Research Article

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Investigation of Turnover Tendency Predictions with Artificial Intelligence and Mathematical Models[1]

Yapay Zekâ ve Matematiksel Modeller İle Yapılan İşten Ayrılma Eğilim Tahminlerinin İncelenmesi

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Abstract

In today's business world, human resource management is becoming increasingly important and human resource processes are becoming more complex. Companies are implementing many new practices to increase employee engagement. The common goal of these efforts is to positively affect labor turnover by increasing employee happiness and job satisfaction.
However, it is quite difficult to predict the tendency to quit. Since employees do not share their decision to leave with their employers, employers are caught off guard when they learn about the decision to leave.
In this context, artificial intelligence technologies offer employers the opportunity to predict employee turnover trends and take measures accordingly. The aim here should be to identify the reasons that trigger turnover and enable them to make improvements in these areas, rather than identifying the employee who will leave. Artificial intelligence algorithms and mathematical modeling allow companies to analyze employee data and learn the underlying causes of employee turnover.
In addition, human resources analytics studies include a series of processes from employee recruitment to performance evaluation, from training to turnover management. With artificial intelligence and HRIA applications, these processes are managed more efficiently and effectively. In this way, HRIA helps businesses increase their competitive advantage.

Keywords: Artificial Intelligence, Human Resources, Human Resource Analytics, Employee Engagement, Resignation Tendency.
JEL Codes: C63,C65,C83

Özet

Günümüz iş dünyasında insan kaynakları yönetimi giderek önem kazanmakta ve insan kaynakları süreçleri daha karmaşık hale gelmektedir. Şirketler çalışan bağlılığını artırmak için birçok yeni uygulamayı hayata geçiriyor. Bu çabaların ortak hedefi, çalışan mutluluğunu ve iş tatminini artırarak işgücü devrini olumlu yönde etkilemek.

Ancak işten ayrılma eğilimini tahmin etmek oldukça zordur. Çalışanlar ayrılma kararlarını işverenleri ile paylaşmadıkları için işverenler ayrılma kararını öğrendiklerinde hazırlıksız yakalanmaktadır.

Bu bağlamda yapay zeka teknolojileri işverenlere çalışan devir eğilimlerini tahmin etme ve buna göre önlem alma fırsatı sunuyor. Burada amaç, ayrılacak çalışanı tespit etmekten ziyade, işten ayrılmayı tetikleyen nedenleri tespit etmek ve bu alanlarda iyileştirmeler yapmalarını sağlamak olmalıdır. Yapay zeka algoritmaları ve matematiksel modelleme, şirketlerin çalışan verilerini analiz etmesine ve çalışan devrinin altında yatan nedenleri öğrenmesine olanak tanır.

Ayrıca insan kaynakları analitiği çalışmaları, çalışan işe alımından performans değerlendirmesine, eği-

[1] *"Predicting employee intentions to leave and quiet quitting in the finance sector with human resource analytics methods" produced from the thesis titled.*

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timden işten ayrılma yönetimine kadar bir dizi süreci içeriyor. Yapay zeka ve İRİA uygulamaları ile bu süreçlerin daha verimli ve etkin bir şekilde yönetilmesi sağlanıyor. Bu sayede İKİA, işletmelerin rekabet avantajını artırmasına yardımcı oluyor.

Anahtar Kelimeler: Yapay Zeka, Insan Kaynakları, Insan Kaynakları Analitiği, Çalışan Bağlılığı, Işten Ayrılma Eğilimi.
JEL Kodları: C63,C65,C83

Introduction

Türkiye, In the business world, the most important resource of organizations is the human resources working in the business and its stakeholders. Businesses should try to increase the performance of their employees, motivate them and reduce the tendency to leave the job in order to achieve the success they desire in the medium and long term.

Instead of investing in precise research to understand employees' motivation to leave or their motivation to stay, most companies invest in additional benefits or measures to search for talent. [1] However, increasing the engagement of existing employees will both reduce costs and improve the quality of work in the medium term. The last resort should be to let an undesirable employee leave and replace them with a new employee.

