DOI: https://doi.org/10.24297/ijmit.v21i.9844

Analyzing Healthcare Attrition using Machine Learning and Traditional Statistical Techniques

Sumali Conlona[1], Yue Gaob[2], and Haitao Liuc[3]

[1] Department of Marketing, Analytics and Professional Sales, University of Mississippi, University, MS, USA

[2]School of Business, Clark University, Worcester, Massachusetts, USA

[3]Independent Researcher, Boston, Massachusetts, USA

[1]sconlon@bus.olemiss.edu, [2]YuGao@clarku.edu, [3]hliu5@wpi.edu

Abstract

It is important to understand what might cause healthcare professionals to leave their jobs. In this research, we therefore analyze data on employee attrition in the healthcare sector to determine which factors motivate these professionals to leave or stay in their current careers. We combine the flexibility of machine learning techniques with the transparency of traditional statistical techniques, such as logistic regression analysis, to understand the data. With an accuracy rate of 95.6%, based on several factors in this study, we find that one of the primary reasons these healthcare professionals leave their jobs is excessive overtime requirements. Using a deeper analysis involving logistic regression, we determine the quantitative effects of our different explanatory variables. We also find that job satisfaction does not seem to have as much explanatory power as several other variables, and that it does not seem to be a mediating variable in explaining attrition.

Keywords: Healthcare Professional's Job Attrition, Human Resource Analytics, Machine Learning, Data Analytics

Introduction

Healthcare professionals' job satisfaction is especially important since healthcare significantly impacts people's well-being. If healthcare professionals are satisfied with their jobs, their performance should be high, which means that overall healthcare quality should be improved. In addition, one would expect the overall cost of healthcare to be lower since the problem of employee turnover should be reduced.

A healthcare system with professionals who are satisfied with their organization should be able to better provide high-quality health services. Unfortunately, a recent 2023 survey by Qualtrics, as reported in the 2023 Healthcare Experience Trends Report, found that healthcare ranked last for employee satisfaction compared to 27 other industries (Burky, 2023). Their survey of 3,000 healthcare employees across 27 countries found that only half of the employees believe they are paid fairly, while 38% feel that they are at risk of burnout, and 39% are considering quitting their organization (Burky, 2023). In addition, Qualtrics also found that, based on 9,000 customer surveys, they ranked hospitals among the lowest across industries as places to work (Burky, 2023). In contrast, while a large fraction of healthcare professionals are not satisfied with their jobs, the demand for healthcare professionals will be growing in the near future. A report prepared for the Association of American Medical Colleges (AAMC) by IHS Market Ltd. (2021) predicted that there will be a shortage of approximately 37,800 to 124,000 primary care physicians by 2034. Thus, there is a serious need to analyze healthcare professionals' job satisfaction and attrition, to determine what factors motivate them to be satisfied or dissatisfied with their jobs.

Even though there have been many studies on employee job satisfaction, retention, and attrition, employees in different domains have different reasons for being satisfied or dissatisfied with their jobs. Thus, there is a need for more studies in specific domains to evaluate the in-depth reasons why employees are satisfied or dissatisfied with their jobs. For example, Conlon (2021) studies what causes data scientists to change jobs and what types of jobs or locations they switch to. She found that many data scientists move from jobs located in smaller cities to jobs in larger cities, once they become more mature with their skill levels. In the hotel business, Haldorai et al. (2019), for example, analyzed the factors affecting hotel employees' attrition and turnover by using survey questionnaire data from five-star hotel employees in the Kuala Lumpur region. They found that Push-Pull-Mooring (PPM) factors, used widely in the travel and tourism literature, significantly impact turnover intentions. In general, PPM theory consists of a three-dimensional model (push, pull, and mooring). The "push" represents the negative factors that force people away, the "pull" represents the positive factors that attract people, and the "mooring" represents the factors that involve interpersonal and cultural issues that can either encourage or discourage employees fr000000000000000000000000000000000000000000000000000000000000m leaving or staying at their jobs. More on push, pull, and mooring research can be found in Lee (1966).

Research analyzing employee satisfaction involves survey data and related techniques. Recent research using machine learning has been successful in performing deep data analysis. In healthcare, for example, machine learning has been used in various applications such as drug discovery and development, predictive analytics, clinical decision support, robotics in surgery, etc.

Much research using machine learning (ML) to analyze employees' job satisfaction shows that ML can predict the major causes of job satisfaction or dissatisfaction in many areas. For example, Conlon et al. (2021) use machine learning techniques to predict whether IT employees are satisfied with their jobs or not, achieving high accuracy rates. In this research, we analyze which factors are likely to cause healthcare professionals to leave their jobs. After finding the major causes of employee attrition, we further analyze more precisely how those factors influence employees' decisions to leave their jobs. Thus, in this research, we ask:

RQ1: Using machine learning techniques to analyze the data, what are the major causes of healthcare professionals' decisions to leave their jobs?

RQ2: Which machine learning algorithms best predict healthcare employee attrition?

In addition, given the intuitive role we expect job satisfaction, in particular, to play in attrition, we add a third research question,

RQ3: Does measured job satisfaction play a role in explaining attrition, either directly or as a mediating variable?

Our findings contribute to the body of research in that we combine the flexibility of deep machine learning techniques with the transparency and simplicity of traditional statistical techniques to better understand the data. One of our major findings is that overtime is by far our most important predictor of attrition. Of course, our data was collected during the COVID period, and that might play a role in the importance of overtime.

We also find that, while measured job satisfaction makes a minor contribution to predicting attrition, it plays a less important role than several other variables, such as shifts, job involvement, and environmental satisfaction. It is also not a mediating variable, having almost no correlation with variables that one would expect to be related to job satisfaction, such as job involvement and environmental satisfaction. Thus, it does not seem to be a good proxy for our other explanatory features. However, the smaller effect of job satisfaction may be partly due to the different ways in which different respondents interpreted the question.

The rest of the paper is organized as follows: The next section reviews the literature on employee satisfaction and attrition, how machine learning techniques have been used in analyzing these factors, and how they have been used in the analysis of healthcare professionals' decisions in particular. The data and techniques we use in our analysis are then presented. The subsequence section discusses the results of the data analysis. The implications of our results are then discussed, followed by a conclusion and discussion of the business and policy implications of this research.

Related Work

Employee Job Satisfaction and Attrition

One of the major problems that organizations face is employee attrition. Employee attrition can cost businesses a great deal to find replacements. Otto (2017), at Employee Benefit News (EBN), referred to data from the Work Institute's 2017 Retention Report, which showed that, if an employee leaves a company, it will cost the employer 33% of that worker's annual salary to hire a replacement. For example, for a median salary of $45,000 a year, finding a replacement costs the firm about $15,000 per person (Bolden-Barrett, 2017). As explained by Hinkin and Tracey (2000), these costs include:

- Predeparture (costs that are incurred once an employee has given notice),
- Recruitment (promotional materials, advertising, and recruiting sources),
- Selection (identifying the most suitable candidates - Interviewing, background and reference checks, and travel expenses),
- Orientation and Training (almost everyone requires some formal or informal training),
- Productivity Loss (this is the largest percentage of the total costs, up to 70 percent in some cases).

