Pitts et al., 2011; Weaver, 2015; Wynen et al., 2013; Wynen & Op de Beeck, 2014). These studies primarily identified numerous main effect predictors in regression models, indicating most of the predictors can be applied to the entire population. However, these regression approaches have some limitations for conducting more accurate prediction on turnover intention. Because they aim for prediction for the entire population, they may not predict variables that impact turnover intentions of a relatively small subgroup within the entire population. In addition, if there are too many predictors in a regression model, results can be difficult to interpret. Because standard parametric methods (e.g., traditional regression models) are unable to examine or uncover complex predictor interactions, a novel and advanced methodological approach is necessary for exploring data more accurately and generating interpretable results.

Prediction of turnover intention yields several important benefits for federal agencies. First, identifying the most important predictors that index risk for turnover intentions provides insight into mechanisms of turnover intentions. Second, characterizing at-risk subgroups allows agency leaders to create more effective and tailored interventions to address turnover intention for a specific subgroup based on an empirical evidence. The current study used Classification and Regression Trees (CART) analysis to efficiently explore numerous predictors to make easily interpretable and accurate predictions of turnover intentions. Using an array of literature-based predictor variables of turnover intentions, this study identifies (a) subgroups of federal employees at higher risk for turnover intentions, (b) significant predictors that index the risk, and (c) suggests tailored interventions.

Literature Review

Predictors of Turnover Intention in Federal Government

Individual characteristics. Prior studies identified that employees' attitude and behaviors are influenced by some individual characteristics: sex, educational attainment, organizational tenure, supervisory status, and racial/ethnic minority. Sex or educational attainment showed inconsistent relationships with turnover intention. While some studies found no significant associations between sex and turnover intention (Wynen & Op de Beeck, 2014), others concluded that males are more likely to leave their organization (Ertas, 2015). Educational attainment is referred to as the level of education that an individual has completed. Some studies indicated that there is no relationship between education level and turnover intention (Liss-Levinson et al., 2015) while others found that employees with higher educational degrees are less likely to quit their jobs (G. B. Lewis, 1991). Despite these inconsistent relationships, most studies have included sex and educational attainment as significant predictors of turnover intentions in the public sector. Regarding organizational tenure, previous studies determined that employees who have worked longer are less likely to leave their organization (Pitts et al., 2011). Turnover rates tend to sharply decline after working more than 5 years and then slowly continue to decline up to about the 15 years (G. B. Lewis, 1991). Longer organizational tenure possibly mitigates employees' intentions to leave. Supervisory status appears to influence employees' decision to leave their organization (Ertas, 2015; Pink-Harper & Rauhaus, 2017; Rubin, 1973; Weaver, 2015). Finally, racial/ethnic minority status has been considered as an important factor that influences employee behavior in the workplace (Weaver, 2015). Creating a favorable work environment for minorities influences their intentions to leave the organization.

Organizational factors. Organizational factors are variables that describe how organizations influence employees and how employees perceive and interact with organizations. Three major domains in organizational factors are (a) job characteristics, (b) organizational policies, and (c) workplace environment (Wynen et al., 2013).

Job characteristics. Based on prior research, five aspects of job-relevant characteristics are considered: job satisfaction, personal accomplishment, workload, meaningfulness, and goal clarity. Regarding *job satisfaction*, previous research findings consistently indicate that job satisfaction is strongly and significantly related to employees' intentions to leave (Liss-Levinson et al., 2015). *Personal accomplishment* is referenced as a favorable aspect of work (Wynen et al., 2013), meaning employees who feel higher personal accomplishment in their job are assumed to be less likely to leave their organization. Regarding *workload*, a heavy workload results in emotional, physical, and mental burnout in the workplace and thus increases employees' intentions to leave (Brannon et al., 2002). Thus, it is assumed that higher workload increases turnover intentions (S. Kim, 2005). *Meaningfulness*, employees' perceptions of how much they think their work is satisfying and meaningful, also influences turnover intention (Ertas, 2015). Employees who think of their work as meaningful are less likely to leave their organizations. Finally, previous studies indicate that *goal clarity* is negatively associated with turnover intention (Ko & Hur, 2013). Employees who understand the relationship of their job to organizational goals are less likely to leave their organization.

Organizational policies. Several personnel policies such as pay, family-friendly policies, training and skill development, and diversity management play important roles in influencing turnover intentions (Moynihan & Landuyt, 2008). Extrinsic rewards such as *pay* increase employees' motivation; employees with higher pay satisfaction are less likely to leave their organizations than ones with lower pay satisfaction (Wynen & Op de Beeck, 2014). In a survey of local, state, and federal agencies, about 52% of survey respondents agreed or strongly agreed that *family-friendly policies* in organizations reduced turnover (Durst, 1999). Balancing work and family responsibilities promotes individual and organizational performance by reducing employees' turnover (S. Kim, 2012). However, *training and development* are inconsistently associated with turnover intention. While training and development opportunities are found to mitigate turnover (Curry et al., 2005), an investment in training and employee development may increase turnover by improving their employability (Ito, 2003). Either way, training and skill development is expected to influence turnover intention. Having opportunities for *promotion and career development* has a negative influence on turnover (Cotton & Tuttle, 1986; Griffeth et al., 2000). Porter and Steers (1973) argued that employees who are not satisfied with promotion and advancement opportunities are likely to leave for preferable alternatives. Thus, promotion opportunity is likely to reduce turnover intention (Pitts et al., 2011). *Diversity management* policies and practices have been found to mitigate potential conflicts among diverse employee groups and thus strengthen social integration in organizations (Choi, 2009). As a result, diversity management is negatively associated with turnover intention.

