A Review of the Predictive Modeling of Employee Attrition and its Extension for Talent Management in View of HR Disruption

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Systematic Review

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Abstract

This is a review paper of the different predictive models which have been developed for determining employee attrition and it also provides a strategic guideline that the human resource management team can consider implementing in the wake of digital disruption. In the first half of the paper, the introduction to predictive models of attrition has been discussed about the methodology used to refer to the different journal databases and years of publication along with the key variables that have been used. In the discussion section, the gaps have been identified as to why the existing models fail to establish the exact reasons and ascertain the level of attrition properly especially as we see in the case of the massive resignations that are taking place in the workplace through a set of questions which identify the specific areas, yet to be considered in the models. Finally, based on the review, the hybrid conceptual framework has been developed to provide a direction in the future as to how organizations can consider breaking down their structure and in turn capture their emotions and data and finally apply it to determine the reasons and levels of employee attrition.

1. Introduction

Employee attrition is one of the major pains that organizations need to deal with. Especially, in the period of covid-19, through the rapid use of digitization, the phenomena of attrition are happening at a faster pace (Smet et al., 2021). There have been numerous techniques that have been used by organizations to predict employee attrition so that they can ascertain the level of the leakage of employees of the organization and in turn can appropriately hire at a definite level. Some of the research papers have used machine learning to predict employee attrition and suggest that organizations may also follow the same (Setiawan et al., 2020; Usha and Balaji, 2021; El-Rayes et al., 2020; Al-Darraj et al., 2021; Pratt et al., 2021; Khera et al., 2019; Alduayj et al., 2018; Fallucchi et al., 2020; Saradhi et al., 2011; Fan et al., 2012; Yahia et al., 2021; Rombaut et al., 2017). Rombaut et al. (2017) recommended the use of a human resource database for the prediction of employee attrition as it would give a more accurate result. However, the lack of knowledge of the states of the emotions of the employees was something that some of the research did not highlight. Sharma et al. (2019) studied the application of machine learning to predict the emotional intelligence of individuals but it was not linked to employee attrition. On the other hand, researchers focus attention on how the human resource department of organizations should concentrate on applying the technologies to the HR function to manage talent in a better way amidst the digital transformation (Sivathanu and Pillai, 2018). Minbaeva (2020) suggested that the HR of tomorrow should focus on the major global trends while pointing out the ways to bridge the gap existing between the upsurge of technology and the skill of employees. The usage of people analytics for talent management and some of the practices which are followed by the organizations that are utilizing the usage of people analytics have been mentioned in earlier research (Saling et al., 2020; Green, 2017). Schuler (2014) laid out a 5-C framework that talks primarily about the challenges faced by the organizations, highlighting the context and the consequences that they may face for the situations. Boudreau et al. (2011) also highlighted how the future HR leaders of tomorrow would need to sway away from the traditional functional and operational duty to link with an interdisciplinary field on extracting knowledge from such fields to apply the same in the context of HR for better and sustainable organizational culture, and overall creating a more dynamic environment. With the upsurge of covid-19, the world has seen massive resignation incidents and various companies and individuals have been surveyed to identify certain reasons as toxic culture, lack of career growth, and less attention and value by the supervisors to name a few (Sull et al., 2022; Buffett, 2021). As a result of the prevailing uncertainty and more complex dynamics of individuals of the organizations, the previous research which suggested the way forward for better talent management has neglected the void that has occurred due to the more rapid change of digital transformation. To identify the gap and bridge the same this research work primarily focuses on the three steps. First, a review of the
literature on the prediction of employee attrition with special reference to talent management has been done. Second, the gap has been identified and questions have been put forward. Third, the conceptual framework has been drawn which aims to bridge the gap of prediction of attrition to the management of talent in the age of digitization. The organization of the paper is as follows: In section 2, the methodology used and the ways of approaches have been given. In section 3, the predictive models which have been done by previous researchers have been mentioned in a table. In section 4, the review of the literature has been done. In section 5, the discussion starts which identifies the gaps in the form of research questions followed by the conceptual hybrid framework in section 6. Finally, in section 7 the paper concludes with the author’s opinion.