Thus, to avoid employee attrition, it is essential to understand what causes attrition to happen. A great deal of research has been done to analyze factors influencing employees' job satisfaction and attrition. Locke (1976) defines job satisfaction as "a pleasurable or positive emotional state resulting from the appraisal of one's job or job experiences" (p. 1304). Studies identifying reasons for employee job satisfaction or dissatisfaction include Spector (1997), who lists 14 common aspects of employee job satisfaction, including appreciation, communication, coworkers, fringe benefits, job conditions, nature of the work, organization, personal growth, policies and procedures, promotion opportunities, recognition, security, and supervision. Similarly, Aziri (2011) and Singh and Jain (2013) listed several employee job satisfaction factors, including compensation and benefits, job security, working conditions, relationships with superiors, promotion and career development, leadership styles, workgroup factors (group dynamics, cohesiveness, and affiliation), personal variables, and others.

Some research, including Hulin and Judge (2003), finds that employee job satisfaction is influenced by psychological factors, including cognitive (evaluative), affective (or emotional), and behavioral factors. They state that behavioral components of job satisfaction can be related to other key factors such as working conditions, stress levels at work, etc.

In terms of employee turnover factors, several are important, including:

1) Job specific turnover factors, such as tenure, pay, overall job satisfaction, and the employee's perceptions of fairness (Cotton and Tuttle (1986)).

2) Personal or demographic variables, specifically age, gender, ethnicity, education, and marital status (Holtom et al. (2008); Sacco & Schmitt (2005)).

3) Other factors, including general career development concerns, work-life balance values, managers' behavior, compensation and benefits, and well-being.

In the Work Institute's 2022 Retention Report (2022), the list of reasons for employees to leave their jobs in 2021 were:

Reasons-for-Leaving Categories:
· Career: Opportunities for growth, promotion, achievement, security, or to attend school
· Job: Stress, availability of resources, training, job characteristics, empowerment, or products
· Health & Family: Child or elder care, work-related health, or non-work-related health
· Work-Life Balance: Travel, commuting, or scheduling preferences
· Total Rewards: Base pay, benefits, bonuses, or commissions
· Relocation: Employee-initiated, company-initiated, or spouse-initiated
· Management: Professional behavior, support, knowledge and skills, or communication
· Environment: Organizational culture, facilities or physical environment, mission and values, safety, diversity, or coworkers
· Retirement: Personal decision to exit the workforce
· Involuntary: Termination or layoff
· General Employment: miscellaneous issues not assigned to other categories

Source:
https://info.workinstitute.com/hubfs/2022%20Retention%20Report/2022%20Retention%20Report%20-%20Work%20Institute.pdf

The Work Institute's Retention Report studied 34,000 respondents and found that 75% of employee turnover cases were preventable (2017 Retention Report: Trends, Reasons & Recommendations). Thus, finding the causes of employees' job satisfaction/dissatisfaction and attrition should be helpful in preventing employee attrition problems.

Machine Learning Techniques and their Applications in Human Resource Management

Among many sub-areas of artificial intelligence (AI), machine learning (ML) has been particularly successful. It has been applied to many business applications, such as finance, marketing, sales, product recommendation, dynamic pricing, etc.

ML has also been used in human resource management. For example, ML is used in predicting employee turnover (Punnoose & Ajit, 2016), analyzing employee attrition (Alao & Adeyemo, 2013; Fallucchi, 2020; Nagadevara, 2008; and Ray & Sanyal, 2019) and analyzing and predicting employee engagement (Golestani et al., 2018). Jain et al. (2021) use ML to analyze employees' job satisfaction. For employee churn analysis, Bendemra (2019) used ML techniques to show that the causes of employees leaving their jobs include: Monthly Income (employees with higher wages are less likely to leave), Overtime (people who work overtime are more likely to leave the company), Age (25–35 are more likely to leave), Distance From Home (Employees who live further from home are more likely to leave the company), Total Working Years (more experienced employees are less likely to leave), Years At Company (Employees who hit their two-year anniversary should be identified as potentially having a higher risk of leaving), Years With Current Manager (A large number of leavers leave 6 months after they have worked for their current managers). More information about research using machine learning techniques for predicting employee turnover can be found in Akashes et al., 2024.

Machine Learning Techniques and Their Applications in Healthcare Professional Management

Machine learning techniques have been helpful in healthcare applications such as predicting patient outcomes (Chakraborty et al., 2024; Chaw et al., 2024; Dharmarathne et al., 2024; and Raza, 2022), analyzing patients' data for diagnosis (Raza, 2022), and improving health policies (Mahmoudian, 2023), etc. For healthcare professionals, job satisfaction and attrition are essential areas of study (Kupietzky, 2023). Kupietzky (2023) states that if healthcare professionals are satisfied with their jobs, this can improve their job performance, which can save healthcare costs and improve overall healthcare quality (Kupietzky, 2023).

Previous studies related to healthcare professional job satisfaction found that the factors that affect their job satisfaction include workload, level of autonomy and decision-making authority, collegial relationships, burnout, organizational culture and leadership, career advancement, workplace violence, and harassment. Some demographic factors, such as age, gender, and years of experience are also important (Bhatnagar and Kalpana, 2012; Galanis's, 2021; Abdullahi et al., 2023; House et al., 2022; Wei et al., 2023; Lu et al., 2012). Major research on healthcare attrition can be found, for example, in Abdullahi et al., 2023; Bahlman-van Ooijen et al., 2023; Galanis et al., 2021; Rushton et al., 2015; Wei et al., 2023; and Wilson 2022 (see below for more on Bahlman-van Ooijen et al., 2023, Galanis et al., 2021 and Rushton et al., 2015).

Data & Methodology

In this study, we employ the dataset "Employee Attrition for Healthcare," posted at Kaggle.com. The data set is a synthetic, publicly available dataset modified from the original IBM HR Analytics data to reflect the healthcare domain. Table 1 presents variable names and descriptions for the dataset. This dataset contains 1,676 observations with 35 features (including the target feature). The target feature, attrition, consists of the value 'Yes' (employee left the company) and 'No' (employee did not leave the company). Among 1,676 employees, 199 indicated that they left their companies, and 1,477 did not leave the company, as shown in Table 2. Sample records from our dataset are illustrated in Figure 1.

Table 1. Variable Descriptions.

Variable Name	Description
Employee ID	Primary key for employees
Age	Employee age
Attrition	Did employee leave company or not?
BusinessTravel	Travel_Rarely, Travel_Frequently, or Non_Travel for work
DailyRate	How much an employee made in one day
Department	Department/Field employee worked
DistanceFromHome	Distance from home in minutes
Education	Years of education completed
EducationField	Employee's major/minor or academic focus
Employee	Employee count per row; this is always equal to 1
EnvironmentSatisfaction	Employee environment satisfaction on a scale from 1-4
Gender	Male or female
HourlyRate	Hourly rate of employee
JobInvolvement	Job involvement on a scale from 1-4
JobLevel	Job level on a scale from 1-4
JobRole	Job roles include: Nurse, Therapist, Administrative, Other
JobSatisfaction	Job satisfaction on a scale from 1-4
MaritalStatus	Single, Married, Divorced
MonthlyIncome	Total monthly income of employee

MonthlyRate	Total monthly rate of employee
NumCompaniesWorked	The number of companies an employee has been employed at
Over18	Employee is over the age of 18
OverTime	Employee did overtime
PercentSalaryHike	Percent of employee's salary raise
PerformanceRating	Performance of an employee on a scale from 1-4
RelationshipSatisfaction	Employee's personal relationship satisfaction on a scale from 1-4
StandardHours	Total hours an employee works in two weeks
Shift	0) PRN* 1) 7am - 3:30pm 2) 2 pm - 10:00pm, and 3) 9pm - 7:00am
TotalWorkingYears	How many years employee worked
TrainingTimesLastYear	How many training events employee had last year
WorkLifeBalance	Employee's rating of work life balance on a scale from 1-4
YearsAtCompany	The number of years an employee has been at current company
YearsInCurrentRole	The number of years an employee has been in current position
YearsSinceLastPromotion	Years since employee's last promotion
YearsWithCurrManager	How many years employee has been with their current manager

Note: *PRN (pro-re nata), under "shift," indicates employees who are only called in to work when the employer needs them.

