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Predicting employee attrition and explaining its determinants

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ABSTRACT

An increased focus on utilizing data analytics to tackle human resource (HR) issues and make more informed and data-driven decisions is spreading in firms and public institutions. One of the major challenges faced by organizations is employee turnover, which can have negative impacts on productivity, performance, and overall corporate reputation. In light of these considerations, this study endeavors to predict employee attrition by deploying Machine Learning (ML) models on real-world data obtained from a prominent Italian financial corporation. Although the use of ML to predict attrition and investigate the main employers-employees features is documented in literature, what characterizes our study is the investigation of the crucial dimension of feature direction. Nonetheless, recognizing this directional aspect is pivotal for HR managers entrusted with making informed decisions. In our research, we employ the SHAP (SHapley Additive exPlanation) algorithm to not only identify feature contributions but also to assess their direction. Beyond mere algorithm implementation, our study interprets the outcomes within the specific context of HR decision-making. This comprehensive approach effectively highlights the inherent limitations of standalone algorithms, which may produce only partial results, capturing the importance of a feature, but missing its direction. Indeed, sometimes, while the feature is well known, its direction is somehow counterintuitive, thus requiring a deeper investigation and understanding. In a period like the present one, where the new production paradigms and the Covid-19 pandemic altered the consolidated labor market, new phenomena are emerging and only a profound understanding of the contextual novel dynamics can foster well-informed decision-making processes.

1. Introduction

The rise of the Fourth Industrial Revolution has brought about a radical transformation of business processes, organizational forms, work quality, and working conditions. The technical change brought about by digitalisation and the advent of the green transition paradigm have brought significant changes to the labor market and the management of the workforce. In addition, the Covid-19 pandemic has accelerated these changes.

In particular, HR managers today face the challenge of attrition, which has emerged as a significant concern within organizations. While attrition was previously viewed as an internal and natural process, the post-pandemic period has witnessed an unusually large increase in voluntary resignations, commonly referred to as the 'Great Resignation' (Serenko, 2022).

The causes of increased attrition include people's experience with remote work facilitated by smart tools and processes, as well as their desire to maintain work-life balance and the advantages of remote work (Serenko, 2022). Consequently, it becomes necessary to address attrition using new approaches due to its detrimental effects, such as direct costs associated with replacement, recruitment, selection, placement, and orientation (Sheidaee et al., 2022; Prabakaran and Vetrivel, 2017; Taylor et al., 2006), as well as indirect costs including employee demoralization, loss of implicit knowledge, negative organizational image, and reduced productivity (Sheidaee et al., 2022; Balcha, 2019; Taylor et al., 2006). Reducing employee turnover has long been acknowledged as beneficial for organizations in various ways, posing a significant challenge (Chang, 2009).

Understanding the causes and consequences of attrition is vital for organizations, as certain effects can have a domino effect if a critical

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Table 1
Literature review on the causes of attrition.

Categories	Causes	Definitions	References
People	Tenure	"The length of time that an employee has been in the employment of an organization" (McEnrue, 1988; cited by Pahos & Galanaki, 2022)	Cohen, 1993; Balcha, 2019; Taylor et al., 1996.
	Relationships	"Day to day interactions between co-workers, managers and employees. These relationships are a natural part of the work environment and induce certain behaviors in individuals" (Mokuoane, 2014). Relationships can take many forms: they may be destructive (e.g., contempt) or constructive (e.g., support) and depleting or life giving (Gelbard et al., 2018).	Parker & Skitmore, 2005; Fasbender & Drury, 2021; Varadharaj & Irfan, 2019.
	Performance & potential	Employee's performance is defined as "expected job related work of employees and how fit the activities were performed" (Saleem & Amin, 2013); while employee's potential is defined as "the employee's expected work performance, taking into account his/her ability, influence and commitment" (Smerek & Šupolová, 2019).	Wigert, 2018; Woo & Maertz, 2012.
	Expectations	"The perceptions versus the reality regarding the position" (Turner, 2013).	Colding, 2006; Rhodes, 1983.
Management/ culture	Organizational culture	"Shared perceptions of organizational work practices within organizational units" (Van den Berg & Wilderom, 2004)	Abdullah et al., 2021; Zhang et al., 2018; Shanker, 2018.
	Compensation & benefit practices	'Compensation' is defined as "the total amount of the monetary and non-monetary pay provided to an employee by an employer in return for work performed as required" (Heathfield, 2016), while 'employee benefits' are defined as "all forms of consideration given by an entity in exchange for service rendered by employees" (Mirea et al., 2012).	Varadharaj & Irfan, 2019; Martinson & De Leon, 2018; Nishat Faisal & Al-Esmael, 2014.
	Communication	"The listening to concern, as well as the ease with which ideas are exchanged among groups and cliques" (Zigarmi & Sinclair, 1979)	Negassa, 2016; AlSayyed & Braiki, 2015.
	Tasks	"Concrete sections of time that include actions towards a goal; the task outcome" (Schoegje et al., 2018)	Colding, 2006; Abeble, 2016; Nishat Faisal & Al-Esmael, 2014.
	Transfer	"The act of an employee moving to a different position in an agency for purposes not linked to a planned increase or decrease in responsibility" (Edward, 2018).	Negi, 2013.
	Promotion & growth opportunities	A 'job promotion' is defined as "the act of any employee being moved to a different position that carries greater responsibility and is compensated at a higher level than the employee's present position (Grierson, 2008; cited in Atim, 2015). 'Growth opportunities' are defined as "the expected utility of one's present job for future attainment of valued career outcomes. Furthermore, growth opportunities are employees' perceptions of the extent of potential knowledge and skill acquisition for the purpose of career advancement" (Pack, 2005).	Selhadin, 2019; Pace and Kisamore, 2017; Nishat Faisal & Al-Esmael, 2014.
	Organizational changes	"A generative mechanism whereby organizational change schemas emerge from the organizing process" (Knoche, 2006)	AlSayyed & Braiki, 2015; Cunningham, 2006.
	Leadership style	"A set of attitudes, behaviors, beliefs and values" (Sola et al., 2016)	Negi, 2013; Abeble, 2016.
	Lack of flexibility	'Job Flexibility' refers to the degree of freedom employees have in determining the duration, location, and amount of work they perform. It encompasses the authority given to employees to choose when and where they carry out their work responsibilities (Krishnan et al., 2020).	Negi, 2013; Abeble, 2016; Wang & Chen, 2013.
	Lack of job security	'Job security' refers to an individual's belief that their job or a significant aspect of it is stable (as cited in Tabor & Dalton, 2021, based on Davy, Kinicki, & Scheck, 1991).	Negi, 2013.
	Recognition	"A constructive reaction, based on judgment of the person's contribution, both in terms of carrying out the job, and of personal investment" (Fall, 2015; cited in Sandrin et al., 2019).	Colding, 2006; Wang & Chen, 2013; Imani, 2013.
Work environment	Training & orientation	Employee training' refers to the systematic acquisition and development of knowledge, skills, and attitudes necessary for employees to effectively perform their tasks or improve job performance (Tharenou, Saks and Moore, 2007, p. 252, cited in Bednářová et al., 2015). 'Orientation', on the other hand, involves adjusting to a new environment, situation, customs, or set of ideas (Bennett, 1996).	AlSayyed & Braiki, 2015; Imani, 2013, Memon et al., 2017.
	Organizational factors	"Those variables that affect the organizational structure that the organization could adjust to suit its changing environment" (Teo, Tan, & Buk, 1997, p. 96; cited by Nurdin et al., 2012).	Zhang et al., 2018; Balcha, 2019; Baloch et al., 2022.
	Psychological workplace environment	"The values or organizational culture inside the company. It consists of working organization, attitudes, beliefs, practices and daily routine of the organizational workplace environment" (Burton, 2010; cited in Sahiri, 2015).	Singh & Singh, 2017; Mauno et al., 2014; Sheehan et al., 2018.
	Physical/technical workplace environment	"The external and internal office layout, temperature, comfort zone and the arrangement of office work setting in the workplace" (Hajjar *et al.*, 2010; cited in Sahiri, 2015).	Negi, 2013; Selhadin, 2019; Prabakaran & Vetrivel, 2017.
External environment	External labor market	"The outside environment within which the hiring entity operates and has a direct or indirect influence on the current and potential supply and demand situation for labor as an economic resource" (Fyfe, 1980).	Negi, 2013; AlSayyed & Braiki, 2015; Varadharaj & Irfan, 2019.
	Home-work commuting	The term 'commute' refers to the repeated trip between two or more locations, with a particular focus on the journey between home and work (Sullivan, 2015; Kung et al., 2014).	Sullivan, 2015; Kung et al., 2014.
	Other social and economic factors	"Society-related economic factors, such as income, education, employment, social class, etc." (American Psychological Association, 2017; cited in De Silva & Palihakkara, 2020).	Negassa, 2016; Ayuure, 2013.
Personal correlates	Private life events	"The social or family life or personal relationships of an individual"[a]	Negassa, 2016; Wang & Chen, 2013; Abeble, 2016.
	Demographic characteristics	"Characteristics that describe differences in society based on Age, Gender, occupation, education, religion, ethnicity, income, family type, marital status, geographic location and social class" (Sunyoto, 2013: 2; cited in Nasution, 2021).	Balcha, 2019; Negassa, 2016; Wang & Chen, 2013.