Workplace environment. According to organizational behavior (OB) theories, individual behavior is strongly influenced by work environments in which they are situated (Terborg, 1981). In this study, eleven work-related environmental indicators are considered: (a) *Organizational satisfaction* describes observation and perceptions of employees on how satisfied they are with the organization considering everything. Empirical findings indicate that high satisfaction with organizations was predictive of lower turnover intentions (Liss-Levinson et al., 2015). (b) Regarding *coworker relations*, a good relationship with coworkers is critical for getting the work done successfully and retaining employees in their work. In general, good relationships with coworkers are negatively associated with turnover behavior (Cotton & Tuttle, 1986). (c) For *supervisory support*, social exchange theory suggests that turnover intention and behavior are affected by work-related supports from supervisor, organization, and other employees (Maertz et al., 2007; Smith, 2005). Supportive supervisory increases employee's productivity in their jobs (London et al., 1999). Thus, it is assumed that employees who feel they are well supported by their supervisor are less likely to leave their organization. (d) S. Kim (2012) found that *effective supervisory communication* is negatively related to turnover intentions. For instance, job-related communication with supervisor may increase job satisfaction and thus reduce turnover intentions. (e) According to leader–member exchange theory, *managerial trustworthiness* forms the basis for leader–subordinate exchanges. Previous studies found that managerial trustworthiness is positively associated with work attitudes such as turnover intention (Ko & Hur, 2013). (f) Empirical studies show that *organizational procedural justice* significantly influences employee's attitudes and behaviors such as turnover intention and job satisfaction (Choi, 2011). Thus, employees who perceive procedures as fair are less likely to leave their organization. (g) *Creativity* measures how much employees perceive openness to creativity and innovation in organizations. Previous studies have shown that organizational support for creativity and innovation is significantly related to lower turnover intentions (Ertas, 2015). (h) Regarding *employee empowerment*, empirical findings suggest that employee empowerment has a negative impact on turnover intention (i.e., S. Y. Kim & Fernandez, 2017; Pink-Harper & Rauhaus, 2017; Pitts et al., 2011). (i) *Performance-oriented culture* has been considered an important predictor of turnover intention. Pitts et al. (2011) argued that employees who are not rewarded for their good performance are more likely to leave the organization. (j) *Loyalty* is defined as "the allegiance or sense of duty that an individual may exhibit for an organization or agency" (Weaver, 2015, p. 443). Employees with higher loyalty are less likely to leave the organization. (k) Liss-Levinson et al. (2015) showed that employees who feel supported by their organization are less likely to leave their organization; thus, *organizational support* is a potential predictor of turnover intention in the workplace.

Method

Data

Data were drawn from 2018 Federal Employee Viewpoint Survey (FEVS), a nationally presentative sample of U.S. federal employees. The U.S. Office of Personnel Management implements the FEVS to assess federal employees' perceptions toward their work environments, work experiences, leadership of supervisors, and agencies.

The FEVS contains important variables that impact successful organizations, including broad topic areas such as personal work experiences, supervisor, satisfaction, leadership, and agency. In the 2018 FEVS, 598,003 of 1,473,870 federal employees in 82 federal government agencies were invited to the survey and completed it at a 40.6% response rate. All full-time and part-time, permanent, nonseasonal employees were eligible to participate. Survey data were collected between April and May 2018.

Measures

Predictor variables. All study measures (survey items with responses used in the current study) can be found in Supplementary Table 1.

Individual characteristics. Prior studies identified several correlates consistently associated with turnover intention, including sex (i.e., Ertas, 2015; Ko & Hur, 2013; Wynen & Op de Beeck, 2014), minority (i.e., Pink-Harper & Rauhaus, 2017; Weaver, 2015), educational attainment (i.e., S. Kim, 2012; Liss-Levinson et al., 2015), supervisory status (i.e., Ertas, 2015; Pink-Harper & Rauhaus, 2017), and organizational tenure (i.e., G. B. Lewis, 1991; Pitts et al., 2011; Wynen et al., 2013). Sample survey items used to measure these variables include the following: "How long have you been with the Federal Government (excluding military service)?" and "What is your supervisory status?" (see Supplementary Table 1 for details).

Organizational factors

Job characteristics. Seven variables relevant to job characteristics were selected: *job satisfaction* (i.e., Ertas, 2015; S. Y. Kim & Fernandez, 2017; Pitts et al., 2011), *personal accomplishment* (i.e., Ertas, 2015; Wynen et al., 2013), *workload* (i.e., Wynen et al., 2013; Wynen & Op de Beeck, 2014), *meaningfulness* (i.e., Ertas, 2015; S. Y. Kim & Fernandez, 2017; Weaver, 2015), and *goal clarity* (i.e., Ertas, 2015; Ko & Hur, 2013; Weaver, 2015). Sample survey items that measure these variables include the following: "Considering everything, how satisfied are you with your job?"; "My work gives me a feeling of personal accomplishment"; and "My workload is reasonable."

Organizational policies. Eleven variables relevant to organizational policies were included: *pay* (i.e., Wynen et al., 2013; Wynen & Op de Beeck, 2014), *family-friendly policies* (i.e., Durst, 1999; S. Kim, 2012), *training and skill development* (i.e., Curry et al., 2005; Ito, 2003), *diversity management* (i.e., Choi, 2009), and *promotion and advancement policy* (i.e., Cotton & Tuttle, 1986; Griffeth et al., 2000; Porter & Steers, 1973). Sample survey items that measure these variables include the following: "Considering everything, how satisfied are you with your pay?"; "My supervisor supports my need to balance work and other life issues"; and "How satisfied are you with your opportunity to get a better job in your organization?"

Work environment. Thirty-six variables relevant to organization environments were chosen: *organizational satisfaction* (i.e., Liss-Levinson et al., 2015), *coworker* *relations* (i.e., Cotton & Tuttle, 1986), *supervisory support* (i.e., London et al., 1999; Maertz et al., 2007; Smith, 2005), *supervisory communication* (i.e., S. Kim, 2012), *managerial trustworthiness* (i.e., Ko & Hur, 2013), *organizational procedural justice* (i.e., Choi, 2011), *creativity* (i.e., Ertas, 2015), *employee empowerment* (i.e., S. Y. Kim & Fernandez, 2017; Pink-Harper & Rauhaus, 2017; Pitts et al., 2011), *performance-oriented culture* (i.e., Pitts et al., 2011), *loyalty* (i.e., Weaver, 2015), and *organizational support* (Liss-Levinson et al., 2015). Sample survey items that measure these variables include the following: "Considering everything, how satisfied are you with your organization?"; "The people I work with cooperate to get the job done"; "My supervisor provides me with constructive suggestions to improve my job performance"; "My performance appraisal is a fair reflection of my performance"; and "I recommend my organization as a good place to work."