Table 2. Distribution of the Target Feature

# Attritions	
# Yes	199
#No	1477
Total	**1676**

EmployeeI	Age	Attrition	BusinessTr	DailyRate	Departmei	DistanceFr	Education	EducationI	Employee(	Environme	Gender
1313919	41	No	Travel_Rai	1102	Cardiology	1	2	Life Scienc	1	2	Female
1200302	49	No	Travel_Fre	279	Maternity	8	1	Life Scienc	1	3	Male
1060315	37	Yes	Travel_Rai	1373	Maternity	2	2	Other	1	4	Male
1272912	33	No	Travel_Fre	1392	Maternity	3	4	Life Scienc	1	4	Female
1414939	27	No	Travel_Rai	591	Maternity	2	1	Medical	1	1	Male
1633361	32	No	Travel_Fre	1005	Maternity	2	2	Life Scienc	1	4	Male
1329390	59	No	Travel_Rai	1324	Maternity	3	3	Medical	1	3	Female
1699288	30	No	Travel_Rai	1358	Maternity	24	1	Life Scienc	1	4	Male
1469740	38	No	Travel_Fre	216	Maternity	23	3	Life Scienc	1	4	Male
1101291	36	No	Travel_Rai	1299	Maternity	27	3	Medical	1	3	Male
1430504	35	No	Travel_Rai	809	Maternity	16	3	Medical	1	1	Male
1196281	29	No	Travel_Rai	153	Maternity	15	2	Life Scienc	1	4	Female
1207951	31	No	Travel_Rai	670	Maternity	26	1	Life Scienc	1	1	Male

EmployeeI	HourlyRat	JobInvolve	JobLevel	JobRole	JobSatisfa	MaritalSta	MonthlyIn	MonthlyRa	NumComp	Over18	OverTime	Pe
1313919	94	3	2	Nurse	4	Single	5993	19479	8	Y	Yes	
1200302	61	2	2	Other	2	Married	5130	24907	1	Y	No	
1060315	92	2	1	Nurse	3	Single	2090	2396	6	Y	Yes	
1272912	56	3	1	Other	3	Married	2909	23159	1	Y	Yes	
1414939	40	3	1	Nurse	2	Married	3468	16632	9	Y	No	
1633361	79	3	1	Nurse	4	Single	3068	11864	0	Y	No	
1329390	81	4	1	Nurse	1	Married	2670	9964	4	Y	Yes	
1699288	67	3	1	Nurse	3	Divorced	2693	13335	1	Y	No	
1469740	44	2	3	Therapist	3	Single	9526	8787	0	Y	No	
1101291	94	3	2	Nurse	3	Married	5237	16577	6	Y	No	
1430504	84	4	1	Nurse	2	Married	2426	16479	0	Y	No	
1196281	49	2	2	Nurse	3	Single	4193	12682	0	Y	Yes	
1207951	31	3	1	Other	3	Divorced	2911	15170	1	Y	No	

Figure 1. Sample Data

We utilize DataRobot (https://www.datarobot.com/) to perform our predictive analysis. DataRobot is an advanced machine-learning tool designed to streamline the model-building process. This tool automates the execution of numerous state-of-the-art machine learning algorithms, requiring only the provision of data with a target feature. This tool is appropriate to find the widest range of possible explanatory features in our initial, exploratory, analysis.

The algorithms' performances are assessed using key metrics such as the area under the receiver operating characteristic (ROC) curve, LogLoss, the F1 score, and accuracy. The ROC curve plots the true positive rate against the false positive rate at each threshold. The area under the ROC curve, known as the AUC, provides a single measure of performance across all possible thresholds by computing the entire two-dimensional area under the ROC curve. Another important metric is LogLoss, or cross-entropy loss, which measures the discrepancy between the predicted probabilities and actual outcomes; lower values indicate better performance. The F1 score combines the precision (the number of true – i.e., correctly predicted – positives divided by the number of predicted positives) and recall (the number of true positives divided by the number of observations that should have been identified as positive) to assess predictive performance. Finally, accuracy is the fraction of correct predictions (whether positive or negative) made by the model. The top-performing algorithms, as indicated by these metrics, are presented to the user as candidates for further selection based on individual preferences.

In addition to the top-performing algorithms, DataRobot further provides the most impactful features used in predicting the target values. This allows the user to conduct in-depth analyses of the most important features, enhancing their understanding and improving decision-making processes.

Once the initial machine learning results are obtained, traditional econometric models are employed for prescriptive analysis of the determinants influencing healthcare professionals' attrition. With the important features suggested by DataRobot as inputs, logistic regression was performed using STATA18 (StataCorp. 2023. Stata Statistical Software: Release 18. College Station, TX: StataCorp LLC) to more clearly discern the quantitative impacts of these features on employee attrition. This approach aims to provide insights into the quantitative relationship between the identified features and employee attrition in healthcare companies.

In addition, since "job satisfaction" was not included among the explanatory features selected by DataRobot algorithms, we do follow-up analysis using logit and linear regression models to determine whether job satisfaction plays a significant role in predicting attrition, either on its own or as a proxy for other features.