(*continued on next page*)

Table 1 (*continued*)

Categories	Causes	Definitions	References
	Physical & mental conditions	"Dynamic, subjective manifestations of illness or wellness" (Lyon, 2005).	El-Rayes et al., 2020; Negi, 2013.
	Educational level	"The highest completed level of education" (Boschman et al., 2021).	Woo & Maertz, 2012; Abeble, 2016.
	Personality attitudes and characteristics	The concept of 'attitude' encompasses an individual's mindset or tendency to behave in a specific manner, shaped by their experiences and disposition (Pickens, 2005). 'Personality characteristics' refer to a person's established patterns of behavior and reaction (Bartlett & Palisano, 2000)	Balcha, 2019; Abeble, 2016; Negi, 2013.
	Individual preferences	In economics, 'preferences' are defined as subjective evaluations in which an individual judges one thing to be better than another, taking all things into consideration (Hausman, 2012).	Negi, 2013; Abeble, 2016.

[a] https://www.collinsdictionary.com/dictionary/english

mass of resignations occurs. Identifying employees prone to attrition and understanding the reasons behind it is crucial for developing retention policies and strategies (Alao and Adeyemo, 2013). The increasing digitalisation of work relationships has provided more data for HR functions, allowing the implementation of new tools and methodologies to enhance the assessment and advancement of human capital. However, quantitative analyses predicting attrition remain limited due to strict privacy regulations, challenges in data collection and the lack of familiarity of HR professionals with data-driven approaches (Lismont et al., 2017; Dahlbom et al., 2020). Academic researchers are also subject to such limitations and obtaining HR data from companies is often difficult *per se* because they are likely to be strategically sensitive. Thus, researchers are often forced to rely on artificial datasets to study, analyze, and predict attrition. Finally, HR professionals are seldom familiar with data-driven approaches (Dahlbom et al., 2020). This is a major drawback because collaboration between researchers and practitioners is valuable. In view of the above, the collaboration between researchers and HR professionals in exploring machine learning techniques has become essential for understanding the drivers behind employee attrition and enabling suitable, data-driven interventions.

The novel contribution of our paper, compared to the existing literature, lies in the integration of the SHAP method (SHapley Additive exPlanation), a facet that is absent in other studies. Although a few studies employ Feature Importance, it solely illuminates the significance of factors while disregarding their direction. This direction is notably vital for HR managers, who must decide on appropriate actions concerning the variable. The recent study conducted by Chung et al. (2023) investigated the optimal models for predicting employee attrition, underscoring the need to explicate and analyze the effects of "the main variables on the dependent variables" in future studies. Indeed, if in the past the HR and employees' dynamics were well known and often stable in a sector, in recent years an evolution and a change in the determinants of attrition has been observed (Tessema et al., 2022). Consequently, our study attempts to explain the factors that determine employee attrition by applying the SHAP algorithm that calculates the average marginal contribution of each feature, also considering the direction in which it operates. In order to accomplish this, it not only focuses on algorithm implementation but also on comprehending how to make decisions based on algorithmic outcomes, all while considering the contextual backdrop. This approach unveils an insightful facet that emphasizes the insufficiency of algorithms in isolation; their mechanisms often possess traits that are non-obvious or even counterintuitive. Hence, a comprehensive understanding of the context is crucial for making well-informed decisions.

The paper's structure entails a literature review in Section 2, covering (i) turnover predictors, (ii) machine learning techniques for attrition prediction, and (iii) interpretation methods. Section 3 presents the specific case study, outlining the methodology. Section 4 deals with the explanation, implementation, and performance evaluation of various machine learning techniques, with a focus on the most successful model's results. Additionally, the SHAP method's implementation and outcomes are discussed. Finally, Section 5 offers concluding observations.

2. Literature review

The literature review is organized into two separate streams: the first is oriented to map the causes of employee attrition, and the second analyses the (machine learning) techniques employed to predict employee abandonment.

2.1. Literature review on the causes of attrition

This section presents a classification of the causes of employee attrition that has emerged through a detailed examination of the literature.

The predictors of employee attrition identified in the reviewed papers are summarized in Table 1. However, to provide a more synthetic and clustered view they are presented according to Ishikawa's visual diagram of causes and effects (Ishikawa, 1976; Headvisor, 2022) in Fig. 1.

We categorized the reasons for attrition into two main groups: internal and external. Within each category, we further grouped similar variables into classes. These classes were organized into five categories: those related to (i) individuals, (ii) management and company culture, (iii) the work environment, (iv) the external environment, and (v) personal factors. Internal causes are related to the environment inside the firm, while external causes are related to the psychological elements of the employee and private life events, which are related to the environment outside the workplace (Sauber, Snyir, and Sharifi, 1991).

We use the Ishikawa diagram to contextualize and synthesize key variables relevant to attrition. It serves as a conceptual framework to identify theoretically relevant variables highlighted in the literature, guiding the selection of predictors for empirical testing. Specifically, the diagram incorporates variables from the literature, derived from both theoretical and empirical models, that may influence attrition. In this case study, we focus on the available variables, representing a meaningful subset of those outlined in the Ishikawa framework.

A recent study emphasizes a model, grounded by the established framework of Attachment Theory, that integrates key variables affecting the *Intention To Stay* (ITS) with an organization, which is opposed to attrition (Patrick et al., 2024). Central predictors (Fig. 2) include *Person-Job Fit* (PJF), the alignment between job requirements and employees' abilities (Patrick et al., 2024; Li and Park, 2018; we can measure it in our case with variables such as Job Description, Level, Rank, Department and Age), *Psychological Attachment* (PA), the bond linking an individual to the organization (Patrick et al., 2024; Yip and Walker, 2018; we can measure it in our case with variables such as Salary, Bonus, Retention and Premium), and *Organizational Attractiveness* (OA), defined as a general positive attitude toward the organization (Patrick et al., 2024; Slåtten and Svenkerud, 2019; we can measure it in our case with variables such as Hours, Tenure and Contract). While in Fig. 1 we listed and clustered the reasons for attrition found in the literature, the attachment theory mainly focuses on the internal variables HR manager can measure and use as levers to reduce the attrition.