There are many factors affecting the decision to leave the job. Determining these factors is not possible only with observational information. Supporting observations with models based on analytical data will ensure accurate determination. In her 2018 article, Hila Chalutz Ben-Gal conducted a return on investment (ROI) based review of human resources (HR) analytics. This study showed the positive results of Human Resource Analytics (HRA) applications [2].

With artificial intelligence, it is possible to identify the factors that trigger the turnover process. In order to maximize employee performance and loyalty, it is necessary to identify the factors that trigger turnover. Examining the studies on identifying these factors offers a great opportunity for businesses.

Conceptual Framework

The word 'work engagement' emerged in 1990 as the emotional, physical and cognitive involvement of employees in their roles [3]. Underlying this relatively short history is the

sense of belonging. Increasing the sense of belonging has become one of the most critical issues for businesses today.

Turnover propensity has significant impacts on organizations' workforce management strategies and performance objectives. Therefore, it is a concept that needs to be addressed comprehensively. Organizations can reduce turnover rates by increasing the motivation and commitment of their employees. Thus, it creates a competitive advantage in terms of achieving business goals.

Although employees are the main asset, they are also the most important cost [4]. However, employees should not only be seen as a cost item. Employees are also the most important source of revenue generation for a business. Employee engagement should be considered and focused on in this context.

The analytical dimension should always be considered when addressing employee engagement. HR analytics is a relatively new term that first appeared in the academic literature in 2004 [5]. Although it is new, it has a great impact on businesses and businesses have started to spread these practices rapidly. The returns of these practices of businesses have also been revealed in the studies in the literature. An MIT study conducted in 2011 concluded that top-performing organizations use HR Analytics applications five times more than low-performing organizations [6]. These studies in the literature and the experiences of businesses in daily life have shown the benefits of HRIA applications to businesses. These outputs have led businesses to invest more in this area.

The departure of a key employee is not only a loss in terms of business continuity, but also damages the business in different ways in terms of transferring knowledge to a competitor. Delays in work due to the process of replacing the departed employee bring with them various alternative costs.

With advancing digitalization, it has become easier to create data sets that identify the factors that trigger employee turnover. Structured and unstructured data sources are

becoming more accessible to human resource (HR) professionals, enabling them to better analyze the complexity of workforce decision-making [7]. HR professionals have reached a point where they can easily collect a lot of data on employee engagement. Processing the data with artificial intelligence and mathematical models, identifying the factors that trigger turnover will guide the business on where to focus resources and increase resource efficiency.

Many academic studies have examined the relationship between HR practices and organizational success. It has been clearly seen that if organizations follow successful HR practices, they increase their profitability [8]. Acting on this knowledge, organizations have started to implement many practices to increase employee engagement. These practices include training, stock options, changes in work environments, flexible working opportunities, etc.

To reduce high turnover, HR organizations need the help of HR analytics [9]. Without the support of

HR analytics, it will be difficult to identify employee trends and it will not always be possible to make the right decisions as they will be based on personal judgments. Especially in companies with tens of thousands of employees spread across the country, making these predictions with only manager observation poses many risks. The accuracy of determinations based on personal observations may be met with skepticism by employees. A trend forecast that is not based on an analytical basis may interpret a short-term loss of motivation as a tendency to resign and cause worse consequences.

A high level of labor turnover can be caused by different reasons. These include inadequate wage levels, hiring the wrong employees in the first place, poor morale and low motivation. Such reasons make the decision to change jobs easier in a vibrant local labor market that offers more and perhaps more attractive opportunities to employees [10]. Salary is an important factor, but not the only one. Especially for Millennials and Generation Z, work-life balance, development opportunities and additional benefits may be more important than salary in decision-making. Before predicting turnover tendency, the expectations of the employee should be fully understood during recruitment and it should be examined whether the organization meets these needs.