2. Methodology

The review of the literature was done about the process and principles of initially identifying the area of work, doing an exhaustive search, approaching with a purpose to ask the desired questions, and finally coming to developing a conceptual framework through qualitative analysis (Jesson et al., 2011). To search in the databases, the keywords that were used are: “employee attrition”, “employee turnover”, “machine learning for attrition”, “predictive modeling of employee attrition”, “attrition and talent management”, “attrition and HR disruption”, “talent management and disruption”, to name a few. Also, the databases that were used to search the journals are Science Direct, Emerald Insights, ProQuest, Ebsco, IEEE Xplore, and Google Scholar. Apart from this, a few website-based articles were also referred which were found through the Google search engine. In the process of reviewing the articles, a total of 34 journals and websites were referred to which included 30 journals, out of which 17 were ADBC-ranked journals, 8 were Scopus Indexed, 2 were Web of Science indexed and 3 were Conference papers. A total of 4 website-based articles were also referred to which mostly portray the recent trends of employee attrition in organizations across the world. The papers were published in the range from 1993 to 2022, while Emerald and Elsevier were the top two publishers of the articles. A detailed breakup of the insights is given in Fig. 1.

Also, a word cloud was created for the content of the articles which were found using the keywords as mentioned above. This is depicted below in Fig. 2.

3. Review Of Predictive Models

The review of the predictive models for the determination of the level of employee turnover is important since the latter half of the research focuses on the theory based on mathematical models. Here in this section, a review of such predictive models which have been applied by the researchers has been focused on and has been listed in the form of columns with timelines and methodologies applied in brief.
Table 1  
Summary of the models used for prediction of employee attrition