The study by Patrick et al., 2024 provides a theoretical framework that integrates a range of variables previously considered in isolation into a cohesive model. Moreover, this model reveals and quantifies the causal dependencies among the variables (indicated in bold in Fig. 2), which collectively influence an individual's propensity to stay or leave an organization. Within this set of variables affecting retention, our work identifies a subset that organizations can actively monitor—indicated in black in Fig. 3—while unavailable data are shown in light gray. Our study positions itself within this framework, aiming to offer insights based on the specific variables that impact the phenomenon of attrition and that directly contrasts the motivation or tendency to remain within the organization.

Using the available data in the company's HR dataset, we identified several variables in our dataset that correspond with key factors discussed in the literature. Fig. 3 presents a summary of these alignments, highlighting how our variables relate to factors known to influence attrition. In Chapter 3, we provide a detailed overview of the data, including justifications for the variables selected as well as those excluded.

2.2. Methods for predicting employee turnover

The modeling process involves selecting models based on various machine learning methods used in the experimentation (Fallucchi et al., 2020). In this section, we provide an overview of approaches employed in the research literature.

When predicting employee attrition, models and machine learning tools consider two primary and complementary dimensions: (i) identifying the value of churned employees based on key performance indicators like process quality, productivity, economics, and financials, and (ii) addressing class imbalance. Class imbalance, defined as an unequal representation of classification categories in a dataset (Chawla et al., 2002), poses a challenge. In our case, out of 5767 observations, 309 employees resigned, while 5458 remained in their organization. Conventional classifiers tend to prioritize the dominant class, resulting in neglect of the minority instances (Menardi and Torelli, 2014).

We adopted the classification approach used by Fareri et al. (2020) to categorize machine learning techniques for predicting employee attrition. Table 2 offers an organized overview of the literature, classified into three primary objectives (goal). Rows represent the suggested methods in the literature, while columns represent the intended purposes. Each cell indicates the authors who proposed each method for specific goals.

In our analysis, we found that Random Forest (RF) emerged as the most effective method, consistent with previous literature. RF is a supervised machine learning algorithm that employs multiple decision trees for classification and regression tasks (Alduayj and Rajpoot, 2018). Although it ranked third in performance compared to XGBoost and Gradient-Boosting-Trees algorithms in the study by Zhao et al. (2019), RF demonstrated marginal performance improvement with increased complexity in El-Rayes et al.'s (2020) investigation.

Addressing class imbalance in the dataset, various methods have been proposed and utilized in the literature. These include ROSE (Ribes et al., 2017; Menardi and Torelli, 2014), ADASYN (Alduayj and Rajpoot, 2018; Forough and Momtazi, 2022), SMOTE (Ribes et al., 2017; Chawla et al., 2002), Up-sampling (Ribes et al., 2017), Down-sampling (Ribes et al., 2017; Esmaieeli Sikaroudi et al., 2015), and Weighting (Ribes et al., 2017; Chen et al., 2004). Our selection was the ROSE method, which exhibited superior performance in the literature (Ribes et al., 2017). ROSE generates artificial data by employing a smoothed bootstrapping technique that combines over-sampling and under-sampling. This approach promotes equal importance among classes and provides a larger sample, particularly for the minority class (Ribes et al., 2017; Menardi and Torelli, 2014).

2.3. Methods for interpreting machine learning output

Chung et al.'s work (2023) emphasizes that simply predicting employee attrition is not enough. To enhance the effectiveness of these models in organizational management, a detailed analysis of how key variables influence the outcomes is crucial. Understanding the reasons behind decision-making is fundamental for improving organizational processes (Seng and Chen, 2010). However, many machine learning algorithms are considered black box models, lacking direct explanations for their predictions (Casalicchio et al., 2019; Tan et al., 2023). These models employ complex decision rules that are difficult for humans to comprehend, hindering insights into the application domain (Zien et al, 2009). Identifying the most influential features in machine learning outputs is key to better understanding the problem at hand (Zien et al. 2009). Although deep learning and ensemble models achieve high accuracy, they are harder to interpret compared to simpler models like linear models (Nohara et al., 2022). To address this issue, Explainable Artificial Intelligence (XAI) has emerged as a promising research avenue aimed at assisting both users and developers of machine learning models in comprehending the rationale behind model behavior. Feature Importance and Shapley Additive exPlanation (SHAP) are one of the most widely used explanation techniques in XAI (Saarela and Jauhiainen, 2021).

Feature Importance.

The Feature Importance technique measures the importance of a feature in the model's predictive performance, regardless of the direction of the feature effect (Casalicchio et al., 2019; Saarela and Jauhiainen, 2021). It assigns a score to each input feature in a given model, signifying its relative importance. The computation involves measuring the rise in the prediction error of the model following the permutation of a feature. If the error increases, the feature is considered "important" since the model depends on it for the prediction. Conversely, if the error remains the same after permuting the feature, it is deemed "unimportant" since the model disregarded the feature for the prediction (Shin, 2021; Molnar et al., 2018; Molnar, 2018). The recent work on attrition by Chung et al. (2023), already cited above, belongs to this group. They in particular highlight the effectiveness and the limitations of analyses based merely on Feature Importance and not considering features direction.

Feature Importance identifies significant factors but disregards their direction. While understanding a variable's importance is essential, a contrary direction can lead HR to reevaluate its policies. Without this insight, HR may erroneously believe they are making effective decisions when, in fact, their actions may produce the opposite results. Therefore, it is critical to analyze both the significance and direction of variables for informed HR decision-making.

Shapley Additive exPlanation (SHAP).

To overcome the limitations underlined, a more advanced model has been introduced by Lundberg and Lee (2017). It is named SHapley Additive exPlanations (SHAP), which provides a comprehensive approach to understanding predictions and determining the impact of different input variables on model predictions but also revealing the direction of each variable's influence on the output (Mazzanti, 2020; Cakiroglu et al., 2023). There have been several methods proposed to interpret predictions from complex models, but Lundberg and Lee (2017) showed that the SHAP Value method outperforms existing methods, as it better aligns with human intuition as demonstrated by user studies, and more accurately differentiates between model output classes. The SHAP Value calculates the individual impact of each feature on the model's prediction; the 'players' are the features, and the 'game' evaluates the target variable (Mazzanti, 2020). The SHAP method simulates that only some features are present (playing) and some are absent (not playing).

Concluding Observations.