Decisions based on personal observations also involve biases. Biases lead to discrimination in the workplace and various analytical tools should be used to control these biases [11]. It must be clearly demonstrated to employees that how promotions, wage increases, performance bonuses or training opportunities are distributed among employees is determined by using analytical methods.

The factors affecting the decision to leave the organization can be categorized under two headings: internal and external factors.

External factors generally refer to individual and external factors. Individual factors include characteristics such as career goals, work-life balance, health status, while external factors may include economic conditions, industry trends, competition, etc.

Businesses should not ignore these factors in order to reduce turnover. The potential of how artificial intelligence technology can be used to analyze these factors has also been discussed in the literature and its benefits have been demonstrated by various studies.

The rapid development of technology and the fact that artificial intelligence applications can be easily used by the end user have offered new opportunities to the human resources management of enterprises in this respect. Human resources management includes a series of processes from employee recruitment to performance evaluation, from training to turnover management. With artificial intelligence and HRM applications, these processes are managed more efficiently and effectively. In this way, HRM helps businesses increase their competitive advantage.

Artificial intelligence in recruitment and selection processes can help assess the skills and suitability of candidates by using big data analysis and machine learning techniques in recruitment and selection processes. Especially in CV screening, job interviews and personality assessments, AI can help to achieve objective and consistent results.

One of the most important triggers of the turnover process is undoubtedly hiring the wrong employee. Human resources analytics methods benefit businesses in this respect. Nowadays, detailed data about the prospective employee can be collected through methods such as personality inventories and job entry tests. These data can be processed with HRIA applications to determine which employees are more suitable for the corporate culture. In addition, more accurate recruitment will be made by comparing the rights offered by the organization with employee expectations.

Another area of use for human resource analytics is training and development. The development of technology and high digitalization has led to changes in the qualifications sought in the labor market. These changes have increased the importance of training and development of existing employees. The use of HRD applications in identifying training needs and preparing training inventories will increase efficiency in this area. Thus, a more effective employee-specific training plan can be prepared.

Reshaping job descriptions in line with the state of technology is another important issue for engagement. HR can restructure jobs following a four-step process to achieve the optimal combination of humans and machines [12]. Figure 1 illustrates these four steps. With this method, training and development needs that will occur within the framework of changing job needs and job descriptions can be predicted and planned for employees.

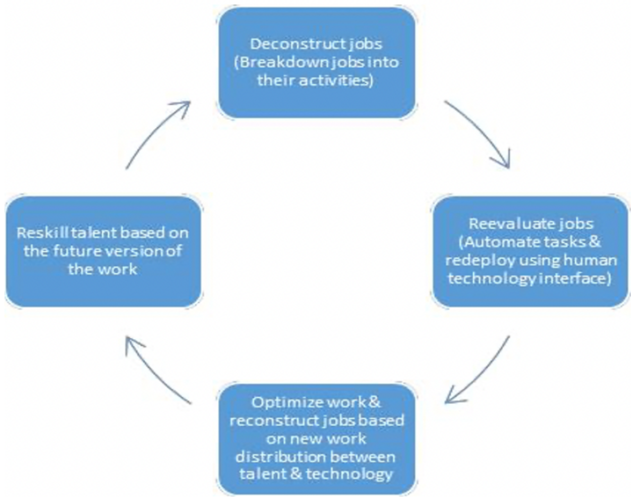

Figure 1. A four-step model for redefining jobs

Another element that increases engagement is performance management. Artificial intelligence can be used to make performance appraisal processes more efficient and objective. Feedback processes can be improved by monitoring employees' goals, achievements and development areas with artificial intelligence algorithms. To improve talent management decisions, HR-related data needs to be systematically collected, analyzed and interpreted. This has led to the frequent use of HR Analytics in talent management [13]. Promoting a successful employee or assigning him/her to a different field will not always lead to positive results. It is important that the expectations of the employee and the new task are compatible. At this point, managers' opinions should be supported by analytical models.