<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Methodology /Algorithm</th>
<th>Objective</th>
<th>Publisher</th>
<th>Data Sources</th>
<th>Dependent Variable</th>
<th>Independent Variables</th>
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</thead>
<tbody>
<tr>
<td>Raman, et al. (2019)</td>
<td>Correlation and Hypothesis Testing</td>
<td>Finding out whether the features of email and the sentiments reflect whether the faculty will leave or not</td>
<td>Emerald</td>
<td>Email Data Sample Survey</td>
<td>Attrition of faculty of B-schools</td>
<td>General and specific email communication features, Communication after office hours, Internal communication, Email sentiment</td>
</tr>
<tr>
<td>Setiawan et al. (2020)</td>
<td>Logistic Regression</td>
<td>To find the level of attrition and its dependence on particular variables</td>
<td>IOP Publishing</td>
<td>Survey data</td>
<td>Employee Attrition</td>
<td>11 were significant some of them are job satisfaction, frequency of business travel, years worked in the company, years with a manager</td>
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<tr>
<td>Usha and Balaji (2021)</td>
<td>Naïve Bayes, Decision Tree, J48, Random Forest, and K Means Clustering</td>
<td>To identify which algorithm could predict attrition with better accuracy</td>
<td>IOP Publishing</td>
<td>Survey Data</td>
<td>Employee Attrition</td>
<td>Around 20 variables were considered which consisted of demographic details and satisfaction level</td>
</tr>
<tr>
<td>El-Rayes, et al. (2020)</td>
<td>Decision Tree, Random Forest, Gradient Boosted Tree</td>
<td>Identifying the probability of an employee leaving the job during the transition</td>
<td>Emerald</td>
<td>Anonymous Resumes from Glassdoor</td>
<td>Employee Switch</td>
<td>Salary Increase, Firm rating, Firm foundation year</td>
</tr>
<tr>
<td>Al-Darraj, et al. (2021)</td>
<td>Deep Learning (Neural Network)</td>
<td>Predicting who will leave the company and who will not</td>
<td>MDPI</td>
<td>IBM Analytics dataset</td>
<td>Employee Attrition</td>
<td>A total of 35 variables were used, out of which overtime, job level, and monthly income were the most important determinants</td>
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<td>Pratt, et al. (2021)</td>
<td>Random Forest</td>
<td>Prediction of who was likely to leave and what the top factors affecting</td>
<td>University of Latvia</td>
<td>IBM HR Analytics dataset from Web</td>
<td>Employee Attrition</td>
<td>Altogether 35 variables were present and out of them, age, monthly income, total years of experience, years spent in the company and with the current manager were the most significant</td>
</tr>
<tr>
<td>Khera and Divya (2019)</td>
<td>Support Vector Machine</td>
<td>To develop a predictive model for employee attrition in the IT sector</td>
<td>Sage</td>
<td>Survey Data</td>
<td>Employee Attrition</td>
<td>A total of 22 variables were taken and gender, business travel and the total number of companies worked earlier were found to be irrelevant</td>
</tr>
<tr>
<td>Alduayj and Rajpoot (2018)</td>
<td>Support Vector Mechanism, K-Nearest Neighbour, Adaptive Synthetic Approach (ADASYN)</td>
<td>To compare different machine learning algorithms for attrition prediction and identify the best algorithm</td>
<td>IEEE</td>
<td>IBM Watson Analytics Synthetic dataset</td>
<td>Employee Attrition</td>
<td>A total of 32 features were selected and top 12 features were identified as the important ones (overtime, years of experience, job level, income, etc.)</td>
</tr>
<tr>
<td>Fallucchi, et al. (2020)</td>
<td>Gaussian Naïve Bayes, Logistic Regression, K-nearest neighbor, Decision tree classifier, Random Forest classifier, Support Vector Mechanism</td>
<td>Different algorithms were compared to analyze and identify the best algorithm among them</td>
<td>MDPI</td>
<td>IBM Analytics dataset</td>
<td>Employee Attrition</td>
<td>35 features from the dataset were used and Gaussian Naïve Bayes was found to have the best recall</td>
</tr>
<tr>
<td>Author(s)</td>
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<td>Saradhi and Palshikar (2011)</td>
<td>Support Vector Mechanism, Random Bias, Naïve Bias</td>
<td>Algorithms were compared to predict employee churn and a value model was developed to identify how many valuable employees left</td>
<td>Elsevier</td>
<td>Company-specific data</td>
<td>Employee Churn</td>
<td>Initially, 25 variables were considered, and later derived data sets were used, i.e., a total of 12 such variables (employee number, project name, on-site/off-site, experience with the client organization, etc.)</td>
</tr>
<tr>
<td>Fan, et al. (2012)</td>
<td>Self-Organizing Map and Hybrid Artificial Neural Network</td>
<td>Finding the reasons for the loss of employees in organizations</td>
<td>Elsevier</td>
<td>Sample survey through questionnaire</td>
<td>Employee Turnover Intentions</td>
<td>24 variables were involved and upon factor analysis, the 7 factors identified were: organization system, satisfaction, stress, organization promise, officer promise, ethical climate, individual data</td>
</tr>
<tr>
<td>Yahia, et al. (2021)</td>
<td>Voting Classifier (after Select K Best and Recursive Feature Elimination)</td>
<td>To shift the focus from big data to deep data so that the data quality is also focused</td>
<td>IEEE</td>
<td>Survey data through questionnaire, Web data on HR Analytics</td>
<td>Employee Attrition</td>
<td>16 features were finalized and then finally 11 (Performance in Job, Involvement in Job, Training, Business Travel, Age, etc.)</td>
</tr>
<tr>
<td>Rombaut and Guerry (2017)</td>
<td>Decision Tree and Logistic Regression</td>
<td>To check if the HR database can be relied on for the prediction of employee turnover</td>
<td>Emerald</td>
<td>Data of Belgium Company</td>
<td>Employee Turnover</td>
<td>6 demographic factors (gender, age, nationality, marital status, number of children, health) and 7 work-related factors (grade, work volume, salary, distance from office, work pressure, sector of work, and individualism in work)</td>
</tr>
</tbody>
</table>
### 4. Findings From Literature