While some authors in the literature concerning employees attrition

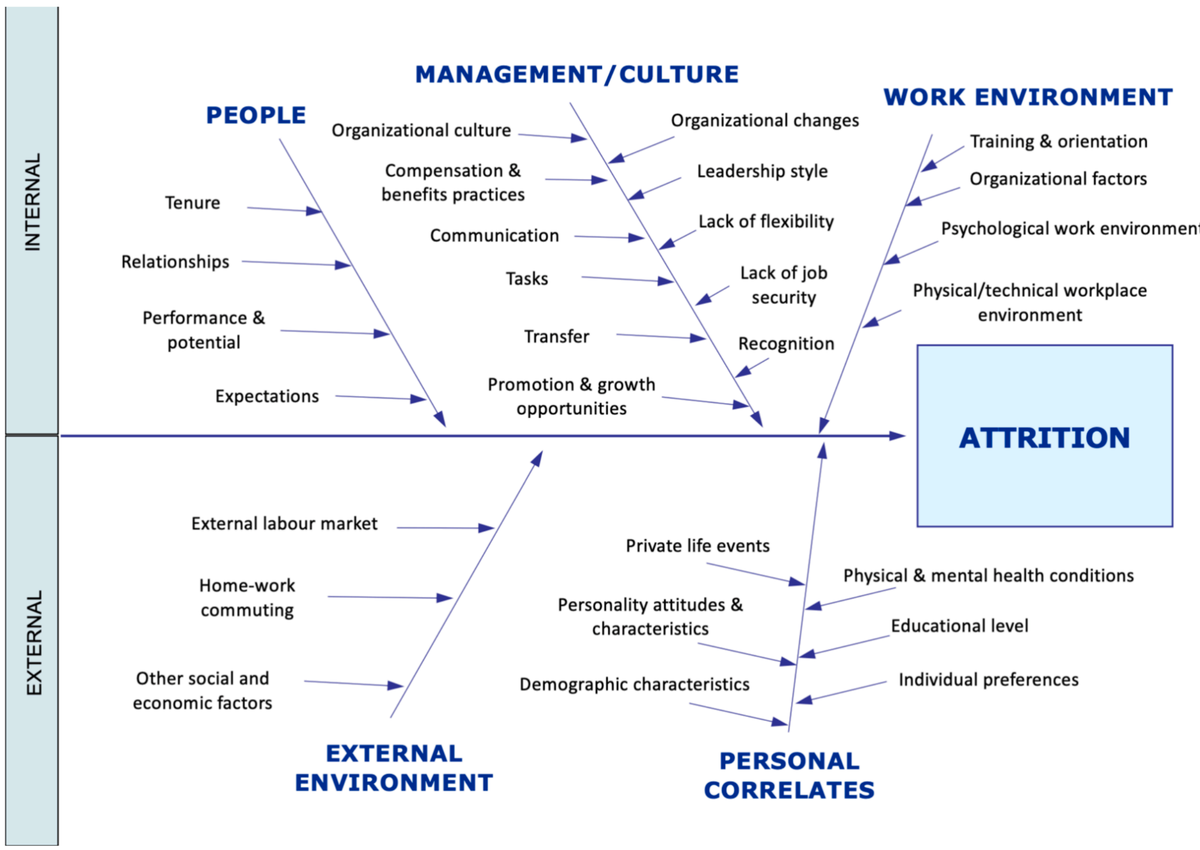

Fig. 1. Ishikawa diagram of the causes of attrition present in the dataset.

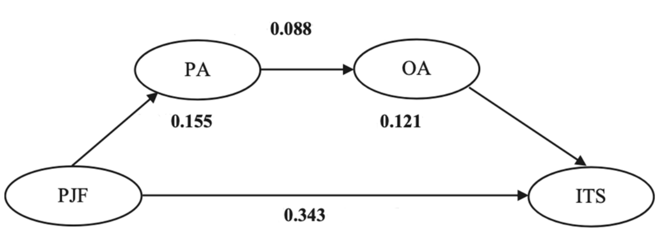

Fig. 2. Key variables affecting the intention to remain (source: Patrick et al., 2024).

use Feature Importance, this method only highlights the significance of factors without indicating their directional impact. To date, no study has analyzed both the effect of the main variables on the dependent variables and the direction of the relationship, which can be examined using the SHAP method. This aspect is crucial for HR managers when deciding on appropriate actions regarding variables. In our study, we found cases where predicting the existence of a relationship was straightforward, but the direction of the relationship led to unexpected and counterintuitive conclusions. This aspect of interpretability must be considered to avoid making counterproductive decisions when developing attraction and retention policies within companies and in their business functions.

3. Employee attrition: approach, data and model

This section outlines the procedures for constructing and deploying a predictive model and elucidating the factors influencing employee attrition. It is organized starting from the description of the chosen approach, explains the data and dataset, and ends with the application of predictive models.

3.1. Approach

We adopt Microsoft's Team Data Science Process (TDSP) framework[1], also cited in Fallucchi et al. (2020) and Oliveira (2021) as a methodological approach. TDSP is an agile, iterative data science methodology designed to provide efficient predictive analytics solutions and smart applications.

The TDSP approach was adopted to capture employee attrition motivations as well as to build a predictive model and consists of six phases: 1) *Business understanding* specifies the key variables that, according to existing knowledge, allow us to investigate attrition (see section 2.3). 2) *Data acquisition and understanding* collects, cleans, and prepares data extracted from Human Resources Information System (HRIS), in cooperation with the company's human resources department (see sections 3.2 and 3.3). 3) *Modeling* phase aims to describe data about employees and provide a variety of exploratory analyses relevant for understanding the contributing key factors and trends to attrition (see section 4.2). *Evaluation* selects the best prediction model according to standard metrics (see section 4.1). 5) *Deployment* involves training and implementing the chosen model to identify potentially departing employees. We further explored a crucial organizational aspect: determining the employee characteristics that most accurately predict attrition, aiding in the development of effective retention policies. Using the varImp function from the *Caret* package in R (Kuhn, 2008), we assessed variable importance. Subsequently, we computed SHapley Additive exPlanations (SHAP) metrics for each variable, enabling identification of strategic intervention areas. This analysis was conducted using the *iml* package in R, an enhanced version of the Kernel SHAP method for approximating

[1] Microsoft Docs: Team Data Science Process. Available online: https://docs.microsoft.com/it-it/azure/machine-learning/team-data-science-process/

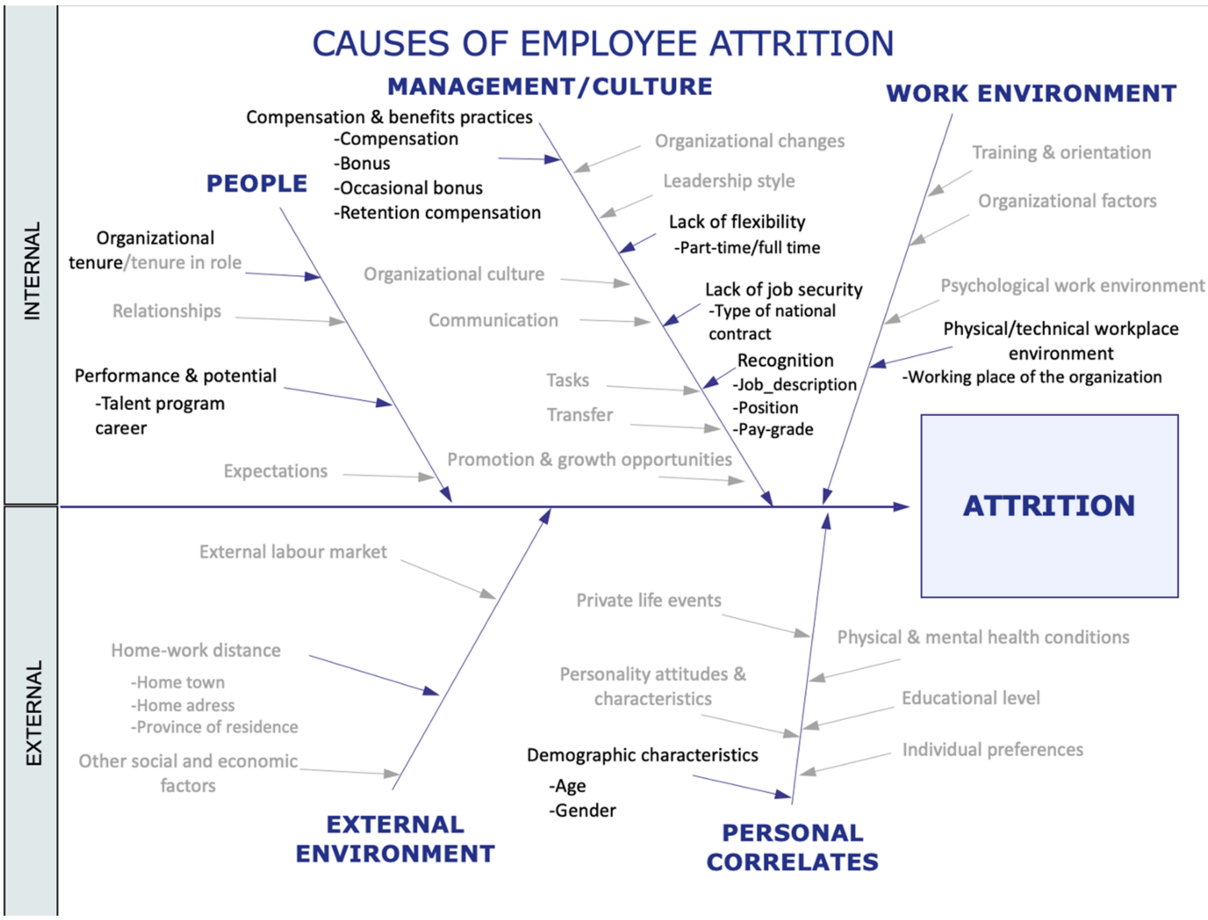

Fig. 3. Ishikawa diagram of the causes of attrition present in the dataset.