Specific data about employees such as age, qualifications, skills, project work, rewards, technological skills, conceptual skills can be used for performance measurement. Employee performance can be measured using statistical tools such as mean, correlation, regression, Chi-square test [14]. Measuring employee performance with analytical methods will be more convincing in terms of the validity of the result. Performance measurements and related rewarding systems in which the effect of personal evaluations is low increase success. Otherwise, the decisions made may be met with skepticism by employees.

The use of HR analytics in the performance analysis (PA) system will exclude personal biases and biased assessments. Thus, the results for employees are certain to be fairer. This further positively influences employee satisfaction with the PA system, which in turn increases employee willingness to improve performance [15]. In this environment, successful employees will be less likely to leave their jobs.

Artificial intelligence can make performance management processes more efficient and objective. Data analytics and algorithms can make it easier to monitor and evaluate employee performance and provide recommendations for feedback. Effective performance management will strengthen employee engagement with the company and reduce turnover.

According to a study conducted by Deloitte consulting firm, human resource analytics has a strong correlation with performance evaluations and organizational profitability. Companies that use HR analytics extensively have 82% higher average annual profits than those that do not [16].

Technologies such as big data analysis, prediction models, artificial intelligence can help to have an idea about which factors affect employees' tendency to leave their jobs. Despite this, it is seen that businesses do not allocate sufficient resources. A study by Deloitte found that although 71% of companies consider HR analytics a high priority in their organizations (31% very important), its use is very limited [17]. Businesses should allocate more resources to HRIA studies that are seen as a priority and make more use of these applications during the recruitment phase.

Predicting turnover trends offers employers the opportunity to intervene in a timely manner and retain talented employees. In this context, artificial intelligence technology offers a new approach to turnover prediction, helping businesses to manage this process more efficiently. HR analytics can therefore be defined as the systematic identification and measurement of human drivers of business outcomes in order to make better decisions [18]. With different artificial intelligence and HRA models, better identification of the key elements that connect employees to the company and taking remedial actions on these elements will maximize engagement. At this point, many different models and variable sets have been examined in the literature.

The preparation of these models requires HR staff to have sufficient technical knowledge and to work in collaboration with analytics teams. Undoubtedly, models prepared by HR teams that are not analytically competent will not be valid. An analytical perspective is also required when interpreting the outputs of existing models. In an article published by the Chartered Institute for Personnel and Development in 2013, the HR analytics dimension of the employee-employer relationship was examined. In this context, the importance of HR functions being competent enough to ask the right questions in order to access the right data was emphasized [19]. In order to prevent this, HR teams need to be trained more on technology. It should be ensured that they understand these technologies better and use them effectively and correctly.

Thanks to big data analysis and algorithms, organizations can predict employee turnover using data such as past performance, absenteeism levels, and promotion history. HR analytics provides descriptive, predictive and perspective analysis [20]. In order to prepare analyses in a healthy way, it is necessary to collect the necessary data set in a complete and healthy way. These data sets may differ for each sector and business. For this reason, the data set should be added to the model in its widest form at the first stage, and then it should be narrowed down by examining it specifically for the sector and the enterprise.

Predictive analysis, including numerous statistical techniques such as modeling and data mining, uses current and historical data to predict future outcomes [21]. When adding historical data to the data set, the conjuncture at that time should be taken into account and the data should be interpreted accordingly. For example, while all companies were working remotely during the Covid 19 period, remote working behavior was at a negligible level before, remote working expectations before, during and after the Covid 19 period should be examined in the light of this information and added to the dataset.

Identifying turnover propensity involves a challenging process to understand a situation that is difficult to detect by traditional methods. As mentioned, identifying this tendency by manager observation alone involves different risks. The use of artificial intelligence (AI) technologies to make predictions free from observations based on personal interpretation stands out as a critical approach to understanding and predicting silent resignation and turnover trends.

Artificial intelligence is a technology that increases the competencies of companies in terms of analyzing big data, finding patterns and developing predictions based on this information. In the field of human resources management, AI techniques can affect many areas, from recruitment processes to performance management, from training to turnover prediction.