Turnover intention outcome. Some scholars caution against using turnover intention as a surrogate of actual turnover in federal government agencies. Given age and experience as the unit of analyses, the results showed strong correlations between turnover intention and actual turnover. On the contrary, turnover intention showed a negative correlation with actual turnover at the organizational level (Cho & Lewis, 2012). Cohen et al. (2016) have also found the same findings that turnover intention rate is not significantly related to actual turnover at the organizational level. Along with this caution, it is recommended that while organizational-level research on turnover uses actual turnover at the organizational level, individual-level study employs turnover intention at the employee level. As this study examines employees' perceptions on organizational workplace environments and its relations to turnover intention at the individual level, the use of turnover intention is appropriate for the purpose of this study.

Turnover intention is measured using one survey item: "Are you considering leaving your organization within the next year, and if so, why?" Responses include "No," "Yes, to take another job within the Federal Government," "Yes, to take another job outside Federal Government," and "Yes, other." Turnover intention was coded as a combined binary outcome to assess employees' overall intention to voluntarily leave their organizations. The responses were recoded "0" for "No" and "1" for "Yes, to take another job within the Federal Government," "Yes, to take another job outside Federal Government," and "Yes, other."

Data Analysis Plan

Data preprocessing. To initiate the CART model analysis, a total of 598,003 survey results were split into two data sets using simple random sampling without replacement. The first subset was considered the model training set and consisted of approximately 80% of the entire data. The second subset was used to validate model accuracy as a test set and consisted of approximately 20% of the data. As part of data screening, missing cases in all variables were examined. Results showed that missing cases in turnover intention outcome variable is 5% and varied in 59 predictor variables between 0.2% (e.g., loyalty) and 10.5% (e.g., racial/ethnic minority). Given the substantial evidence that racial/ethnic minority is significantly associated with turnover intention (i.e., Pink-Harper & Rauhaus, 2017; Weaver, 2015), the decision was made to retain racial/ethnic minority predictor in the data analyses. CART analyses were conducted with complete cases of turnover intention outcome (N = 567,838).

CART modeling. CART modeling was used to identify predictors of turnover intention and to distinguish subgroups of federal employees at high risk for turnover intention. Because CART makes no underlying distributional assumptions about predictors or outcomes and effectively handles nonlinear outcomes by means of partitioning (R. J. Lewis, 2000), we primarily modeled turnover intention outcome as a combined binary (1 = yes vs. 0 = no). In addition, we constructed a series of CART models to predict each category of turnover intention outcome (e.g., 1 = yes, to take another job within the Federal Government; 1 = yes, to take another job outside Federal Government; 1 = yes, other vs. 0 = no), but are not reported here, as the results of this additional analysis were similar to the analysis in which turnover intention was treated as a combined binary outcome.

CART is a nonparametric, algorithm-based method that uses a recursive binary partitioning process to identify important predictors and classify mutually exclusive and exhaustive subgroups based on a defined outcome (Zimmerman et al., 2016). The CART algorithm examines all possible predictors that would contribute to model accuracy and then selects the predictor with the highest association to the defined outcome and repeatedly partitions the data set according to predetermined splitting rule.

After preprocessing data and readying it for modeling, the analysis initiated a systematic comparison of potential CART models after taking account for sampling weights. Hyperparameter tuning was performed using a grid search of model components, including the complexity parameter of the tree, the minimum size of a node required before splitting the node, the minimum number of observations necessary for each terminal (leaf) node, and the maximum depth of the tree. Maximum depth was constrained to six layers (excluding the root node) to compartmentalize an interpretable number of subgroups at risk for turnover intention, as the number of terminal nodes in models with depths of over six grew exponentially. The performance of the models of various sizes and types is evaluated with cross-validation (Hapfelmeier et al., 2012). Throughout the hyperparameter tuning process, internal 10-fold cross-validation was used to resample the data and provide a stable measure of internal AUC (area under the receiver operating characteristic curve) for each model.

CART procedure evaluated every predictor at each split point to determine which splits were optimal. The criterion used to split the data was the Gini impurity index, although entropy or information gain can be used to similar ends. The Gini index of a node t is expressed as follows:

$$\widehat{G_j} = 2\frac{N_{1j}\ N_{2j}}{N_j\ \ N_j},$$

where 1 and 2 represent the response classes and N represents the number of observations (Hapfelmeier et al., 2012). Furthermore, the optimal spilt for a predictor maximizes the Gini gain of a node to its left and right child nodes, expressed as the following:

$$\widehat{\Delta G_j} = \widehat{G_j} - \left(\frac{N_{Lj}}{N_j} \widehat{G_{Lj}} + \frac{N_{Rj}}{N_j} G_{Rj} \right),$$

where N_{Lj} represents the number of observations sent to the left node (Hapfelmeier et al., 2012).

If the pruned tree does not significantly detract from the quality of the model, we use the pruned tree, as it is simpler and more interpretable. The strategy we use to prune the tree (or, in this case, prevent the tree from growing further) is imposing a penalty for the tree having more splits than it needs. To do this, we control the complexity parameter, as defined by the following formula (Therneau et al., 2014):

$$R_{cp}(T) \equiv R(T) + cp \times |T| \times R(T_1),$$

where T_1 is a tree without any splits, $|T|$ is the number of splits for the tree, and R represents the risk. The higher the complexity parameter, the smaller the tree. Because the complexity parameter is a cost on the model, when the cost of adding splits is high, the model results in fewer splits. Likewise, the lower the complexity parameter, the larger the tree. A complexity parameter of 1 represents a tree with no splits. The optimal complexity parameter identifies the best number of splits to avoid underfitting or overfitting the CART model.

To identify the optimal complexity parameter, the analysis tested different parameter values and used cross-validation to determine the predictive performance of each parameter. The best complexity parameter maximizes cross-validated accuracy. In this analysis, we use 10-fold cross-validation. To explore various values of the complexity parameter, the model-building algorithm prevents further splitting of the tree when an additional split does not improve the fit of the model by the specified threshold.