Shapley values (Jullum et al., 2021). (see section 4.2).

3.2. Data

The present study was conducted in collaboration with a large Italian financial company. A total of 5,767 observations about its employees, 309 of which (5.4 % of sample) voluntarily resigned, were collected. A total of 27 employee features are mapped in the data set: 20 qualitative (unordered or ordered) and 7 quantitative. ‘Resign’ is the output variable (‘No’ = employees that did not leave the company, ‘Yes’ = employees that did). ‘Stay’ cases were collected over the period from January 2012 to June 2019, while ‘resignation’ cases from the beginning of 2019. Because the two classes come from different periods, the dependence of the phenomenon over time could not be assessed.

We examined available variables in our dataset and compared them to those in the existing literature. The 14 variables used for our analysis and their positioning according to the literature are presented in Table 3.

We used these variables to train and test different models to identify the one with the best predictive performance, which then becomes the focus of a deeper analysis.

3.3. Data preprocessing

The preparation of data is a complex and crucial aspect of any machine learning project because each dataset is different and each project is unique. Moreover, the cleaner the data, the better the process. As Fallucchi et al. (2020) argue, careful consideration should be given to the early stages of Business Understanding and Data Understanding, as this will make the subsequent stages of the process more straightforward.

We selected the relevant features from the initial dataset. Each employee observation contains 14 variables: Gender (male or female), Department (the department an employee works in), Rank (managers, directors, and executives or lower ranks), Contract (type of contract), Level (within each type of contract), Talent (whether an employee is on a special career track), Bonus (whether an employee has received a compensation for tasks they have performed beyond their contractual duties), Hours (either part-time or full-time), Retention (whether an employee contract includes a compensation if they do not leave the company over a specified period), Age class, Tenure class (at the company), Job Description, Log Salary (log10 scale), and Log Premium (log10 scale), a premium accorded to any employee if they reach some performance targets. Because Log Salary and Log Premium have the same magnitude, there is no need to scale or center them. We removed the variables ‘Education level’, ‘Potential’, ‘Climate’, ‘Number of children’ and ‘Leadership’ from the inputs because most of the values are absent in cases of employees who resigned. This happens because, regarding the variables that represent a description of personal characteristics (‘Education level’ and ‘Number of children’), the company policy provides that, when the employee leaves the organization, the relative information is deleted. For ‘Potential’, ‘Climate’, and ‘Leadership’ most of the employees who left have not had this type of assessment, possibly due to misreporting, lack of information in the HRIS or deletion of information after employees’ resignation.

3.4. Application of predictive models

Based on our literature review (Appendix 1), we selected and tested the most promising predictive models to identify the best classifier for the use case. We analyzed a couple of simple models as Naïve Bayes,

Table 2
Models and machine learning tools caption.

		GOAL Predicting employee attrition	Overcome class imbalance	Identify how many of the churned employees were "valuable"
METHOD	SVM	Alduayj & Rajpoot (2018); Chung et al. (2023)		
	NB	Zhao et al. (2019); Fallucchi et al. (2020)		
	RF	Alduayj and Rajpoot (2018); Zhao et al. (2019); Chung et al. (2023)		
	KNN	Alduayj & Rajpoot (2018)		
	XGBoost	Zhao et al. (2019); Punnoose & Ajit, 2016		
	GBT	Zhao et al. (2019); Punnoose & Ajit (2016)		
	LR	Chung et al. (2023)		
	XGB	Chung et al. (2023)		
	ANN	Chung et al. (2023)		
	DT	Zhao et al. (2019); Punnoose & Ajit (2016)		
	ROSE		Ribes et al. (2017); Menardi & Torelli (2014)	
	ADASYN		Alduayj & Rajpoot (2018)	
	SMOTE		Ribes et al. (2017); Chawla et al. (2002)	
	UP-SAMPLING		Ribes et al. (2017)	
	DOWN-SAMPLING		Ribes et al. (2017)	
	EQUALLY-SAMPLING		Esmaieeli Sikaroudi et al., 2015	
	WEIGHTING		Ribes et al. (2017); Chen et al. (2004)	
	EMPLOYEE VALUE MODEL			Saradhi & Palshikar (2011); Foley (2019); Maharjan (2021).

Abbreviations:
RF → Random Forest; NB → Naïve Bayes; LR → Logistic Regression; DT → Decision Tree; SVM → Support Vector Machine; ANN → Artificial Neural Network; XGB → XGBoost; SVM → Support Vector Machine; GBT → Gradient Boosted Trees KNN → K-Nearest Neighbors.

implemented on RStudio with the *naivebayes* package (Majka, 2019) and Logistic Regression, implemented in RStudio with the package *glmnet* (Friedman et al., 2010) plus a series of more complex methods, Decision Tree, implemented in RStudio with the *rpart.plot* package (Milborrow, 2020) and Random Forest, implemented with the *randomForest* package (Liaw and Wiener, 2002). Naïve Bayes must be considered the baseline, actually it is not recommended in the literature as a predictive model. As shown in Table 4, this is the simplest algorithm as it relies on an often faulty assumption of equally important and independent features, disregarding correlations between variables (Lantz, 2019). We also chose Logistic Regression to provide a benchmark for model comparison. For Logistic Regression, we used three types of regularization methods: Lasso, Ridge, and Elasticnet ('Mix'), which is a combination of the former (Zou and Hastie, 2005); in Mix we set 30 % weight to Ridge and 70 % to Lasso, and penalty by cross validation. We trained each classifier on our dataset and selected the one with the best performance.

We performed two experiments in which the data were randomly divided into (i) an 80 % training set and a 20 % test set, and (ii) a 70 % training set and a 30 % test set; the same sets are used for all models. We trained all models through ten-fold cross validation on the training sets; each trained model was then used to predict and test on the 20 % and 30 % sets, respectively. Finally, we used the ROSE method to address the issue of class imbalance, and we implemented it through the ROSE package in R (Lunardon et al., 2014).

Table 4 provides a summary of the strengths and weaknesses of the machine learning algorithms considered in this study (source: Lantz, 2019). This comparison highlights the advantages and limitations of each model, supporting a more informed selection of the most suitable model for predicting employee attrition.

4. Results and discussion

4.1. Predictive algorithm selection

The following section presents a performance evaluation of the implemented algorithms. In this regard, we employed a series of conventional metrics that evaluate the predictive ability of algorithms in various ways: the *Area Under the Curve* (AUC) (Zayas-Gato et al., 2022; Fawcett, 2006); *Sensitivity* (or *true positive rate*) (Rodríguez-Ruiz et al., 2019; Roy et al., 2022); *Specificity* (or *true negative rate*) (Rodríguez-Ruiz et al., 2019; Fawcett, 2006) and *Accuracy* (Chicco and Jurman, 2020).

All measures are computed on the test sets, both for 80:20 and 70:30 splits between training and test sets, respectively.