Setiawan V.D. divided the analysis process into five steps in his wear and tear analysis studies

- Data Voting and Business Insight: Collecting and analyzing data to better understand what the main objectives of the study should be.
- Data Preprocessing: The step of preprocessing the data so that it is suitable for the analysis method. Pre-processing may involve cleaning the data, transforming the data or creating new variables that can bring useful information for the analysis steps.
- Exploratory Data Analysis (EDA): This step creates textual and visual summaries of the dataset highlighting some of the characteristics of the data.
- Model Selection and Training
- Model Testing and Evaluation: Evaluating the performance of proposed models

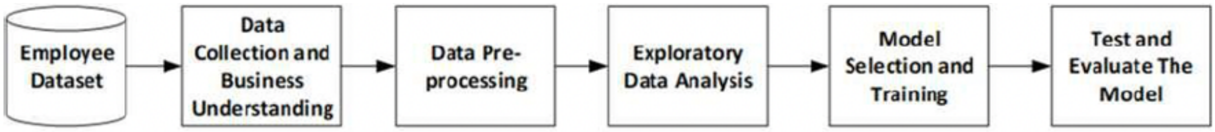

Figure 2 Wear analysis steps.

The most important stage in RDA applications is the collection of the right data in the right context and the necessary pre-processing of these data. Undoubtedly, the same data can mean different things in different contexts. For example, a person who does not tend to quit his/her job in the finance sector may express his/her intentions differently during a crisis when economic data are very bad or during periods of goal realization when the pressure is very intense. Analyzing this data independent of the context will negatively affect the research results.

Lenka Girmanová, Zuzana Gašparová, in their article published in 2018, examined the reasons for employee turnover by choosing deep data mining methods for analysis, namely association rule search and predictive decision trees. At the end of this study, the dissatisfaction of employees and their tendency to leave their jobs were confirmed by the analysis [22].