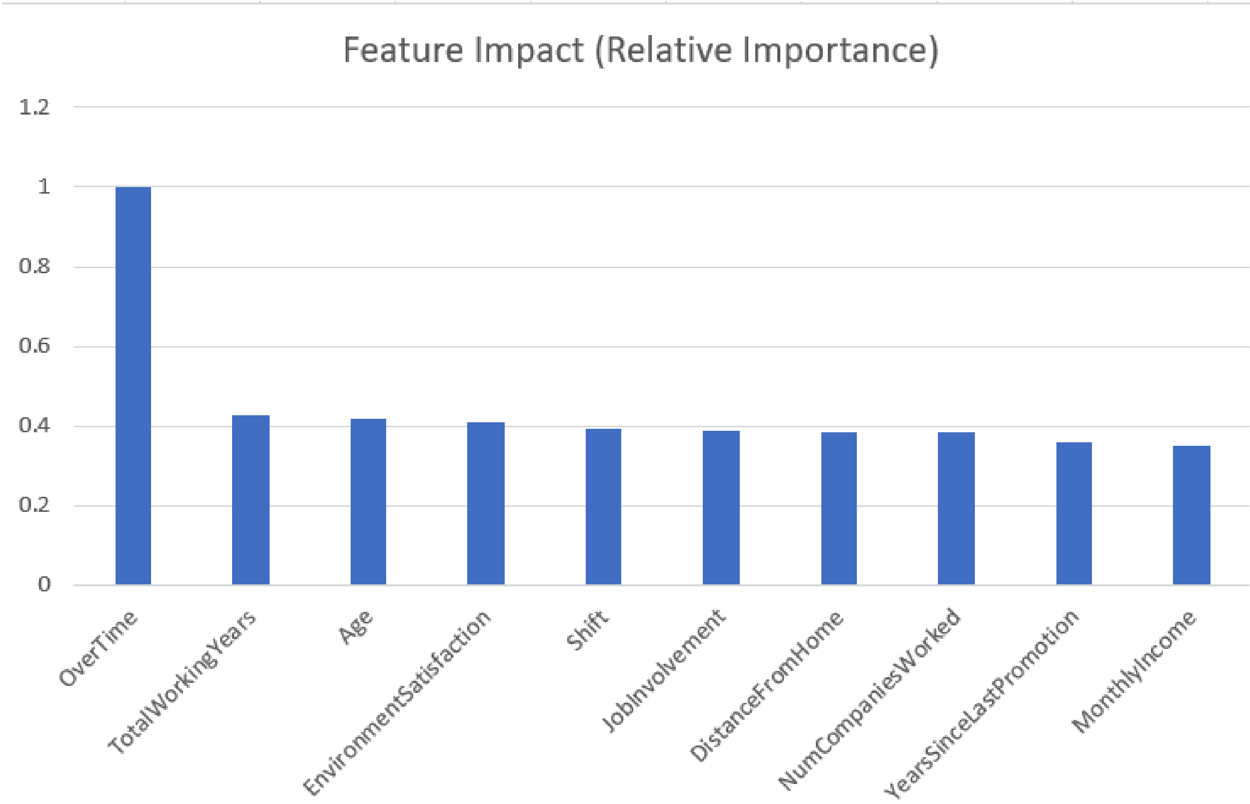
Results

The top-performing algorithms recommended by DataRobot are the Elastic-Net Classifier, the eXtreme Gradient Boosted Trees Classifier (XGBoost), and the Light Gradient Boosted Trees Classifier (LightGBM), as shown in Table 3.Table 3. Performance Metrics by Algorithm

Algorithms	AUC	LogLoss	F1	True Positive Rate (Sensitivity)	False Positive Rate (Fallout)	True Negative Rate (Specificity)	Positive Predictive Value (Precision)	Negative Predictive Value	Accuracy
Elastic-Net Classifier (L2 / Binomial Deviance)	0.9711	0.1408	0.8462	0.9529	0.0471	0.7021	0.9792	0.9405	0.7378
eXtreme Gradient Boosted Trees Classifier	0.967	0.1478	0.7368	0.8974	0.0707	0.9293	0.625	0.9857	0.9256
Light Gradient Boosted Trees Classifier with Early Stopping	0.9653	0.1482	0.7586	0.8462	0.0505	0.9495	0.6875	0.9792	0.9375
Elastic-Net Classifier (mixing alpha=0.5 / Binomial Deviance)	0.957	0.1585	0.6897	0.7692	0.0606	0.9394	0.625	0.9688	0.9196

The Elastic-Net Classifier predicts very well, with an AUC of 0.9711, a log loss of 0.1408, an F1 score of 0.8462, a true positive rate of 95.29%, a false positive rate of 4.71%, and a true negative rate of 70.21%. This algorithm correctly predicts 97.92% of workers who actually left the company. The Elastic-Net Classifier is a machine learning method with regularization to overcome the overfitting problem. The typical regularizations are L1 (Lasso) and L2 (Ridge). L1 regularization forces the coefficients of the less important features to be zero, while the L2 penalty shrinks the feature coefficients to relatively small values. The advantage of the Elastic-Net classifier is that it blends the L1 and L2 penalties.

In terms of AUC and Log loss, XGBoost achieves the second highest AUC of 0.967 and the second lowest Log Loss of 0.1478. XGBoost is an ensemble method in a gradient-boosting framework, which combines the predictions from a series of weak learners to create a strong learner. The next two algorithms perform with comparable accuracy, suggesting a degree of robustness in the fits of these four algorithms.



The most important features identified by DataRobot are shown in Figure 2. They are OverTime, TotalWorkingYears, Age, EnvironmentalSatisfaction, Shift, JobInvolvement, DistanceFromHome, NumCompaniesWorked, YearsSinceLastPromotion, and MonthlyIncome. Of these ten factors, overtime is by far the most important. The importance of overtime is consistent with much of the literature. E.g., Bahlman-van Ooijen, et al. (2023) cite Kox et al. (2020) as mentioning "Lack of job satisfaction due to heavy workload." See also Galanis et al. (2021) and Rushton et al. (2015).

One key benefit of the above machine learning techniques is that they can capture very complex, highly nonlinear relationships. However, to further investigate the determinants of attrition, and check for the robustness of our results, we reanalyze our data using a simpler, more restrictive, but also more transparent, logistic regression.

Results from our logistic regression analysis are shown in Table 4, including both coefficients and the effects of the different factors on the odds ratio. A logistic regression is a regression of the form

$$y_i = \frac{e^{\beta_0+\beta_1 x_{1i}+\ldots+\beta_n x_{ni}+\varepsilon_i}}{1+e^{\beta_0+\beta_1 x_{1i}+\ldots+\beta_n x_{ni}+\varepsilon_i}},$$

with y_i the binary dependent variable and $x_{1i}, x_{2i}, \ldots x_{ni}$ the explanatory features. This expression, in turn, implies an odds ratio of the form

$\ln ln\, \pi_i/(1 - \pi_i) = \beta_0 + \beta_1 x_{1i} + ... + \beta_n x_{ni}$.

Therefore, the effect of a one-unit increases in, e.g., x_{1i}, will be to increase the odds ratio, $\pi_i/(1 - \pi_i)$, by a factor of e^{β_1}. In our case, the odds ratio represents the ratio of the odds of attrition occurring to the odds of attrition not occurring. This can vary between zero and infinity, representing probabilities of attrition ranging from extremely low to extremely high. Table 4 shows that healthcare professionals who were engaged in overtime work were a remarkable 22.35 times more likely to leave the company, in terms of odds ratio, than those who did not work overtime. Again, this was by far the most important feature.

Our results also suggest that as healthcare professionals get one more year of work experience, they are 16% less likely, in terms of the odds ratio, to leave the company. The coefficient for age indicates that when people get one year older, they are 7% less likely to leave the company. The coefficient and odd ratios for environmental satisfaction demonstrate that healthcare employees who are more satisfied with their work environment are less likely to leave the company. Healthcare employees who do regular shifts are less likely to leave compared to pro-re nata (PRN) employees (employees who are only called in to work when the employer needs them). In particular, an employee who does a 7am-3:30pm shift experiences a reduction of 77.9% in the odds of leaving the company compared to a PRN employee; an employee who does a 2pm-10pm shift experiences a reduction of 90.5% in the odds of leaving the company compared to a PRN employee, and an employee who does a 9pm-7am shift experiences a reduction of 82.5% in the odds of leaving the company compared to a PRN employee.

Meanwhile, a healthcare employee who has more job involvement, lives closer to the workplace, or has worked for fewer companies is less likely to leave the company. In addition, an employee who has had one more year since the last promotion is 16% more likely to leave, while an employee with $1000 more monthly income is 10% less likely to leave. These results all make intuitive sense.