The performance results of the predictive algorithms are presented in Table 5. In general, all methods demonstrate good performance in the classification task. Performance appears fairly aligned for both the 80:20 and 70:30 data splits. Regarding the various performance measures, differences between the analyzed models can be inferred. In terms of AUC they all have similar performance on both splits, with values between 81.6 and 87.2, while Random Forest differs markedly from the others, with values close to 100. The sensitivity and specificity of the various models average around 80, but Random Forest has a far better ability to correctly classify observations. Finally, regarding the values recorded for accuracy, in general, the models do not appear very accurate; in fact, only logistic regression and decision tree come in around 80, while Random Forest again performs better. This confirms findings in the literature, indicating that Random Forest achieves higher accuracy than other models and well even with large datasets.

Therefore, the final choice was the Random Forest algorithm with an 80:20 split between train and test set. This model was used to identify the main groups of employees who have a heightened likelihood of attrition. Such groups are the likely targets of interventions to reduce voluntary resignation.

Table 3
The positioning of the dataset's variables according to the literature.

Categories	Causes	Dataset variables	Typology
People	Organizational tenure	Tenure class	Numerical
	Performance & potential	Talent	Categorical
Management/ culture	Compensation & benefit practices	Salary	Numerical
		Bonus	Categorical
		Retention	Categorical
		Premium	Numerical
	Lack of flexibility	Hours (part-time/ full-time)	Categorical
	Lack of job security	Contract	Categorical
	Recognition	Job description	Categorical
		Level	Categorical
		Rank	Categorical
Work environment	Physical/technical workplace environment	Department	Categorical
Personal correlates	Demographic characteristics	Age	Numerical
		Gender	Categorical

4.2. Identification of the factors that most influence attrition

The most relevant results of the descriptive statistics of the data set are reported in Table 6. Descriptives indicate that resignation is inversely related to Age and Tenure; additionally, the frequency of resignation for males is higher than for females. It is probable that the wage level plays a crucial role in predicting attrition as the salary and Premium distributions tend to be lower for employees who left the company as compared to those who remained (Fig. 4). While these features are possibly cross-correlated and correlated with other variables (*e.g.* Salary depends on Tenure), it is likely that they are significant determinants of attrition.

We assessed the importance of each factor in predicting employee attrition using the Random Forest algorithm and found that the results are in line with those of the exploratory analyses and provided other important information.

Fig. 5 presents the analyzed factors and their relevance in predicting the likelihood of voluntary resignation. HR managers should prioritize the most significant elements when formulating HR policies. Firstly, it is crucial to provide adequate economic coverage for employees, including stipulated salaries and incentives, as the Log Premium and Log Salary factors have the greatest influence. The Job Description factor's importance suggests a strong correlation with the nature of the tasks performed. The factors of Bonus, Retention, Hours, and Rank appear to have limited relevance. On the other hand, the Tenure Class, Age Class, and Gender factors (refer to Fig. 4 and Table 6) exhibit greater mobility among employees with shorter tenures. This implies that the duration of employment affects an individual's sense of belonging to the organization (Cohen, 1993). Consequently, implementing long-term retention policies and career development plans becomes essential for HR strategies. The significance of the Age factor suggests a connection between work and personal life, as younger individuals display higher mobility compared to older individuals who exhibit greater stability. Table 6 indicates an attrition rate of 15.9 for the Age group 18–25, whereas the rate is significantly lower at 1.4 for the Age group 50–65. Furthermore, Gender plays a significant role, with male workers being slightly more inclined to resign, although the difference is not substantially high, as evident from Table 5. Lastly, the Level, Contract, and Department factors lie in the middle of the graph. These variables reflect the employee's position within the organization and can influence their perception of recognition, job satisfaction, and job security.

As we can observe, Variable Importance indicates the significance of factors but not the direction (direct or inverse) of the relationship between the independent and dependent variables, in this case the probability of attrition. Specific graphs analyzing the relationships among individual variables are useful to study and explain dependencies among variables examined. The graph below illustrates the relationship between the most significant variable, the logarithm of the Premium, and the likelihood of employee turnover. As with the previous figures, on the vertical axis, the probability of resignation is shown as a deviation from the median value calculated across all individuals in the dataset. Therefore, a negative (positive) value for a particular case indicates that the probability is lower (higher) than the median. It illustrates an inverse relationship: as the logarithm of the Premium increases, the likelihood of turnover decreases (Fig. 6). A similar trend is observed with the logarithm of the Salary, although to a more modest extent (Fig. 7).

Manual analysis of individual variables and their impact on the dependent variable is highly time-consuming, especially when an organization aims for a comprehensive analysis of each departmental policy.

Aggregated analyses offer insights into average behaviors and the influence of various drivers on attrition. However, since attrition is specific to individual employees, the analysis should be more granular and detailed, tailored to the particular scope chosen for study. This could involve focusing on a specific department or an individual employee the organization wishes to retain.

As such, broad analyses may not always capture the unique factors influencing attrition, such as departmental climate or personal behaviors. Variations can arise, for instance, from identical job descriptions across different departments or facilities within the same organization, where attrition varies a lot due to specific factors.

The following sections will clearly outline these dependencies and their positive, neutral, or negative effects. Using the SHAP algorithm helps clarify the relationships between variables and their directional effects, aiding HR managers in identifying the appropriate actions to take.

As an example, we consider the variable "Employee's Job", which ranks as the third most important factor, when selecting a case to apply the SHAP method. Fig. 8 presents the relationship between the Job Description and the probability of leaving. On the vertical axis, the probability of resignation is shown as a deviation from the median value calculated across all individuals in the dataset. Therefore, a negative (positive) value for a particular case indicates that the probability is lower (higher) than the median. For reasons of data confidentiality, we have used numbers to indicate job descriptions.

The most interesting job descriptions are cases that have a strong and positive (3, 7, 15, 18, 23 and 24) or negative (2, 9, 19, 20) impact on the probability of attrition. To exemplify the application of the SHAP method, we focus on Job Description number 24 because the company

Table 4
Strengths and weaknesses of the machine learning algorithms considered (adapted from Lantz, 2019).

Algorithm	Strengths	Weaknesses	Main Applications
Naïve Bayes (baseline)	*Fast, handles noisy/missing data well, works on large/small datasets, easy probability estimates*	*Assumes feature independence, less reliable probability estimates, struggles with numeric features*	*Text classification (e.g., spam detection)*
Logistic Regression	Versatile, interpretable relationships, widely applicable	Assumes specific model form, needs numeric data, requires statistical understanding	Population behavior analysis, causal inference, forecasting
Decision Tree	Human-readable model, versatile, efficient	Overfits easily, biased towards features with many levels	Credit scoring, customer behavior analysis, medical diagnosis
Random Forest	High accuracy, handles noise/missing data, manages large feature sets	Not easily interpretable, computationally intensive	Large datasets with numerous features

Table 5
Performance metrics of models by train-test splits.

Model Type		Split on Train and Test set	Values of Criteria (%) AUC on Test	Sensitivity on Test	Specificity on Test	Accuracy on Test
Naïve Bayes		80:20	81.6	73.8	74.9	74.8
		70:30	83.5	80.4	75.4	75.6
Logistic Regression	LASSO	80:20	85.2	72.1	77.3	77
	RIDGE		85	83.6	68	68.8
	MIX		85.4	72.1	74.8	74.7
	LASSO	70:30	86.4	77.2	79.7	79.6
	RIDGE		86.2	79.3	77	77.1
	MIX		86.6	77.1	79	78.9
Decision Tree		80:20	86.8	76.1	82	76.3
		70:30	87.2	82	76.1	81.7
Random Forest		**80:20**	**99.9**	**94.4**	**100**	**94.7**
		70:30	99.7	95.8	97.8	95.9

has only few employees (only 7) in this role, and it is critical to retain them.

From aggregated job analysis to specific employee drivers: the case of Job Description #24.