To account for the missing cases, the modeling process included the use of substitute splits. The CART procedure identifies these substitutes (called "surrogates") for every node, regardless of the presence of missing data in the training set (Steinberg, 2009). The first consideration for splitting is to identify the best primary predictor and where it splits the data. After creating the initial split, CART identifies a list of surrogates for cases when data are missing. The surrogates are listed in order of quality emulation of the primary predictor; the first surrogate splits the data most similarly to the primary predictor, the second surrogate splits the data the second-most similarly to the primary predictor, and so on. As data are sent down the tree, CART utilizes the primary predictor and surrogate predictors in order. For example, if an observation is missing data for both the primary variable and the first surrogate variable, it will be sent down the tree using the second surrogate variable (Hastie et al., 2009).

It should be noted that CART model was selected given its advantages over other decision tree modeling programs (e.g., Gradient Boosted Tree). CART analysis yields a single interpretable model, which often is impossible with "black-box" methods and

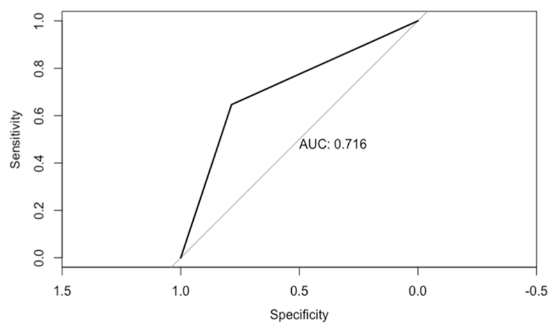

Figure 1. AU-ROC of the classification of turnover intention.
Note. AUC = area under the ROC curve; ROC = receiver operating characteristic curve.

may be difficult in other methods. Ensemble methods produce good prediction but not interpretable models (Sambasivan & Das, 2017). CART model effectively examines interactions among all predictor combinations and enhance interpretation by identifying individuals who are homogeneous in turnover intention via hierarchical tree. With CART model, the current study can identify the most informative predictor and their interactions for each subgroup at risk for turnover intention. In addition, CART methods can handle missing data by using substitute or surrogate variables.

As a supplementary analysis, we run an Extreme Gradient Boosted Tree (Chen et al., 2018) algorithm to predict turnover intention (a combined binary outcome: 1 = yes vs. 0 = no) to replicate the CART model and compare results between the CART model and Extreme Gradient Boosted Tree.

Results and Findings

Tree Structure for the CART Model

After a hyperparameter grid search that evaluated more than 3,000 comparable models, the final three-deep model had a complexity parameter of 1e-06, a minimum node split size of 150 observations, and a minimum terminal node size of 250. Precision, recall, and F-1 score were 0.79, 0.86, and 0.82, respectively. With six hierarchy levels, a total of 12 subgroups formed with six at-risk subgroups (defined as those employees predicted to leave their employer). With this tree structure, the model attains a general accuracy of 74.96% (though class imbalance renders this metric less useful), with an AUC metric of 0.72 (see Figure 1). The tree structure is depicted in Figure 2 below.

Subgroup Interpretation

The CART model of turnover intention generated twelve subgroups. Six subgroups of federal employees at high risk for turnover intention were identified. In this section,

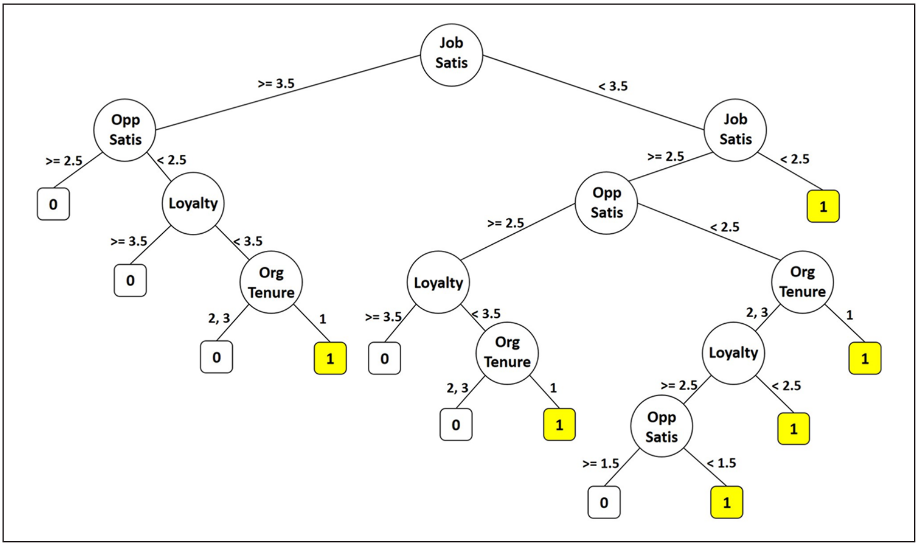

Figure 2. Tree structure of the CART model of turnover intention.
Note. CART = Classification and Regression Tree; JobSatis = job satisfaction; OppSatis = satisfaction with opportunities for promotion and advancement; Loyalty = loyalty to the organization; OrgTenure = length of service in the federal government; In OrgTenure, 1 stands for less than 10 years, 2 for between 10 and 20 years, and 3 for more than 20 years.

we focus on describing the characteristics of the six at-risk subgroups. All the subgroups are summarized in Table 1.

At-risk subgroups with high job satisfaction. Employees in *At-Risk Subgroup 1*, which appeared in the left side of the CART trees, are early career individuals who have worked less than 10 years and have high job satisfaction but show low satisfaction with promotion opportunity. Despite their high job satisfaction, early career workers intend to leave the organization if they have low loyalty to the organization.

At-risk subgroups with low to medium job satisfaction. Among the six at-risk subgroups, the five at-risk subgroups, which appear in the right of the tree models in Figure 2, intend to leave the organization with low to medium job satisfaction. Employees in *At-Risk Subgroup 2* have medium job satisfaction, worked less than 10 years, have medium to high satisfaction with promotion opportunity, and have low to medium loyalty to the organization. These employees intend to leave their organization in the next year unless they are satisfied with promotion opportunity and improve their loyalty to the organization. Like Subgroup 2, *At-Risk Subgroup 3* is also one of the at-risk subgroups with low to medium job satisfaction. However, this subgroup includes relatively middle and longer career workers who have worked more than 10 years and have medium to high loyalty to the organization, but very low satisfaction with promotion opportunity. For middle and longer career employees, it is important to have more

Table 1. Subgroups of Federal Employee at High Risk for Turnover Intention.