Surprisingly, employee job satisfaction is not one of the variables selected by our machine-learning algorithms. This is unexpected since "job satisfaction" is often discussed as a major determinant of attrition. To further check this result, we therefore run a new logistic regression, including job satisfaction, to evaluate whether job satisfaction is, in fact, a strong predictor of employee attrition or not. The results are shown in Table 5. These results do show that job satisfaction has a significant effect on attrition, but, again surprisingly, the effect is much less significant than several of the other included variables. In particular, Job Involvement has a P-value five orders of magnitude larger, Shift (7-3:30) and Number of Companies worked have P-values four orders of magnitude larger, and five other variables are also more significant. Only Shift (9-7:00), Years Since Last Promotion, and Monthly Income are less significant than job satisfaction. Of course, Overtime is again overwhelmingly more significant than job satisfaction and all of the other explanatory features.

Table 4. Logistic Regression Analysis of Employee Attrition (without Job Satisfaction)

Regression Statistics				
Chi Square	556.0902			
Residual Dev.	665.369			
# of iterations	8			
Observations	1676			
	Coefficients	Standard Error	P-value	Odd Ratio
Intercept	3.947967	0.649848635	1.24E-09	51.82987
OverTime	3.106859	0.237722837	4.93E-39	22.35074
TotalWorkingYears	-0.17391	0.033706215	2.47E-07	0.840369
Age	-0.07263	0.016199409	7.34E-06	0.929945
EnvironmentSatisfaction	-0.56068	0.095111602	3.75E-09	0.570822
Shift (7-3:30)	-1.51208	0.238818953	2.43E-10	0.22045
Shift (2-10:00)	-2.35419	0.498273098	2.3E-06	0.09497

Shift (9-7:00)	-1.74457	0.450007403	0.000106	0.17472
JobInvolvolvement	-0.91347	0.145173273	3.13E-10	0.401129
DistanceFromHome	0.068623	0.012576168	4.85E-08	1.071032
NumCompaniesWorked	0.257855	0.042390743	1.18E-09	1.294151
YearsSinceLastPromotion	0.109617	0.047542174	0.021128	1.115851
MonthlyIncome (in $1000)	-0.0001	5.09663E-05	0.045981	0.999898

Our finding that job satisfaction is less significant is consistent with Fang's (2001) finding, as cited in Coomber and Barriball (2007), that "job satisfaction did not exhibit any significant influence on turnover in a sample of Singaporean nurses." See also Wagner (2007), as cited in Halter et al. (2017), that "organizational commitment is a stronger predictor of nursing turnover than is job satisfaction." Of course, the weaker effect of job satisfaction may reflect how respondents interpret the job-satisfaction question, rather than what a more accurately measured level of job satisfaction might have implied.

Table 5. Logistic Regression Analysis of Employee Attrition (with Job Satisfaction)

	Regression Statistics	
	Chi Square	576.0063
	Residual Dev.	645.4529
	# of iterations	8
	Observations	1676

		Coefficients	Standard Error	P-value	Odd Ratio
	Intercept	5.27736	0.737143	8.12E-13	195.8521
1	OverTime	3.211794	0.245288	3.56E-39	24.82357
2	TotalWorkingYears	-0.17852	0.034231	1.84E-07	0.836505
3	Age	-0.07543	0.016549	5.16E-06	0.927343
4	EnvironmentSatisfaction	-0.55849	0.096075	6.13E-09	0.572075
5	Shift (7-3:30)	-1.50205	0.242121	5.51E-10	0.222673
6	Shift (2-10:00)	-2.30054	0.500681	4.33E-06	0.100205
7	Shift (9-7:00)	-1.76676	0.456409	0.000108	0.170886
8	JobInvolvolvement	-0.95735	0.14733	8.14E-11	0.383909
9	DistanceFromHome	0.066614	0.012668	1.45E-07	1.068883
10	NumCompaniesWorked	0.257892	0.042982	1.97E-09	1.294199
11	YearsSinceLastPromotion	0.121595	0.048774	0.012666	1.129297
12	MonthlyIncome (in $1000)	-0.00011	5.24E-05	0.028254	0.999885
13	JobSatisfaction	-0.41352	0.094071	1.1E-05	0.66132

In addition, significance isn't necessarily the same as importance, since it is possible that job satisfaction, while less significant than several of the other included features, may be acting, at least partially, as a proxy for those other features. To investigate this, we therefore perform a traditional linear OLS regression of job satisfaction against the other explanatory features, in Table 6. If job satisfaction is acting as a proxy for the other explanatory features, then we would expect the R^2 on this linear regression to be large. Instead, we find it to be 0.00885, with an adjusted R^2 of 0.0017. The F-statistic is only 1.238, which is insignificant, even at a 10% level. It is therefore extremely unlikely that job satisfaction is serving as a proxy for the other explanatory features, and is therefore likely that it simply does not have as much explanatory power as many of the other included features, at least in our sample.

Table 6. Linear Regression Analysis of Employee Satisfaction

	Regression Statistics				
	Multiple R	0.094098449			
	R Square	0.008854518			
	Adjusted R Square	0.001702536			
	Standard Error	1.10306461			
	Observations	1676			
	ANOVA				
		df	SS	MS	F
	Regression	12	18.07680496	1.506400413	1.238050967
	Residual	1663	2023.457801	1.216751534	
	Total	1675	2041.534606		
		Coefficients	Standard Error	t Stat	P-value
	Intercept	2.941087086	0.175923999	16.71794131	4.09768E-58
1	OverTime	0.040032262	0.060182377	0.665182473	0.506026077
2	TotalWorkingYears	-0.000220376	0.006694714	-0.032917888	0.973744071
3	Age	0.001844667	0.004185029	0.440777565	0.659431289
4	EnvironmentSatisfaction	0.000275759	0.02466387	0.011180699	0.991080688
5	Shift (7-3:30)	-0.011820042	0.059595005	-0.198339479	0.842803751
6	Shift (2-10:00)	0.158933096	0.091578145	1.73549153	0.082839024
7	Shift (9-7:00)	-0.006844895	0.118629403	-0.057699816	0.953994581
8	JobInvolvolvement	-0.064097955	0.037882046	-1.692040458	0.090825602
9	DistanceFromHome	-0.001465901	0.003324182	-0.440981023	0.659284017
10	NumCompaniesWorked	-0.031086671	0.011543225	-2.693066444	0.007150923
11	YearsSinceLastPromotion	-0.005351405	0.009211357	-0.580957345	0.561347874
12	MonthlyIncome (in $1000)	-1.48011E-06	9.03881E-06	-0.163750708	0.869947358

This is a surprising result, for which we do not have a definitive explanation. One possibility mentioned just above, is that our respondents are interpreting the job satisfaction question in an unexpected way. E.g., they may be interpreting it as some sort of residual level of job satisfaction, after controlling for their attitudes towards the other features in the questionnaire. Another possibility is that the unusual circumstances of the Covid19 pandemic pushed other features into the forefront in terms of explaining attrition. A third possibility, of course, is that the role of broad measures, such as "job satisfaction," should be reevaluated, as determinants of attrition, relative to other, more detailed measures of the quality of a job, such as the shift (and, of course, overtime).