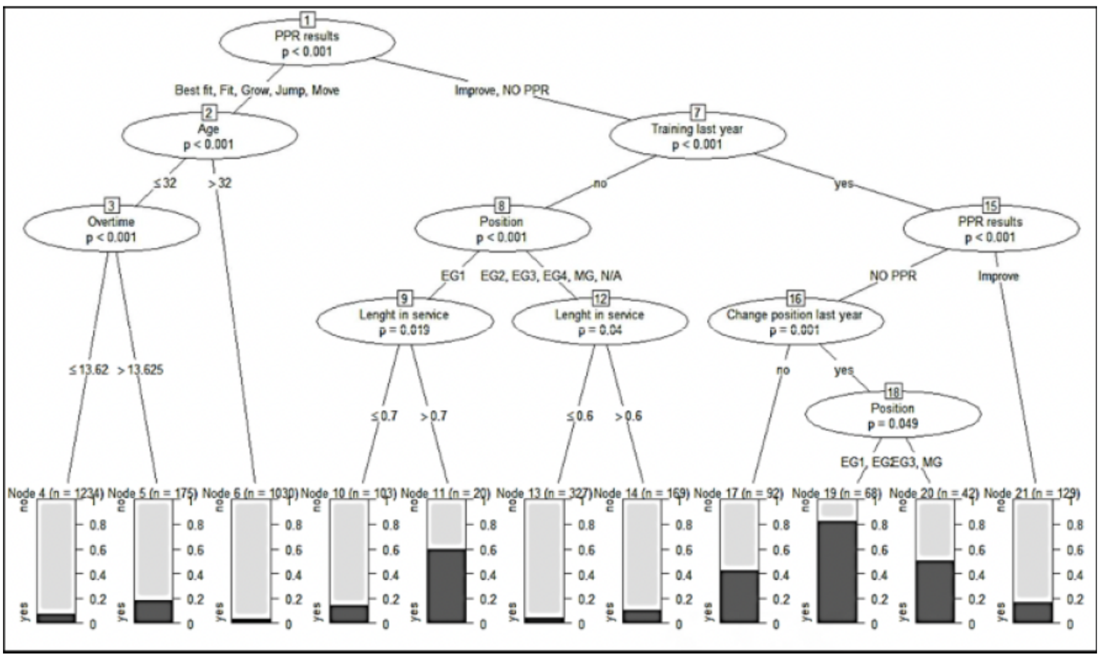

Figure 3. Decision Tree of the ctree Algorithm

These analyses, an example of which can be seen in Figure 3, vary for different sectors, but give a general idea. When the leading dissatisfactions are analyzed, it is seen that dissatisfaction with income, working environment and motivation stand out. Even if their priorities change for different generations, each group of variables are important variables in supporting the tendency to leave the job.

The parameters used in turnover prediction may vary within the framework of sectoral and cultural constraints. In each study, the parameters should be determined in detail within the framework of these constraints. After the model is established, more accurate results can be obtained by removing irrelevant or less effective parameters from the model. Although they vary according to the sector and culture, the parameters to be used in the estimation can be considered in 5 main groups.

These parameters include demographic variables (age, gender, marital status, education level, occupational group, position, salary, number of children, etc.), working conditions variables (workload, working hours, perception of job opportunities, telecommuting, job security, career development, etc.), job satisfaction variables (salary and fringe benefits, Relations with colleagues, top management communication, job stability, job motivation, etc.), organizational commitment variables (commitment to colleagues, emotional commitment to top management, emotional commitment to organizational culture, commitment based on work ethics, commitment to social responsibility, etc.).

Multilayer perception is one of the first neural networks proposed and the structure is shown in Figure 4. It is suitable for simple model classification tasks, such as two classification tasks [23].

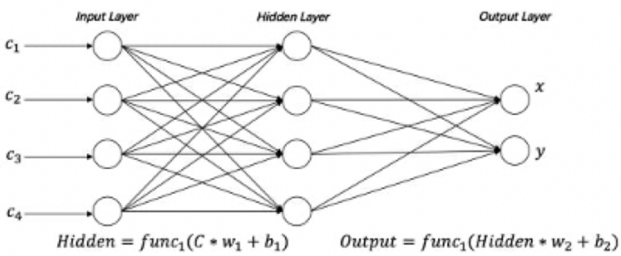

Figure 4. Multilayer perception structure for the binary classification problem.

Multilayer perceptron neural network (MLP) is one of the methods that can be used in human resource analytics to predict employee turnover. By learning from variable data that can predict an employee's propensity to leave, MLP can model which factors are more likely to influence an employee's likelihood of leaving. For example, variables such as employee satisfaction, engagement information, company benefits, performance appraisals, team dynamics and career advancement opportunities are data that can be used by MLP for learning.

There are two main types of decision trees used in data mining:

- Classification tree analysis is used when the predicted outcome is the class to which the data belongs.
- Regression tree analysis is used when the predicted outcome can be considered a real number.

The most common types of decision tree algorithms are CHAID, CART and C4.5. CHAID (Chi-square automatic interaction detection) and CART (Classification and Regression Trees) were developed by statisticians [46]. When analyzing with decision trees, it is important to decide on tree decompositions and select variables. The decision tree divides the data set horizontally according to the importance of the features. Each split represents a specific value of an attribute and the data set is divided into subsets according to these values. During each partitioning process, statistical measures such as the Gini index are used to decide which variables form the best tree and the best representative partitions are selected. The random forest model is a learning method that combines multiple decision trees to select the best outcome.