At-risk subgroup	% at risk	Count at risk	JobSatis	OppSatis	Loyalty	OrgTenure	Description
1	55	9,225	High	Low	Low	1	This at-risk subgroup is comprised of early career individuals with high job satisfaction, but have low satisfaction with promotion opportunity and low loyalty to the organization.
2	54	12e+3	Mid	High	Low	1	This at-risk subgroup is comprised of early career individuals with medium job satisfaction and medium to high satisfaction with promotion opportunity, but feel little loyalty to the organization.
3	55	8,937	Mid	Very low	High	2,3	This at-risk subgroup is comprised of middle and longer career individuals with medium job satisfaction and medium to high loyalty, but have low satisfaction with promotion opportunity.
4	61	9,296	Mid	Low	Very low	2,3	This at-risk subgroup is comprised of middle and longer career individuals with medium job satisfaction, but have low satisfaction with promotion opportunity and very low loyalty to the organization.
5	65	29e+3	Mid	Low	—	1	This at-risk subgroup is comprised of early career individuals with medium job satisfaction but low opportunity satisfaction.
6	74	132e+3	Low	—	—	—	This at-risk subgroup has very low job satisfaction.

Note. JobSatis = job satisfaction; OppSatis = satisfaction with opportunities for promotion and advancement; Loyalty = loyalty to the organization; OrgTenure = length of service in the federal government; In OrgTenure, 1 stands for less than 10 years, 2 for between 10 and 20 years, and 3 for more than 20 years.

opportunities for promotion and advancement to reduce turnover intention. Like Subgroup 3, employees in the *At-Risk Subgroup 4* are relatively longer career individuals who have worked at least 10 years and show medium to high loyalty to the organization. Loyalty to the organization is an important factor that influences whether workers in this subgroup intend to stay in the organization. Unlike Subgroups 3 and 4, *At-Risk Subgroup 5* is comprised of relatively younger workers who have worked less than 10 years. They show medium job satisfaction and medium to high loyalty to the organization. These workers are at greater risk for intention to leave unless they have high job satisfaction and more opportunities for promotion and advancement. *At-Risk Subgroup 6* is a typical at-risk subgroup who intend to leave unless job satisfaction is increased, regardless of other factors such as organizational tenure, satisfaction with promotion opportunity, and loyalty to the organization.

Variable Importance

CART operates in a "greedy algorithm," selecting a predictor at each split that contributes most to the overall model. If two predictors (e.g., A and B) are correlated, CART selects the best one (A) and not the other (B). Even if the other predictor (B) is a good predictor in and of itself, it might not appear in the final model because the information it (B) provides is already provided by the first predictor (A). A predictor's importance is the sum of the improvements in which the predictor splits data, weighted according to the proportion of data in each node split. This calculation includes surrogate splits that are developed in context of missing data values. While the tree depicts the primary splitting predictors, variable importance can reveal masked predictors and nonlinear correlation among the predictor set (Steinberg, 2009). In addition, a predictor may be represented in the tree more than once (both as a primary splitter or a surrogate). A predictor's importance is measured by its total goodness of split measure for each split as a primary splitter, in addition to the goodness of fit for all nodes in which it served as a surrogate splitter (Therneau et al., 2014). The modeling process ranked the following 28 predictors by importance. In this study, 15 high-ranked predictors that have an importance score above 100 are presented in Table 2.

Among the 15 top-ranked variables, 14 predictors were employees' perceptions of work environmental factors (i.e., job characteristics, workplace environment, and organizational policies) and only one predictor was an individual characteristic (i.e., organizational tenure). More specifically, the highest ranked predictor was job satisfaction, followed by organizational satisfaction, loyalty, personal accomplishment, involvement in decisions, meaningfulness to the job, promotion and advancement opportunity, skill development opportunity, organizational tenure, satisfaction with information from management, merit-based promotion, talent utilization, pay satisfaction, leadership development opportunity, and employee development.

As a supplementary analysis, Extreme Gradient Boosted Trees identified that job satisfaction (importance = 0.13) is the strongest predictor of turnover intention, followed by opportunity satisfaction (0.03), loyalty (0.02), organizational tenure (0.02), organizational satisfaction (0.02), policy diversity (0.02), procedural justice (0.02),

Table 2. Variable Importance for the CART Model of Turnover Intention.

Ranking no.	Variable	Importance score
1	Job satisfaction	90,339.50
2	Organizational satisfaction	45,453.74
3	Loyalty	44,281.61
4	Personal accomplishment	35,395.68
5	Involvement in decisions	27,983.77
6	Meaningfulness to the job	24,322.90
7	Satisfaction with promotion opportunity	12,758.71
8	Skill development opportunity	3,472.96
9	Organizational tenure	1,414.19
10	Satisfaction with information from management	458.16
11	Merit-based promotion	431.72
12	Talent utilization	361.11
13	Pay satisfaction	289.11
14	Leadership development opportunity	285.64
15	Employee development	140.81

Note. CART = Classification and Regression Tree.

family-friendly policy (0.02), pay satisfaction (0.0), and pay raise (0.02). The important predictors from Extreme Gradient Boosted Trees largely remain the same as those form the CART model, but some variables relevant to environmental policies (e.g., policy diversity, family-friendly policy) were emerged as new important predictors of turnover intention.

Discussion and Implications

The aims of this study were twofold: to employ CART model as a novel methodology to provide insight into variables that predict turnover intention and to identify subgroups of U.S. federal employees who are at increased risk for turnover intention. Two major findings of CART analyses are the following: (a) perceived comprehensive Human Resource (HR) practices predicted turnover intention, and (b) tailored interventions can be made to influence the characteristics of the six at-risk subgroups.

This study presents data-driven empirical evidence on predictors of turnover intention in HR-related fields using a machine learning approach. CART analysis is used to provide accurate and interpretable prediction model of turnover intention using a wide range of all literature-based predictor variables and their interactions. Findings of the current study suggest that comprehensive HR-related practices should be implemented in specific subgroups of federal employees who have turnover intention by enhancing job satisfaction, increasing satisfaction with promotion opportunity, and creating a favorable workplace environment that raises employees' loyalty to the organization. HR departments in federal government agencies should take a comprehensive HR approach to tailored intervention initiatives for high-risk groups of turnover intention.