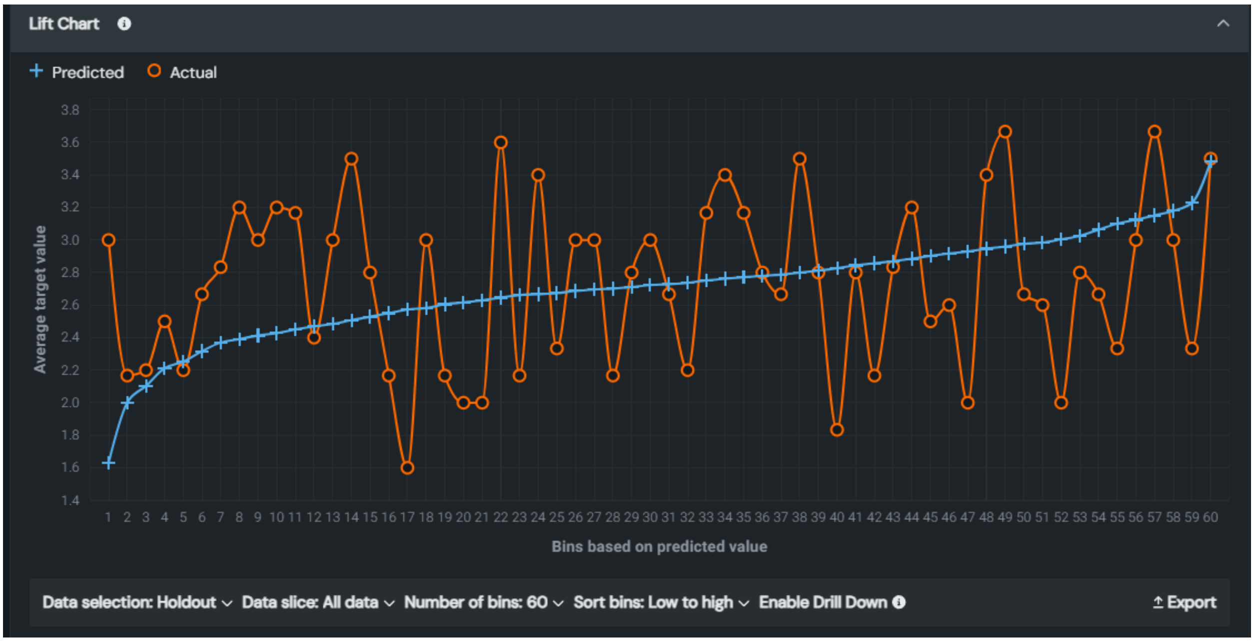


Figure 3. Lift Chart: Blue Line with +'s is predicted job satisfaction, increasing across successive sins, orange line with o's is actual job satisfaction, averaged within bins.

However, a fourth possibility is that the relation between job satisfaction and our other explanatory features is simply too complicated and nonlinear to be captured by a simple linear regression model. This is precisely where a more flexible machine-learning approach can once more become useful. Thus, to confirm our linear regression results with a more flexible model, we again apply DataRobot, which selected the Random Forest Regressor as the algorithm which best fits job satisfaction to the twelve independent variables in our linear regression. The resulting fit can be seen visually in the Lift Chart in Figure 3. This chart arranges the 366 observations in DataRobot's holdout sample in increasing order of predicted job satisfaction and then divides them into 60 "bins" with the average size of 5.60 observations per bin, maintaining the increasing order of the predictions. Thus, each bin has observations with larger predicted job satisfaction than the previous bins. The average value of predicted job satisfaction for these sixty bins is then shown by the blue curve with +'s. The actual average job satisfaction in each bin is then shown by the wavy orange curve with the o's. Of course, since this shows the average within bins, a great deal of averaging is occurring within these bins, even with just 5.60 observations per bin. Nevertheless, as is clear from the diagram, the Random Forest Regressor explains almost none of the variation in job satisfaction, confirming the results of the linear regression.

Discussion

The findings shed light on several key factors influencing turnover among healthcare professionals. First, whether the employee did overtime was by far the biggest contributor to predicting an employee's decision to leave the company. This observation supports previous studies (Alduayj & Rajpoot, 2018; Chung et al., 2023; Fallunchi et al., 2020), as employees who work overtime consistently may experience a poor work-life balance, resulting in health problems, burnout, and dissatisfaction. Another possible reason is that overtime expectations, reflecting the company's culture, may be perceived negatively by all employees, which could contribute to attrition.

Additionally, another strong predictor is the employee's shift. Based on the results from the logistic regression, healthcare employees who do regular shifts are less likely to leave, compared to a PRN employee. Among those who do regular shifts, an employee who does an afternoon shift is less likely to leave the company, compared to a morning or night shift worker. According to many existing studies (Burch et al., 2009, Poissonnet and Veron, 2000; Wilson, 2002; d'Ettorre and Pellicani, 2020; Ferri et al., 2016), shiftwork, especially night-shift work, affects employees' sleep, eating, physical and mental health, and job satisfaction.

Moreover, apart from overtime and shift, several other factors play important roles in influencing attrition. For example, TotalWorkingYears, Age, EnvironmentalSatisfaction and JobInvolvement are additional factors influencing whether healthcare workers leave their current employment.

In addition, using machine learning algorithms, we accurately predict the attrition decisions of healthcare workers, which provides several implications for healthcare organizations. First, accurate predictions of potential attrition decisions can help healthcare companies plan their workforce more efficiently. They can manage workforce shortages proactively, preventing disruptions to essential services. Second, high turnover can be costly, as recruitment, training, and onboarding of new employees require significant resources. Thus, healthcare companies can reduce turnover costs by investing in retention strategies for at-risk employees. For instance, healthcare companies can allocate resources to targeted retention strategies, such as more carefully managing overtime expectations, improving employee support, providing healthier work conditions, offering professional development opportunities, and ensuring competitive compensation. Third, a low attrition rate leads to higher continuity in the healthcare workforce, which in turn, maintains the quality and consistency of patient care. A stable and experienced workforce can positively impact patient outcomes.

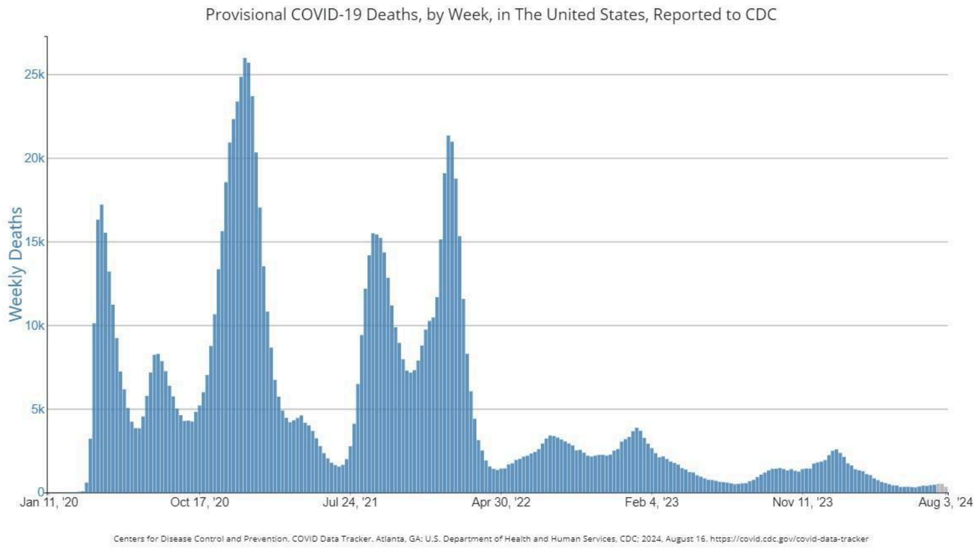


Figure 4. Trends in US COVID-19 Deaths, 2020-2024

Source: https://covid.cdc.gov/covid-data-tracker/#trends_weeklydeaths_select_00

Of course, one major driver of overtime hours in our sample may have been the COVID-19 epidemic. Based on data from the Centers for Disease Control and Prevention (CDC), death rates from COVID-19 were about as high during the period when this dataset was collected (January-December of 2021) as in 2020 (see Figure 4). Since COVID was still extremely severe in this period, it presumably contributed significantly to the burnout that healthcare professionals experienced in our dataset, and so, made a major contribution to the attrition rates we observed, especially for employees working overtime. This finding is similar to findings of Galanis et al. (2021) and others that COVID-19 was one of the major causes of nurses' burnout.