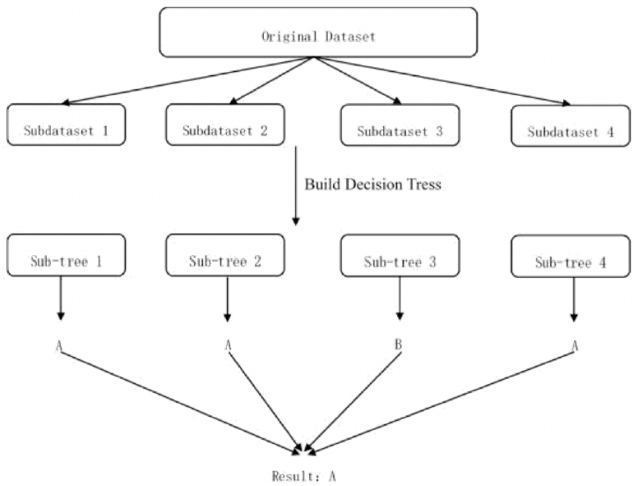

Figure 5. Decision-making process of the random forest

As shown in Figure 5, the dataset extracts 4 sub-datasets to form 4 sub-decision trees, 3 trees are voted as A, one sub-decision tree is voted as B and the final output is A. Among the factors affecting the tendency to leave in this study, Monthly Income, Age, Distance to workplace are the top 3 important characteristics that indicate whether the employee tends to leave or not, marital status is married and women between 40 -50 years old are less likely to leave [24].

Analyses with the random forest method consist of multiple decision trees. Each decision tree is trained independently using randomly selected subsets of the dataset. This process allows each tree to learn different aspects of the data set and improves the overall success of the model. In each tree, the features used to identify splits are also randomly selected. This method ensures that the decision trees are different from each other and makes the model more resistant to overfitting.

"Employee Attrition: What Causes an Employee to Quit?", using Logistic Regression, Random Forest and K-Nearest Neighbor (KNN) methods on a dataset provided by IBM, the study found that the characteristics with the highest correlation were those related to economic factors, such as age, length of employment and monthly income, and employee participation in overtime work. Qualitative attributes such as environment and job satisfaction are associated with attrition, but not to the same degree as other factors [25].

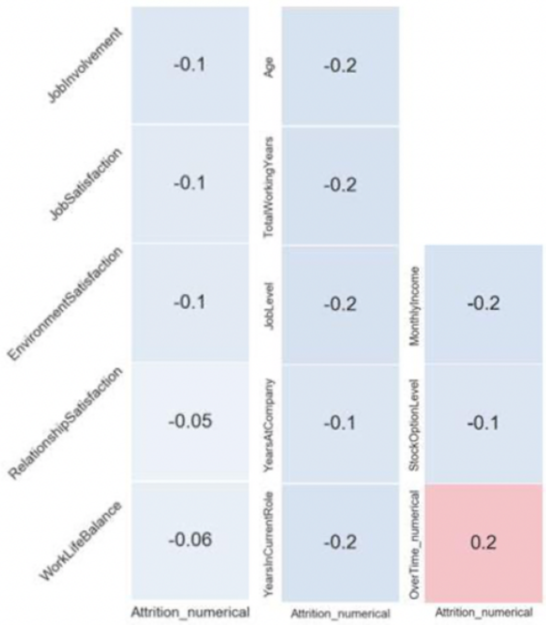

Figure 6. IBM attribute and separation correlation values

The data preparation phase is very important for artificial intelligence-based prediction models. At this stage, the data on past resignation and silent resignation cases should be organized, cleaned and variables should be carefully selected. While preparing this data set, data sets should be differentiated for each sector and company by evaluating them with observations. In order to reduce the subjective effect based on observations, we can start with the largest data set and then work with more refined data sets. Characteristics may include factors such as employee demographics, job performance, organizational commitment level. Differentiating the dataset before and after the pandemic, according to the age of employees and sectors will be necessary to get more accurate results in order to correctly identify the priorities of employees.

After data preparation, model training is performed on the selected machine learning algorithm. In the training phase, the model is tuned to predict turnover and silent resignation trends using historical data sets. The performance of the model is tested on the validation dataset and the hyperparameters are optimized. The trained model makes predictions on new data inputs. Turnover and silent resignation trends are predicted with a given probability. When evaluating the prediction results, the model's performance measures such as accuracy, sensitivity, specificity and F1 score are taken into account.