Tailored interventions for each of the at-risk subgroups can be implemented in a more effective and efficient way. By and large, the CART model divides at-risk subgroups into two, split by the level of job satisfaction. The first at-risk subgroup (At-Risk Subgroup 1) is one with high job satisfaction. This is a very interesting finding of the study. Most previous studies have claimed that employees who have high job satisfaction are not likely to leave the organization (e.g., Liss-Levinson et al., 2015; Pitts et al., 2011). However, CART analysis found this subgroup is at increased risk of turnover intentions, although they have high job satisfaction. This subgroup is comprised of early career workers. They intend to leave the organization unless they are satisfied with opportunities for promotion and advancement and think of the agency as a good place to work. Therefore, if federal agencies can ensure appropriate opportunities for career advancement, it may be possible to increase employee commitment to their work by creating a learning supportive culture (Egan et al., 2004) and, as a result, to improve organizational performance (Gong & Chang, 2008).

The second at-risk subgroup (At-Risk Subgroups 2, 3, 4, 5, and 6) includes employees who have low to medium job satisfaction. Beyond this common element in these at-risk subgroups, employees in At-Risk Subgroup 2 are relatively younger individuals with medium to high satisfaction with promotion opportunity, but low to medium loyalty to the organization. For this at-risk subgroup, it is important to increase younger workers' loyalty to the organization. For this at-risk subgroup, creating a learning supportive organization is helpful for improving employees' loyalty and perception that the agency is a good place to work.

Employees in At-Risk Subgroup 3 are middle and longer career individuals with medium to high loyalty to the organization satisfaction but very low satisfaction with promotion and advancement opportunity. Like younger workers in At-Risk Subgroup 1, increasing opportunities for promotion and advancement for middle and longer career individuals is important to decreasing their intentions to leave the organization. However, middle and longer career workers may have fewer opportunities to get promotion and advancements than younger workers due to the lack of the next level of management positions. For this reason, managers should enhance employees' perception of the fairness of organizational promotion or advancement systems. Two organizational procedural justice variables can promote employees' perception on the fairness of organization promotion systems: establishing well-defined promotion paths for managerial positions and employing competency- or performance-oriented criteria in making promotion decisions (McEnrue, 1989). Thus, HR departments should implement these two organizational procedural justice practices so that middle and longer tenured employees perceive organizational promotion systems as fair.

At-Risk Subgroup 4 is comprised of middle and longer career individuals with very low satisfaction with promotion opportunity and very low loyalty to the organization. This at-risk subgroup has very similar characteristics with At-Risk Subgroup 3, the only difference being the level of loyalty to the organization. Very low loyalty to the organization is a significant factor that affects intentions to leave the organization for this group. Thus, as with At-Risk Subgroups 1 and 2, the same practices to enhance organizational learning culture will improve loyalty of Subgroup 4 to the organization.

At-Risk Subgroup 5 includes early career employees with very low satisfaction with promotion and advancement opportunity. Like At-Risk Subgroup 1, HR departments need to implement the provisions of early career advancement and promotion opportunities so these employees may see the benefit of putting more effort into their jobs to improve opportunities for promotion and thus reduce their intentions to leave the organization.

At-Risk Subgroup 6 includes employees who intend to leave the organization because they have very low job satisfaction regardless of other significant factors. To improve low job satisfaction, managers or supervisors should seek to better understand motivations and issues of individual employees to enhance job satisfaction (Pitts et al., 2011). For instance, managers can enhance employees' job satisfaction by improving employees' perceptions of meaningfulness of work or by providing opportunities for training of employees (Ertas, 2015). Managerial practices that promote self-determination, such as employee empowerment, may also help increase employees' job satisfaction (S. Y. Kim & Fernandez, 2017). Federal agencies will benefit when HR departments implement a variety of practices and systems on how to promote employee engagement and perceived organizational support to increase job satisfaction (Liss-Levinson et al., 2015).

Our findings encourage managers to establish more sophisticated strategic planning on reducing turnover intention among at-risk subgroups and to play a role in shaping employees' perceptions and experiences of risk factors such as job satisfaction, promotion and advancement policies, and favorable work environments. Managers, for instance, may want to establish distinctive strategies for improving promotion and advancement policies for both early career and middle/longer career workers, respectively. For instance, while managers provide younger workers with clear and regular promotion and advancement opportunities by establishing a specific timeline for employee advancement, they build the succession planning that shows clearly defined paths for managerial positions and establish performance-oriented criteria that middle/longer employees should achieve for promotion to managerial positions. In this way, managers can optimize specific strategic planning on high turnover intention for targeted subgroups. Thus, the CART results are very useful for helping managers understand the features of at-risk subgroups with the risk factors and thus develop tailored interventions for targeted at-risk subgroups by considering specific agencies' or work unit's contexts.

Finally, it should be noted that some additional analyses enhance reliability and credibility of the CART model predicting turnover intention in the current study. We conducted two additional analyses: (a) using an ensemble method (e.g., Extreme Gradient Boosted Tree) to compare the results between the CART model and the Extreme Gradient Boosted Tree and (b) using another year of FEVS data (e.g., 2017 FEVS) to replicate the CART model of turnover. Results from the CART analyses with 2017 FEVS data showed that job satisfaction is the most important predictor, followed by loyalty, organizational satisfaction, personal accomplishment, involvement in decision, meaningfulness to the job, satisfaction with promotion opportunity, skill development opportunity, organizational tenure and pay satisfaction. Two analyses yielded very similar results to the CART analysis with 2018 FEVS data and confirmed that our predictive model of turnover intention provide reliable information to develop effective interventions for improving turnover intention among federal employees at risk.

Several limitations in the current study should be noted. First, we did not account for the different characteristics of the federal agencies in the machine learning models of turnover intention. Future research should consider different inherent agency characteristics (e.g., federal agencies employees in public health sector may have more diverse occupational backgrounds with area-specific training) to mitigate confounding effects of agencies. Second, as the design of the current study was cross-sectional in nature, causality could not be analyzed. However, we conducted a series of data analyses to cross-validate the results of the current study using another year of FEVS data (2017) and an ensemble method, which yielded similar results. Third, as the current study used an anonymous and self-report employee survey, the indicators might be susceptible to nonresponse bias and social desirability (Mundia, 2011). Finally, turnover intention cannot accurately describe actual turnover as actual turnover is a longitudinal dynamic process. Given that the FEVS did not collect a variable of employee's actual turnover in a longitudinal design, the current study was unable to establish a predictive value of turnover intention to actual turnover. Future study is needed to identify mechanism between turnover intention and actual turnover behaviors using a longitudinal data.