In the realm of attrition research, although it is often studied as a collective phenomenon, it is imperative to recognize that the decisions made by each individual who leaves an organization are unique. Even though a generalized weighting system for various parameters may be applicable, it is crucial to acknowledge the idiosyncrasies of each particular employee. These idiosyncrasies could significantly diverge, driven by factors such as age disparities, different corporate roles, or varying family-related needs, when compared to their colleagues. Consequently, the transition from an analysis of the entire population to an examination of the specific variables and the weights guiding an individual worker's decision to stay or quit their current workplace becomes a necessary pivot.

According to Table 7, the probability of leaving the company within each Tenure class is medium for the youngest, high between 3 and 10 years, and low after 10 years of company seniority. These findings indicate that, for this position, the competitive advantage in the labor market is acquired after a few years of experience. In addition, among the three types of contract, those who have a credit type have a higher probability of leaving the company.

The trend in the probability of attrition based on the logarithm in base 10 of the total Salary of employees (given by the sum of the Premium and the basic Salary) is presented in Fig. 9. Those who have the lowest income have a fairly high probability of leaving, and as Log income grows, the probability drops significantly.

We consider the case of a single employee to demonstrate how the results can suggest which interventions should be implemented to retain him/her. HR managers should replicate the analysis for each employee with the same Job Description. The employee in question is male, between 30 and 40 years old, has low tenure, has no retention incentive, and has average total compensation.

By calculating the SHAP values, we can see which factors contribute most significantly to the probability that the employee resigns (in this case the probability is high, close to the unit).

According to previous studies (Milborrow, 2020), the graph in Fig. 10 shows SHAP values on the x-axis: values to the left indicate instances that lower the predicted outcome, while those on the right increase it. All features are represented on the left y-axis (Kumar et al., 2020).

Fig. 10 illustrates the marginal contributions and effects of different variables on the probability of employee attrition. These values provide insights into areas that warrant investment to reduce the likelihood of employees leaving the company. A marginal decrease in the attrition probability is observed as the values of Premium and Salary increase. The inverse causality between the Premium and attrition is attributed to its indication of an employee's strong commitment, as it is assigned to those who overcome their contractual obligations. Salary, on the other hand, serves as a means to retain employees, offering an opportunity for organizational intervention.

Conversely, for the present employee as the values of Bonus, Retention, Hours, and Talent increase, the probability of the employee leaving increases as well. Retention and Bonus incentives exhibit unexpected effects.

Generalizing what is happening to the specific employee we can affirm that the awarding of a Bonus to workers who exceed their contractual obligations indicating their strong commitment to the employer results in a reverse causality. This can be attributed to the heightened levels of dedication and absorption seen in employees with exceptional engagement and commitment, which may intensify the problem of burnout, ultimately prompting individuals to depart from the company. This is because, as noted by Maslach et al. (2001), dedicated individuals often overextend themselves in pursuit of their ideals, resulting in exhaustion and eventual cynicism when their efforts fail to achieve their goals.

Similarly, the inverse relationship between retention incentives and attrition is due to organizations offering economic incentives to employees they perceive as likely to leave. Retention incentives, provided by organizations to employees deemed at risk of leaving, serve as an effective strategy for reducing attrition. When an organization offers a retention incentive, it indicates its ability to identify individuals likely to depart. The data regarding the receipt of these incentives is static, often continuing in the database even after expiration. These incentives are time-bound, and their conclusion often coincides with an increased likelihood of departure. Consequently, employees with Retention incentives may eventually leave the company. This outcome validates the organization's ability to target the right employees' intention to leave and to successful (although temporary) use of retention incentives.

Concerning the 'Hours' variable, the graph reveals that full-time commitments are associated with a higher likelihood of leaving compared to part-time commitments. This causal relationship can be explained by the fact that some individuals desire a reduced working hour commitment, which may not be attainable within the organization, prompting them to seek such opportunities externally. Table 8

Table 6
Descriptive statistics of attrition rates (%) by the most relevant features.

	Age (18, 25]	(25, 30]	(30, 40]	(40, 50]	(50, 65]	Tenure (0, 3]	(3, 10]	(10, 20]	(20, 30]	(30, 47]	Gender Female	Male
Attrition rates (%)	15.9	10.0	5.6	3.0	1.4	12.0	10.6	3.4	1.4	0.6	4.7	5.7

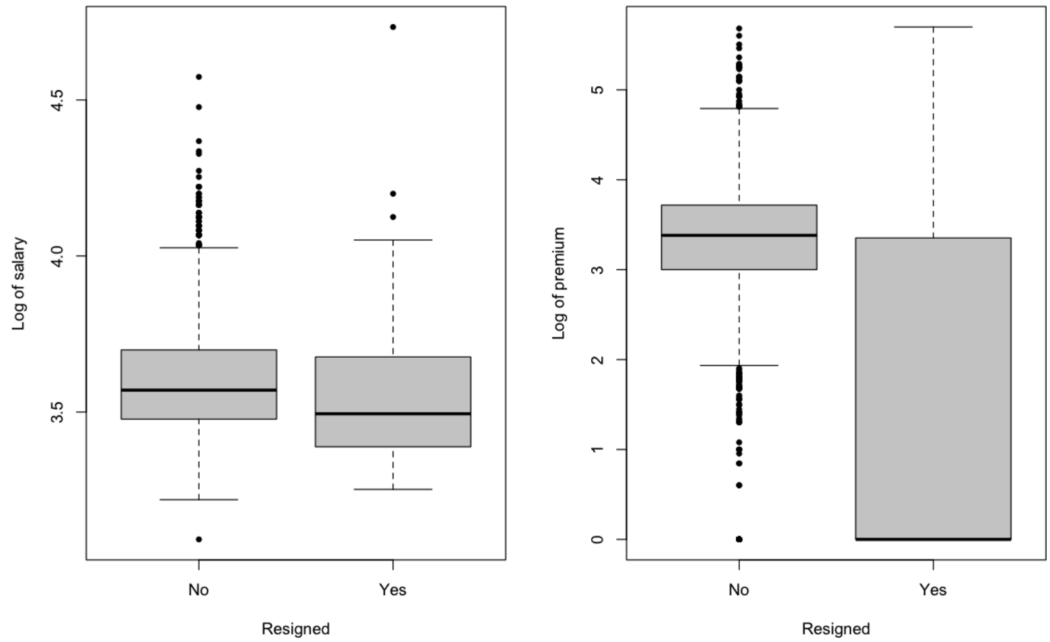

Fig. 4. Distributions of Salary and Premium (log10) versus attrition.

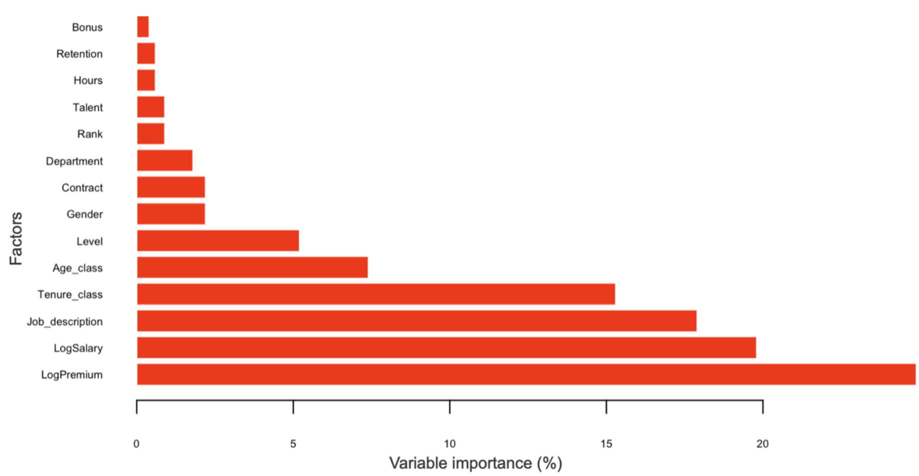

Fig. 5. List of factors in order of importance that are highly associated with attrition.