Finally, one might conjecture that our results may be driven by job satisfaction. Surprisingly, measured job satisfaction does not even appear as one of the ten most important features found in our machine-learning exercise and also appeared to be less important in our more traditional logistic regression analysis. Nevertheless, to investigate the potential role of job satisfaction as a mediating variable, we used linear regression to examine how the twelve variables from our original logit model affected job satisfaction. Surprisingly, our linear regressions found almost no effect of our other variables on job satisfaction, a result we confirmed by returning, again, to a more flexible machine learning approach.

Conclusions

Employee job satisfaction and attrition analysis is important in every area. This research uses machine learning and logistic regression analysis techniques to analyze what causes healthcare professionals to leave their jobs. With more than 95% prediction accuracy rates, using the Elastic-Net classifier algorithm, we found that the major reason why healthcare professionals leave their jobs is because they have to work overtime. Of course, our data was collected during the COVID period, and that might play a role in the importance of overtime. Also, the smaller effect of job satisfaction may be partly due to the different ways in which different respondents interpreted the questions. The shifts in which employees work are also important. Our findings agree with some other prior employee attrition research in the literature, but the strong effects of overtime and the relatively weak effect of job satisfaction merit additional research.

Business and Policy Implications

Research analyzing employee job satisfaction is important in every area of human resource management. Our study shows that it is helpful to analyze different business domains in detail, since each business has unique requirements for its employees. Thus, our findings suggest that, for businesses to maintain their staffs, the company should study, in-depth, the nature of their company's environments, in order to find what causes employee attrition in their industries. For example, the strong negative effect of overtime during the COVID pandemic suggests that healthcare institutions should be well-staffed in anticipation of such healthcare crises. In fact, to the extent that individual employers risk having their staff hired away during a crisis, there might even be a role for government subsidies to encourage all institutions to maintain staffs adequate to meet future healthcare crises.

REFERENCES

1. 2022 Retention Report: https://info.workinstitute.com/hubfs/2022%20Retention%20Report/2022%20Retention%20Report%20-%20Work%20Institute.pdf (Retrieve on 11/16/24).
2. Abdullahi AK, Mosanya AU, Bello N, Musa MK. Evaluation of job satisfaction among pharmacists working in public health facilities. Exploratory Research in Clinical and Social Pharmacy. 2023; 12; doi: https://doi.org/10.1016/j.rcsop.2023.100338.
3. Akasheh MA, Malik EF, Hujran O, ZakiN. A decade of research on machine learning techniques for predicting employee turnover: A systematic literature review. Expert Systems with Applications. 2024; 238(E), doi: https://doi.org/10.1016/j.eswa.2023.121794.
4. Alao D, Adeyemo A. Analyzing employee attrition using decision tree algorithms. Computing. Information Systems & Development Informatics. 2013; 4(1):17–28.
5. Alduayj SS. Rajpoot K. Predicting Employee Attrition using Machine Learning. International Conference on Innovations in Information Technology (IIT). 2018: 93-98; doi: 10.1109/INNOVATIONS.2018.8605976.
6. Aziri B. Job Satisfaction: A Literature Review. Management Research and Practice. 2011; 3(4): 77-86. http://mrp.ase.ro/no34/f7.pdf.
7. Bahlman-van Ooijen W, Malfait S, Huisman-de Waal G, Hafsteinsdóttir TB. Nurses' motivations to leave the nursing profession: a qualitative meta-aggregation. J Adv Nurs. 2023;79(12):4455–71.
8. Bendemra H. Building an Employee Churn Model in Python to Develop a Strategic Retention Plan. 2019; https://towardsdatascience.com/building-an-employee-churn-model-in-python-to-develop-astrategic-retention-plan-57d5bd882c2d (accessed on July 15, 2024).
9. Bhatnagar K, Srivastava K. Job satisfaction in health-care organizations. Industrial Psychiatry Journal. 21(1): p 75-78, Jan–Jun 2012. doi: 10.4103/0972-6748.110959.
10. Bolden-Barrett V. Turnover costs employers $15,000 per worker. 2017; https://www.hrdive.com/news/study-turnover-costs-employers-15000-per-worker/449142/. (accessed on August 11, 2024).
11. Burch JB, Tom J, Zhai Y, Criswell L, Leo E, Ogoussan K. Shiftwork impacts and adaptation among health care workers. Occupational medicine. 2019; 59(3), 159-166.
12. Burky A. Healthcare ranked lowest for employee satisfaction, Qualtrics survey finds. 2023; https://www.fiercehealthcare.com/health-tech/qualtrics-survey-finds-only-half-healthcare-employees-think-they-are-paid-fairly#:~:text=Healthcare%20ranked%20last%20for%20employee,Experience%20Trends%20Report%20from%20Qualtrics (Retrieve on 3/4/24).
13. Chaw JK, Chaw SH, Quah CH, Sahrani S, Ang MC, Zhao Y, Ting TT. A predictive analytics model using machine learning algorithms to estimate the risk of shock development among dengue patients. Healthcare Analytics. 2024; 5; https://doi.org/10.1016/j.health.2023.100290.
14. Chakraborty C, Bhattacharya M, Pal S, Lee S. From machine learning to deep learning: Advances of the recent data-driven paradigm shift in medicine and healthcare. Current Research in Biotechnology. 2024; 7; https://doi.org/10.1016/j.crbiot.2023.100164.
15. Conlon, S. Why Do Data Scientists Want to Change Jobs: Using Machine Learning Techniques to Analyze Employees' Intentions in Switching Jobs. International Journal of Management and Information Technology. 2021; 16, 59-71.