This section reviews the literature from the perspective of the methodologies used by the previous researchers to analyze the reasons and models of employee attrition along with the review of some of the talent management perspectives given smart HR in the journey of digitization. Bennett et al. (1993) used hierarchical regression analysis to conclude that employee turnover is impacted to a great extent by employee benefits while controlling the factors namely firm characteristics, firm setting, and workforce characteristics. Setiawan et al. (2020) predicted the employee attrition level using logistic regression which included the number of companies worked, total years of work, years spent with the current manager, business travel frequency, and job satisfaction to name a few. In another conference, the different machine learning algorithms were compared with arch other after data collection through a survey and it was found that employee pride in working, security in the job, promotion, work-life balance, recognition given by supervisors, employee opportunity to grow were the major factors which impacted the decision of the employee to leave the organization and Naïve Bayes algorithm gave the maximum efficiency while predicting the same (Usha and Balaji, 2021). El-Rayes et al. (2020) studied cross-industry employee attrition using a decision tree and random forest using the data set of 5500 anonymous resumes through the Glassdoor portal and it was found that salary change was the major reason behind employee transition. Some of the hypotheses that were constructed were that if a competing company is offering more than a 40% of salary hike, then the salary will play an important role in attrition along with the fact that employees of those companies who are ranked lower in Glassdoor have more tendency to move rather than a higher ranked company (El-Rayes et al., 2020). Al-Darraji et al. (2021) applied a deep learning algorithm to predict the level of attrition where there were 53 neurons, 7 hidden layers with 100 neurons each, and an output layer. It was found that hours of overtime, level of job, and monthly income were the most determinant factors for an employee to take a decision (Al-Darraji et al., 2021). Pratt et al. (2021) used the random forest algorithm while comparing it with other algorithms and used different parameters like area under curve and accuracy, to conclude that the random forest algorithm was the most efficient. The income of the employees, age, years of work, and rate of pay were the topmost features that influenced the factors among employees to leave the current company (Pratt et al., 2021). Khera and Divya (2019) used predictive modeling for finding out the reasons for employee turnover in the IT industry through a survey across three IT companies and applied a support vector machine algorithm for the same. Alduayj and Rajpoot (2018) initially used imbalanced data set to experiment with the machine learning model for turnover prediction and later used balanced data by converting the imbalanced dataset using oversampling where random forest showed the highest accuracy and F1 score. Through hypothesis testing, the higher intention to quit for IT professionals (both employees and managers), was shown as a reason for higher educational deviance, lower performance orientation, and lower organization citizenship behavior through survey data analysis (Krishnan and Singh, 2010). Their structural equation modeling revealed that organizational deviance was highly related to intention to quit whereas, performance orientation acted as a mediating variable.
between the link of organization citizenship behavior and intention to quit along with the partial mediation effect of performance orientation as a link between deviance of organization and the intention to quit (Krishnan and Singh, 2010). Fallucchi et al. (2020) also used predictive modeling and compared eight models using a synthetic dataset containing thirty-five features out of which income every month, age, distance from home, total years of work experience, and over time were found as predominant factors in influencing attrition and Gaussian Naïve Bias had the lowest false positive cases and the highest recall and true positive cases, inferring as the superior algorithm. Saradhi and Palshikar (2011) compared with customer churn models and extended to employee turnover by drawing the equation of the employee value model which in turn would help in determining whether the employee who left the organization was valuable or not, while re-iterating that support vector machine algorithm was a better fit algorithm for prediction of employee churn. Fan et al. (2012) developed a hybrid model which was yet again based on quantitative predictive modeling which combined the self-organizing map and the backpropagation network which clustered the data into four clusters, based on the turnover tendencies and accuracy of the model was found to more than the individual models. Yahia et al. (2021) suggested the research fraternity of moving away from big data towards deep data where the quality of data will be in focus after removing the duplicate data and thus through a sampling survey after applying proper feature selection like SelectKBest and recursive feature elimination, voting classifier algorithm proved to be the best algorithm with business travel being one of the most significant variables affecting the retention of employees. Rombaut and Guerry (2017) performed the analysis of a database of a Belgium company not only to predict employee leaving but also the patterns such as the turnover rate of employees increasing till they serve in an organization for five years, then decreasing and finally employees whose salaries are lesser and who have a company-sponsored car have a lesser tendency to leave than among two employees who have a similar salary. Kakulapati et al. (2020) applied a k-means clustering approach to identify the clusters where the employees will fall regarding their employability and promotion opportunities by using the corresponding salary ranges for each cluster. Apart from these predictive models for attrition, the emotional intelligence surveyed for certain individuals was also subjected to machine learning using an artificial neural network which predicted the level of emotional intelligence separately using a trait meta-mood scale (Sharma et al., 2019). Younis and Ahsan (2021) tried to give the researchers a different view of predicting the attrition of star employees through the social network analysis where the hypothesis concluded that the in-degree centrality of the influencers inside the network and out-degree centrality of the high performers outside the network, were highly linked to attrition. Ghosh et al. (2013) through a survey among the managers of an organization identified primarily seven factors that influence employees to stay back in the organization among which affective commitment was found to be most significant, followed by normative commitment, goal clarity, employee engagement, and organization culture. Bagga (2013) suggested a separate department within the organization for employee retention after concluding that compensation was the most important reason for retention for the employer but was only the fifth reason for leaving the company. Research in humanitarian organizations showed that in the case of external factors, employment perception was the important factor for attrition, in the case of work-related factors all variables are significant, and in the case of personal factors, information regarding bio-graphics, marital status, aptitude, intelligence and number of dependents were more important factors contributing to attrition (Dubey et al., 2016). Sivathanu and Pillai (2020) did a sample survey among human resource professionals in organizations and concluded that technology in talent management plays an important role in developing high-performing talent so that they can contribute to the organization’s performance. Their study also suggested that talent analytics helps HR to track and predict high-performing employees and thus in turn with the culmination of strategic management helps to attract, develop and retain employees (Sivathanu and Pillai, 2020). This now takes a new turn in the literature review to delve into talent management strategies regarding disruption in the HR domain. Research suggests that the HR practitioners of the future should focus on collective leadership, co-creation through the agile process, personal value proposition, and
segmentation of the workforce, and also, they should focus on organizational culture, structure, leadership, diversity and social responsibility (Boudreau and Ziskin, 2011). Schuler (2014) developed the 5-C framework which consisted of choice, the people involved in talent management, the policies, the challenges concerning talent motivation, engagement relocation, the contingencies (leadership, values, company, culture, economic development, competitiveness of country) and the consequences related to individual satisfaction, career development, coaching, feedback, compensation and benefits, motivation, retention, productivity which aides in effective talent management overall. Saling and Do (2020) visualized the life of Army personnel in the organization and through the systemigram modeling, technique captured the ecosystem of the human capital management of the employees in their life cycle to identify the instances where artificial intelligence can help make better decisions. While talking from an analytical point of view the organizations which adopt people analytics at the workplace typically exhibit a culture of data that is authentic, and clear, utilize the data from across different functions, focus on the projects that matter the most, learn continuously and apply latest technological processes (Green, 2017). While there is a continuous focus on talent management, the disruption created by the digital upsurge has made HR rethink their position in the organization by not just focusing on the operational aspects but also focusing on the interactions among the employees in case of a temporal organization, being digitally more equipped to foster in the digital wave and finally delivering maximum business value by aligning with the core digital principles and practices (Minbaeva, 2020).