Conclusion

The CART model identified at-risk subgroups and significant predictors (e.g., job satisfaction, satisfaction with opportunities for promotion and advancement, loyalty, and organizational tenure) of turnover intention among federal employees. These important predictors vary from individual characteristics to workplace environments and organizational policies. Thus, HR departments should seek to implement comprehensive HR practices to enhance employees' perceptions on job satisfaction, workplace environments and systems, and favorable organizational policies and supports. Finally, this study confirms the importance of variables and builds on a model developed by Kang and Bichelmeyer (2019) that outlines the variables and relationships in a performance equation to better align and improve success for both individual employees and the organizations in which they work.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

In Gu Kang https://orcid.org/0000-0002-7070-5183

Supplemental Material

Supplemental material for this article is available online.

References

Bertelli, A. M. (2007). Determinants of bureaucratic turnover intention: Evidence from the department of the treasury. *Journal of Public Administration Research and Theory*, *17*(2), 235–258. https://doi.org/10.1093/jopart/mul003

Brannon, D., Zinn, J. S., Mor, V., & Davis, J. (2002). An exploration of job, organizational, and environmental factors associated with high and low nursing assistant turnover. *The Gerontologist*, *42*(2), 159–168. https://doi.org/10.1093/geront/42.2.159

Chen, X., Huang, L., Xie, D., & Zhao, Q. (2018). EGBMMDA: Extreme gradient boosting machine for MiRNA-disease association prediction. *Cell Death & Disease*, *9*(3), 1–16. https://doi.org/10.1038/s41419-017-0003-x

Chiu, C.-K., Lin, C.-P., Tsai, Y. H., & Hsiao, C.-Y. (2005). Modeling turnover intentions and their antecedents using the locus of control as a moderator: A case of customer service employees. *Human Resource Development Quarterly*, *16*(4), 481–499. https://doi.org/10.1093/jopart/mun010

Cho, Y. J., & Lewis, G. B. (2012). Turnover intention and turnover behavior: Implications for retaining federal employees. *Review of Public Personnel Administration*, *32*(1), 4–23. https://doi.org/10.1177/0734371X11408701

Choi, S. (2009). Diversity in the US federal government: Diversity management and employee turnover in federal agencies. *Journal of Public Administration Research and Theory*, *19*(3), 603–630. https://doi.org/10.1093/jopart/mun010

Choi, S. (2011). Organizational justice and employee work attitudes: The federal case. *American Review of Public Administration*, *41*(2), 185–204. https://doi.org/10.1177/0275074010373275

Cohen, G., Blake, R. S., & Goodman, D. (2016). Does turnover intention matter? Evaluating the usefulness of turnover intention rate as a predictor of actual turnover rate. *Review of Public Personnel Administration*, *36*(3), 240–263. https://doi.org/10.1177/0734371X15581850

Cotton, J. L., & Tuttle, J. M. (1986). Employee turnover: A meta-analysis and review with implications for research. *Academy of Management Review*, *11*(1), 55–70. https://doi.org/10.5465/amr.1986.4282625

Curry, D., McCarragher, T., & Dellmann-Jenkins, M. (2005). Training, transfer, and turnover: Exploring the relationship among transfer of learning factors and staff retention in child welfare. *Children and Youth Services Review*, *27*(8), 931–948. https://doi.org/10.1016/j.childyouth.2004.12.008

Dalton, D. R., Johnson, J. L., & Daily, C. M. (1999). On the use of "intent to." variables in organizational research: An empirical and cautionary assessment. *Human Relations*, *52*(10), 1337–1350. https://doi.org/10.1177/001872679905201006

Durst, S. L. (1999). Assessing the effect of family friendly programs on public organizations. *Review of Public Personnel Administration*, *19*(3), 19–33. https://doi.org/10.1177/0734371X9901900302

Egan, T. M., Yang, B., & Barlett, K. R. (2004). The effects of organizational learning culture and job satisfaction on motivation to transfer learning and turnover intention. *Human Resource Development Quarterly*, *15*(3), 279–301. https://doi.org/10.1002/hrdq.1104

Ertas, N. (2015). Turnover intentions and work motivations of millennial employees in federal service. *Public Personnel Management*, *44*(3), 401–423. https://doi.org/10.1177/0091026015588193

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behavior: The reasoned action approach*. Taylor & Francis.

Gong, Y., & Chang, S. (2008). Institutional antecedents and performance consequences of employment security and career advancement practices: Evidence from the People's Republic of China. *Human Resource Management*, *47*(1), 33–48. https://doi.org/10.1002/hrm.20196

Griffeth, R. W., Hom, P. W., & Gaertner, S. (2000). A meta-analysis of antecedents and correlates of employee turnover: Update, moderator tests, and research implication for the next millennium. *Journal of Management*, *26*(3), 463–488. https://doi.org/10.1177/014920630002600305

Hapfelmeier, A., Hothorn, T., & Ulm, K. (2012). Recursive partitioning on incomplete data using surrogate decisions and multiple imputation. *Computational Statistics and Data Analysis*, *56*(6), 1552–1565. https://doi.org/10.1016/j.csda.2011.09.024

Hastie, T., Tibshirani, R., & Friedman, J. H. (2009). *The elements of statistical learning* (2nd ed.). Springer-Verlag.

Ito, J. K. (2003). Career branding and mobility in the civil service: An empirical study. *Public Personnel Management*, *32*(1), 1–21.