AI-based predictive models offer employers the opportunity to detect turnover and silent resignation trends earlier and develop strategies accordingly. These models can help employers use resources more efficiently and increase employee job satisfaction.

A review of the literature reveals that HRQA models have been used in many studies to measure employee commitment to work and to predict possible decreases in commitment. In general, economic factors are seen to be prominent factors in turnover, but it is also stated that their importance may decrease in different generations and sectors.

Another method that can be used to predict turnover is the logistic regression model. The following steps should be followed when using the logistic regression model.

- Data Pre-Processing: The answers to the survey questions should be answered on different scales in order to quantify them. Questions that cannot be answered on a scale should be asked categorically. This categorical data should be digitized in the data preprocessing step before the model is built.
- Model Training: In order to reach more accurate results in the logistic regression model, it should be trained with the training data set. In this process, maximum likelihood estimation (MLE) method can be used to determine the coefficients (? values).
- Making Predictions: The logistic regression model calculates the probabilities of the target variables for new data with the coefficients it finds during training iterations. The model uses the values of the independent variables for each row in the data set. It then calculates a probability for each variable.
- Evaluation of Results: The performance of the model is evaluated by comparing the predicted values with the actual values.

Logistic regression is used to estimate the effect of one or more independent variables on a dependent variable. In general, it is a method used to estimate one of two possibilities.

It calculates the probability of each category of the target variable using a process called logit transformation:

$$Logit(p)=log(1\text{-}pp)= \beta 0+\beta 1x1+\beta 2x2+\cdots+\beta nxn$$

The outcome p is the probability that the target variable takes the value "1" (e.g. propensity to quit). $\beta 0,\beta 1,...,\beta n\beta 0,\beta 1,...,\beta n$ are the coefficients of the model and show the effect of each variable on this probability.

Conclusion

Research in the literature clearly demonstrates the importance of human resources, the value of employee engagement for businesses and the benefits of identifying the triggers of turnover. In addition, the benefits of human resource analytics applications, mathematical models and artificial intelligence in these areas have also emerged in the literature.

The literature review was conducted under certain constraints. First of all, the research examines the relationship between human resource analytics and turnover prediction regardless of industry. Studies in the literature may contain different results for businesses in different industries. Another limitation is sociocultural differences. The questions administered in the analyzes in the studies conducted may produce different results in each country and even in each subculture. An important constraint is the time constraint. Especially after the pandemic and with the inclusion of Generation Z in the workforce, expectations from working life have changed. The fact that a relatively short period of time has passed after the pandemic to measure the impact of these changes and that

Generation Z has been in business life for a short time constitutes a constraint for research.

In this respect, turnover tendency should not only be evaluated from a humanities perspective by businesses, but also an engineering perspective should be added to the issue. In case of a multidisciplinary approach, employee engagement can be increased more effectively and labor turnover rate can be improved.

Research in the literature offers us a new perspective on another issue. This is that human resources employees working in organizations today need to increase their competence in technology and data analysis. As the literature clearly shows, employees expect many decisions such as performance evaluation and promotion decisions to be objective and free from personal judgments. This situation reveals the necessity to increase analytical approaches in human resources.

As a result of all these studies, it was clearly seen that artificial intelligence and mathematical models can be used in predicting turnover tendency. This result supports the results of previous studies in the literature.

Every organization should act with this perspective and develop its human resources team in this respect. Investments made in this area will yield returns in a short time with the effects of reducing resignation rates and increasing motivation within the company.

In addition to identifying the tendency, human resource analytics methods can also be used to determine which variables are more effective in increasing this tendency to quit. From this point of view, in future academic studies, the variables that have the most effect on the tendency to quit can be examined in more depth. By finding the sub-variables affecting these variables, the root causes of the tendency to quit can be taken in detail.

In addition, in-depth sector-specific researches and surveys can be conducted to determine which variables affect turnover tendency more in different sectors. Thus, findings that will shed light on both businesses and future research can be obtained.

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