Sivathanu and Pillai (2018) marked the upsurge of smart HR and how the human resource management team needs to embrace the change of adopting the practices of applied artificial intelligence through the life cycle of the employees to overcome the current organizational culture and managing the diverse generation of employees. They suggested a flat hierarchical structure to reduce errors due to communication to foster a culture of innovation and openness (Sivathanu and Pillai, 2018). The ushering of rapid technological influence and the fourth industrial revolution has prompted a re-design of the human resource management architecture with a special focus on the employee, to understand their emotional touchpoints and at the same time has necessitated the HR to adapt to the rapid change in environmental conditions, workforce structure with a touch on the societal benefits so that it can be beneficial to both the employee and employer (Claus, 2019). The literature has had enough depth from the point of predictive modeling of attrition to the talent management practices regarding digital disruption but the recent attrition levels in organizations amidst the pandemic mandate a short study on the present dynamics in the organization. In one of the surveys conducted across thirty-eight industries, it was found that toxicity of the organizational culture, security in the current job, high level of innovation, lack of employee recognition, and lack of employee welfare measures during covid contributed as major reasons for employees to leave while compared to compensation (Sull et al., 2022). In another survey across employers in Australia, Canada, Singapore, the UK, and the US, it was found that low value given by managers, low sense of organization belongingness, lack of trust, care, and work flexibility mattered more to the employees while taking a decision to leave the company and many employees were not even having a job in hand while resigning (Smet et al., 2021). Cook (2021) suggested ways to handle the problem of attrition amidst the uncertain times such as pinpointing the particular reasons for the same, quantifying the results, and focusing on customized approaches for retention but, the economic implication is worse than pre covid times in India where there is an increasing trend of gap inequality among middle- and lower-income groups of people for the reduction in the macros pace of handsomely paid jobs (Mohan, 2022). All the above implications have led the author to revisit the literature and re-think the phenomena of employee attrition and the discussions are highlighted in the next section.