16. Conlon S, Simmons LL, Liu F. Predicting Tech Employee Job Satisfaction Using Machine Learning Techniques. International Journal of Management and Information Technology. 2021;16:72-88.
17. Cotton JL, Tuttle JM. Employee turnover: A meta-analysis and review with implications for research. Academy of Management Review. 1986; 11(1): 55-70. https://doi.org/10.2307/258331.
18. DataRobot. Retrieved from https://www.datarobot.com/.
19. STATA18. StataCorp. 2023. Stata Statistical Software: Release 18. College Station, TX: StataCorp LLC.
20. Dharmarathne G, Jayasinghe TN, Bogahawaththa M, Meddage DPP, Rathnayake U. A novel machine learning approach for diagnosing diabetes with a self-explainable interface. Healthcare Analytics. 2024; 5; https://doi.org/10.1016/j.health.2024.100301.
21. Chung D, Yun J, Lee J, Jeon Y. Predictive model of employee attrition based on stacking ensemble learning. Expert Systems with Applications. 2023; 215; 119364. https://doi.org/10.1016/j.eswa.2022.119364.
22. d'Ettorre G, Pellicani V. Preventing shift work disorder in shift health-care workers. Safety and health at work, 2020; 11(2); 244-247.
23. Fallucchi F, Coladangelo M, Giuliano R, William De Luca E. (2020). Predicting Employee Attrition Using Machine Learning Techniques. Computers. 2020; 9(4), 86. https://doi.org/10.3390/computers9040086.
24. Ferri P, Guadi M, Marcheselli L, Balduzzi S, Magnani D, Di Lorenzo R. The impact of shift work on the psychological and physical health of nurses in a general hospital: a comparison between rotating night shifts and day shifts. Risk management and healthcare policy, 2016; 203-211.
25. Galanis P, Vraka I, Fragkou D, Bilali A, Kaitelidou D. Nurses' burnout and associated risk factors during the COVID-19 pandemic: a systematic review and meta-analysis. J Adv Nurs. 2021;77:3286–302. Doi: https://doi.org/10.1111/jan.14839
26. Golestani A, Masli M, Shami NS, Jones J, Menon A, Mondal J. Real-Time Prediction of Employee Engagement Using Social Media and Text Mining. 17th IEEE International Conference on Machine Learning and Applications (ICMLA). 2018; Orlando, FL, 1383-1387.
27. Haldorai K, Kim WG, Pillai SG, Park T, Balasubramanian K. Factors affecting hotel employees' attrition and turnover: Application of pull-push-mooring framework. International Journal of Hospitality Management. 2019; 83: 46-55. doi: https://doi.org/10.1016/j.ijhm.2019.04.003.
28. Hinkin TR, Tracey JB. The cost of turnover: Putting a price on the learning curve. Cornell Hotel and Restaurant Administration Quarterly. 2000; 41:14–21. https://hdl.handle.net/1813/71741.
29. Holtom B, Mitchell T, Lee T, Eberly M. Turnover and retention research: A glance at the past, a closer review of the present, and a venture into the future. The Academy of Management Annals. 2008; 2(1): 231-274. doi: https://doi.org/10.1080/19416520802211552.
30. House House S, Wilmoth M, Stucky C. Job satisfaction among nurses and physicians in an Army hospital: A content analysis. Nursing Outlook. 2022; 70(4): 601-615, doi: https://doi.org/10.1016/j.outlook.2022.03.012.
31. Hulin CL, Judge TA. Job attitudes. Handbook of psychology: Industrial and organizational psychology (Borman WC, Ligen DR, Klimoski RJ (Eds.), Hoboken, NJ: Wiley; 2003; 255-276.
32. IHS Markit Ltd. The Complexities of Physician Supply and Demand: Projections From 2019 to 2034. Washington, DC: AAMC; 2021. Retrieved: July, 2024. https://digirepo.nlm.nih.gov/master/borndig/9918417887306676/9918417887306676.pdf
33. Jain D, Makkar S, Jindal L, Gupta M. Uncovering Employee Job Satisfaction Using Machine Learning: A Case Study of Om Logistics Ltd. International Conference on Innovative Computing and Communications. Advances in Intelligent Systems and Computing, 2021; Vol 1166. Springer, Singapore. https://doi.org/10.1007/978-981-15-5148-2_33.
34. Kaggle.com dataset. "Employee Attrition for Healthcare." Retrieved from https://www.kaggle.com/datasets/jpmiller/employee-attrition-for-healthcare/data
35. Kox, J., Groenewoud, J. H., Bakker, E. J. M., Bierma-Zeinstra, S. M. A., Runhaar, J., Miedema, H. S., & Roelofs, P. (2020). Reasons why Dutch novice nurses leave nursing: A qualitative approach. Nurse Education in Practice, 47, 102848. https://doi.org/10.1016/j. nepr.2020.102848
36. Kupietzky J. The Role of Employee Satisfaction in the Healthcare Industry. Forbes, 2023. Retrieve 2/17/24 from https://www.forbes.com/sites/forbesbusinesscouncil/2023/06/13/the-role-of-employee-satisfaction-in-the-healthcare-industry/?sh=7b23f5a369a5

37. *Lee ES. A Theory of Migration. Demography. 1966; 3 (1): 47–57.* doi:10.2307/2060063. JSTOR 2060063. S2CID 46976641.

38. Locke EA. The nature and causes of job satisfaction. Handbook of industrial and organizational psychology In M.D. Dunnette (Ed.). Chicago: Rand McNally. 1976; 1:1297–1343.

39. Hong Lu, K. Louise Barriball, Xian Zhang, Alison E. While, Job satisfaction among hospital nurses revisited: A systematic review, International Journal of Nursing Studies, Volume 49, Issue 8, 2012, Pages 1017-1038, https://doi.org/10.1016/j.ijnurstu.2011.11.009.

40. Mahmoudian Y, Nemati A, Safaei AS. A forecasting approach for hospital bed capacity planning using machine learning and deep learning with application to public hospitals. Healthcare Analytics. 2023; 4; doi: https://doi.org/10.1016/j.health.2023.100245.

41. Nagadevara V. Early Prediction of Employee Attrition in Software Companies-Application of Data Mining Techniques. Research & Practice in Human Resource Management. 2008;16:2020–2032. doi: https://doi.org/10.1109/IADCC.2018.8692137.

42. Otto N. Avoidable turnover costing employers big. 2017; Retrieved from Avoidable turnover costing employers big | Employee Benefit News.

43. Poissonnet CM, Véron M. 2000. Health effects of work schedules in healthcare professions. Journal of Clinical Nursing. 2000; 9(1):13-23.

44. Punnoose R, Ajit P. Prediction of employee turnover in organizations using machine learning algorithms. International Journal of Advanced Research in Artificial Intelligence. 2016; 5(9): 22–26. doi: https://doi.org/10.14569/IJARAI.2016.050904.

45. Ray AN, Sanyal J. Machine Learning Based Attrition Prediction. Global Conference for Advancement in Technology (GCAT), BANGALURU, India, 2019; 1-4.

46. Raza S., "A machine learning model for predicting, diagnosing, and mitigating health disparities in hospital readmission. Healthcare Analytics. 2022; 2; doi: https://doi.org/10.1016/j.health.2022.100100.

47. Rushton CH, Batcheller J, Schroeder K, Donohue P. Burnout and Resilience Among Nurses Practicing in High-Intensity Settings. Am J Crit Care. 2015 Sep;24(5):412-20. doi: 10.4037/ajcc2015291. PMID: 26330434.

48. Sacco JM, Schmitt N. A dynamic multilevel model of demographic diversity and misfit effects. Journal of Applied Psychology. 2005; 9(2): 203-231. doi: https://doi.org/10.1037/0021- 9010.90.2.203.

49. Singh JK, Jain M. A Study of Employees' Job Satisfaction and Its Impact of their Performance. Journal of Indian Research. 2013; Vol. 1, No. 4, 105-111.

50. Spector PE. Job satisfaction: Application, assessment, causes and consequences. Thousand Oaks, CA: SAGE. 1997.

51. Wei H, Horsley L, Cao Y, Haddad LM, Hall KC, Robinson R, Powers M, Anderson DG. The associations among nurse work engagement, job satisfaction, quality of care, and intent to leave: A national survey in the United States. International Journal of Nursing Sciences. 2023; 10(4):476-484; doi: https://doi.org/10.1016/j.ijnss.2023.09.010.

52. Wilson JL. The impact of shift patterns on healthcare professionals. Journal of Nursing Management. 2022; 10(4):211-219.