Kang, I.-G., & Bichelmeyer, B. A. (2019). Advancing the knowledge base toward a comprehensive model—Part 1: An empirically tested performance model. *Performance Improvement*, *58*(8/9), 26–36. http://doi.org/10.1002/pfi.21895

Kim, S. (2005). Factors affecting state government information technology employee turnover intentions. *American Review of Public Administration*, *35*(2), 137–156. https://doi.org/10.1177/0275074004273150

Kim, S. (2012). The impact of human resource management on state government IT employee turnover intentions. *Public Personnel Management*, *41*(2), 257–279. https://doi.org/10.1177/0275074004273150

Kim, S. Y., & Fernandez, S. (2017). Employee empowerment and turnover intention in the U.S. federal bureaucracy. *American Review of Public Administration*, *47*(1), 4–22. https://doi.org/10.1177/0275074015583712

Ko, J., & Hur, S. (2013). The impacts of employee benefits, procedural justice, and managerial trustworthiness on work attitudes: Integrated understanding based on social exchange theory. *Public Administration Review*, *74*(2), 176–187. https://doi.org/10.1111/puar.12160

Lewis, G. B. (1991). Turnover and the quiet crisis in the federal civil service. *Public Administration Review*, *51*(2), 145–155. https://www.jstor.org/stable/977108

Lewis, R. J. (2000). *An introduction to classification and regression tree (CART) analysis*. https://pdfs.semanticscholar.org/6d4a/347b99d056b7b1f28218728f1b73e64cbbac.pdf

Liss-Levinson, R., Bharthapudi, K., Leider, J. P., & Sellers, K. (2015). Loving and leaving public health: Predictors of intentions to quit among state health agency workers. *Journal of Public Health Management and Practice*, *21*(Suppl. 6), S91–S101. https://doi.org/10.1097/PHH.0000000000000317

London, M., Larsen, H. H., & Thisted, L. N. (1999). Relationships between feedback and self-development. *Group & Organization Management*, *24*(1), 5–27. https://doi.org/10.1177/1059601199241002

Maertz, 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*(8), 1059–1075. https://doi.org/10.1002/job.472

McEnrue, M. P. (1989). The perceived fairness of managerial promotion practices. *Human Relations*, *42*(9), 815–827. https://doi.org/10.1177/001872678904200905

Moynihan, D. P., & Landuyt, N. (2008). Explaining turnover intention in state government: Examining the roles of gender, life cycle, and loyalty. *Review of Public Personnel Administration*, *28*(2), 120–143. https://doi.org/10.1177/0734371X08315771

Mundia, L. (2011). Social desirability, non-response bias and reliability in a long self-report measure: Illustrations from the MMPI-2 administered to Brunei student teachers. *Educational Psychology*, *31*(2), 207–224. https://doi.org/10.1080/01443410.2010.545049

Pink-Harper, S. A., & Rauhaus, B. (2017). Examining the impact of federal employee wellness programs and employee resilience in the federal workplace. *Journal of Health & Human Services Administration*, *40*(3), 353–387.

Pitts, D., Marvel, J., & Fernandez, S. (2011). So hard to say goodbye? Turnover intention among U.S. federal employees. *Public Administration Review*, *71*(5), 751–760. https://doi.org/10.1111/j.1540-6210.2011.02414.x

Porter, L. W., & Steers, R. M. (1973). Organizational, work, and personal factors in employee turnover and absenteeism. *Psychological Bulletin*, *80*(2), 151–176. http://doi.org/10.1037/h0034829

Rubin, E. V. (1973). The role of procedural justice in public personnel management: Empirical results from the department of defense. *Journal of Public Administration Research and Theory*, *19*(1), 125–143. https://doi.org/10.1093/jopart/mum035

Sambasivan, R., & Das, S. (2017, December). Big data regression using tree based segmentation. *Proceedings of the IEEE India Council International Conference*, *3*, 1–6. https://doi.org/10.1109/INDICON.2017.8488137

Smith, B. D. (2005). Job retention in child welfare: Effects of perceived organizational support, supervisor support, and intrinsic job value. *Children and Youth Services Review*, *27*(2), 153–169. https://doi.org/10.1016/j.childyouth.2004.08.013

Steinberg, D. (2009). *Chapter 10 CART: Classification and regression trees*. https://www.researchgate.net/profile/Dan_Steinberg2/publication/265031802_Chapter_10_CART_Classification_and_Regression_Trees/links/567dcf8408ae051f9ae493fe/Chapter-10-CART-Classification-and-Regression-Trees.pdf

Terborg, J. R. (1981). Interactional psychology and research on human behavior in organizations. *Academy of Management Review*, *6*(4), 569–576. https://doi.org/10.5465/AMR.1981.4285691

Therneau, T. M., Atkinson, E. J., & Ripley, B. (2014). *rpart: Recursive partitioning and regression trees*. https://cran.r-project.org/

United States Office of Personnel Management. (2018, October 25). *2018 Governmentwide management report*. https://www.opm.gov/fevs/reports/governmentwide-reports/governmentwide-management-report/governmentwide-report/2018/2018-governmentwide-management-report.pdf

Weaver, T. L. (2015). Intent to exit: Why do US federal employees leave? *International Journal of Public Administration*, *38*(6), 442–452. https://doi.org/10.1080/01900692.2014.949739

Wynen, J., & Op de Beeck, S. (2014). The impact of the financial and economic crisis on turnover intention in the U.S. federal government. *Public Personnel Management*, *43*(4), 565–585. https://doi.org/10.1177/0091026014537043

Wynen, J., Op de Beeck, S., & Hondeghem, A. (2013). Interorganizational mobility within the US federal government: Examining the effect of individual and organizational factors. *Public Administration Review*, *73*(6), 869–881. https://doi.org/10.1111/puar.12113

Zimmerman, R. K., Balasubramani, G. K., Nowalk, M. P., Eng, H., Urbanski, L., Jackson, M. L., . . . Wisniewski, S. R. (2016). Classification and Regression Tree (CART) analysis to predict influenza in primary care patients. *BMC Infectious Diseases*, *16*(1), 503–513. https://doi.org/10.1186/s12879-016-1839-x

Author Biographies

In Gu Kang is an assistant professor in the department of Organizational Performance and Workplace Learning in the College of Engieerning at Boise State University. His research interests include human and organizational performance and effectiveness, public personnel management, human resource (HR) analytics, and public workforce development.

Ben Croft is a learning analyst in the eCampus Center Research and Innovation Team at Boise State University. His research interests are in developing and evaluating predictive models to identify key factors of an outcome of intersts by applying data science approach to diverse contexts.

Barbara A. Bichelmeyer is the provost and executive vice chancellor at the University of Kansas. Her research intersts focus on studying how educational systems integrate new technologies and how the introduction of new technologies changes educational systems to better support student-centered learning and improved human and organizational performance.