5. Discussion And Proposed Conceptual Hybrid Framework
The above literature has significantly contributed to the development of prediction models to ascertain the level of attrition and also has paved a way for the HR managers in the organization ways to tackle digital disruption and adapt to this rapid technological surge for effective talent management. However, there still exists a gap, since the models which are developed are algorithmic in nature which do not take into account the behavioural aspects of the employees and also the data during the different stages of the employees, are not captured as well. The above-mentioned literature thus creates curiousness in the author’s mind and several questions are raised which are mentioned below:

- How can the predictive models of attrition capture the emotions of the employees?
- Does the employee reflect the same type of emotions entirely during their stay in the particular organization and what is their tendency to leave while in different stages of the organization?
- When does the employee become aware of the mismatch between his capabilities and the values, and goals of the organization such that there is an intent for the employee to leave such an organization?
- When do the employees sense the interest in other organizations in their journey and what are the traces that the emotional transitional states for the employee while they are desirous of taking that path?
- How does the exit interviews impact the employees’ decision and how do they act following the controlling variables implemented by HR?
- Does the HR rely only on the data of the employees in databases or do they also refer to the data captured through a survey or other insights which capture the employee sentiments as well?
- How does the financial growth of any competitor company where the employee moves, impact the decisions of the employee to quit?
- How can HR consider the attrition model based on both the insight and the emotion of the employees into the other decisive areas of talent management which would create a mathematical learning function for the organization?
- Can HR create sustainable human capital through the integration of insight and emotion of the employees using any model that not only uses the algorithms to predict but also qualitative models which encompass the quantitative behaviors of the employees of the organization?
- How does each of the stages which the employee experiences, affect the level of attrition in the organization?

All the above questions drive the author to develop a conceptual framework that will define the steps of attrition and how it occurs during the entire life cycle of an employee particularly in the case of an IT organization since they are badly impacted by the phenomena of employee turnover and ultimately help in effective talent management.

The above figure depicts the hybrid frameworks for measuring the level of attrition only after considering the experience of the employees while they pass through the different stages in the organization while addressing the questions that are raised. In Fig. 3, the framework shows one particular organization where the employee passes through different stages like recruitment and selection, engagement, learning and development, and performance management, and the experiences which are involved are captured through emotions along with the quantitative data that the employee leaves while during one's stay in the organization. Different variables are to be included covering the emotional and the physical aspects of the employees for validating the framework through hypothesis and can be carried out in the future.

6. Conclusion
This paper thus builds upon the literature review of the predictive models that can be used for ascertaining the levels of attrition in organizations followed by a short review of the digital disruption in the human resource management function and how talent management can incorporate the use of technology for better and effective management of human resources. Based on the review, the need for a hybrid framework was proposed so that it could address the gap that exists in the literature through the questions derived. The hybrid frameworks were taken into consideration such that it touches the employee experience, while in the organization and at the same time the employee's emotions through the level of awareness, and intentions to leave the organization. Thus, it is the human resource manager in the organization who will be better able to ascertained the level of attrition not just through data-based attrition models but a combined hybrid framework considering the quantitative analysis as well as the behavior and experience of the employees. Future research can be done to validate this hybrid framework through the analysis of data by constructing a hypothesis and the level of attrition can be measured using advanced algorithms.

References


**Figures**
Figure 1

Insights from Methodology Used
Figure 2
Word Cloud of the Entire Content of Articles

Figure 3
Hybrid Framework for Determining Attrition Level in One Organization