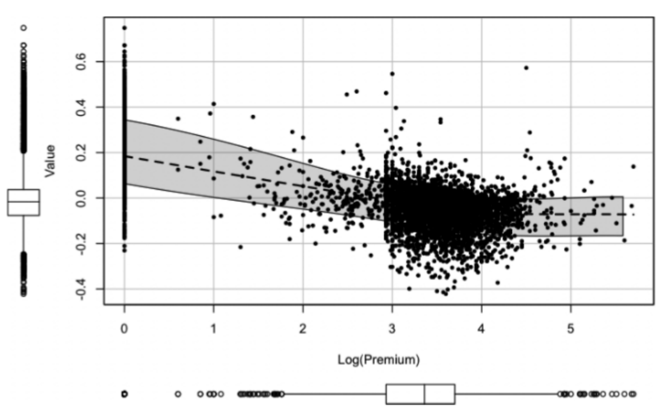

Fig. 6. Relationship between the logarithm of the Premium and the probability of attrition.

demonstrates that female workers, although in the minority, prefer part-time commitments. The prevalence of part-time contracts in lower career brackets, primarily occupied by women, suggests that individuals

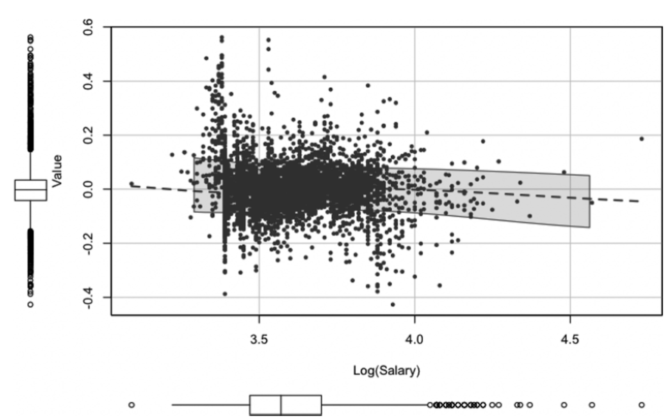

Fig. 7. Relationship between the logarithm of the Salary and the probability of attrition.

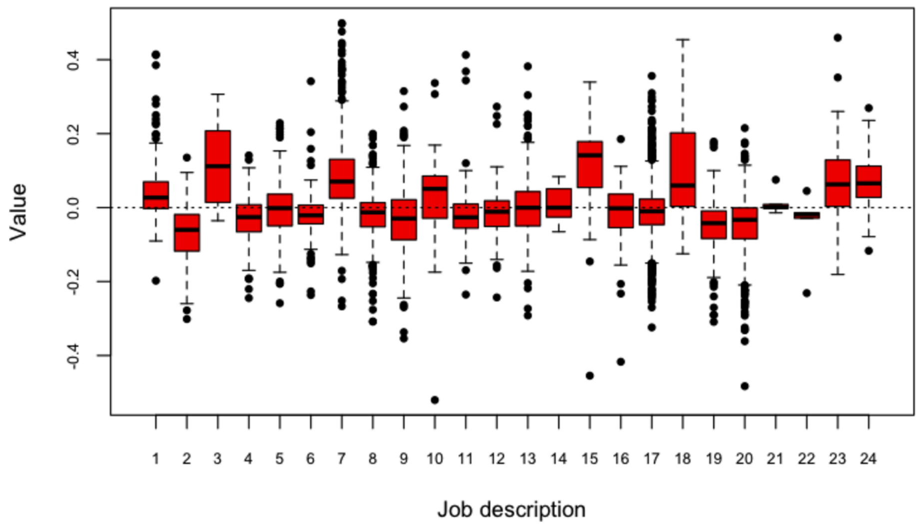

Fig. 8. Relationship between the Job Description and the probability of attrition.

who perceive limited career advancement prospects desire more time for personal life and aspire to work part-time. If the organization fails to accommodate this preference, these individuals may seek such positions elsewhere. To retain these workers, the organization could consider meeting their needs by reducing their working hours.

Talent is another interesting variable and refers to the recognition of employees' potential for skill development and productivity within the organization. Fig. 11 presents the relationship between the logarithm of the Salary and the Talent. The positive marginal impact of Talent on the probability of leaving, as illustrated in Fig. 11, may be attributed to the organization's ability to identify individuals with high potential, who are more likely to explore external job opportunities. Merely including individuals in a privileged talent career program is insufficient for complete retention. Results indicate that individuals with a talent qualification, despite having favorable prospects for career advancement within the organization, are also inclined to seek external opportunities. The fact that individuals in the talent program do not receive higher economic recognition compared to non-participants could incentive the search for a more adequate position and Salary (the absence of an economic incentive associated with the talent program is perceived negatively as a sort of lack of firm commitment). Moreover, Table 9 shows that most talent program members are young, thus naturally seeking for more opportunities and receiving more offers in the labor market. Moreover, with a relatively low tenure and minimal investment in the organization, they perceive a lower cost associated with turnover.

Practical examples of enhancing HR Policies through research.

Once the contribution of each feature to the phenomenon is understood, the company should aim to strengthen, for each employee, the factors indicated on the left side of the SHAP values, while addressing those on the right with policies designed to mitigate their impact, thus reducing the probability that the employee will decide to leave the organization. To connect our findings with actionable HR policies and strategies, we present a concrete example focused on the specific employee case discussed in the previous chapter. This example allows HR managers to understand how these insights can inform practical retention strategies, as SHAP analysis is useful for developing personalized approaches to address individual employee needs and reduce attrition.

To encourage this employee to remain with the company, the organization could first increase the incentives related to Premium and Salary, which show an inverse relationship with attrition in the SHAP values graph. Considering that bonuses are associated with the risk of exhaustion, HR managers could consider reducing the employee's workload or implementing other initiatives to mitigate the risk of burnout. Regarding retention incentives, although they appear on the right side of the graph, they have proven to be ineffective due to their temporary nature. To retain the employee in the long term, the organization should ensure that these incentives are provided consistently. The organization could then address working hours by offering the employee options for more flexible schedules or part-time arrangements. Finally, since merely including individuals in a privileged talent career program is insufficient for complete retention, and given that he/she is inclined to seek external opportunities, the company could offer the employee a promotion or other career advancement opportunities to ensure his/her position remains competitive with the external labor market.

Table 7
Attrition rates by Tenure class and type of contract.

	Tenure			Type of Contract		
	[0, 3]	(3, 10]	(10, 20]	Other	Credit	Managers
Probability of attrition (%)	69.7	99.5	12.7	41	99.4	11.1

Although this example refers to a specific case, it serves as an important demonstration of the procedures, steps, and reasoning necessary to apply this method to any individual case HR managers may have to face. This example offers a replicable approach, ensuring that retention strategies are based on data-driven, customized insights that address each employee's unique needs. Furthermore, while this example relates to a specific case, it is extendable, as we cannot assume that paradigms that were valid just a few years ago are still applicable today. In the evolving labour market following COVID-19, both the identification of variables and their directional influence are essential for questioning hypotheses that were previously accepted as true. This highlights the necessity for HR managers to remain adaptable and careful when applying data-driven insights to different employee scenarios.

Moving from macro to micro perspectives: where rules change.

In the preceding section, at the beginning we conducted a global analysis that highlighted broad trends and factors. This type of analysis typically identifies average elements or considerations, but these may not always determine behaviors within departments or specific job profiles. In departments, the factors influencing decisions can vary in importance or impact, affecting their shape and form. This variability is seen in how identical job descriptions can exist across different

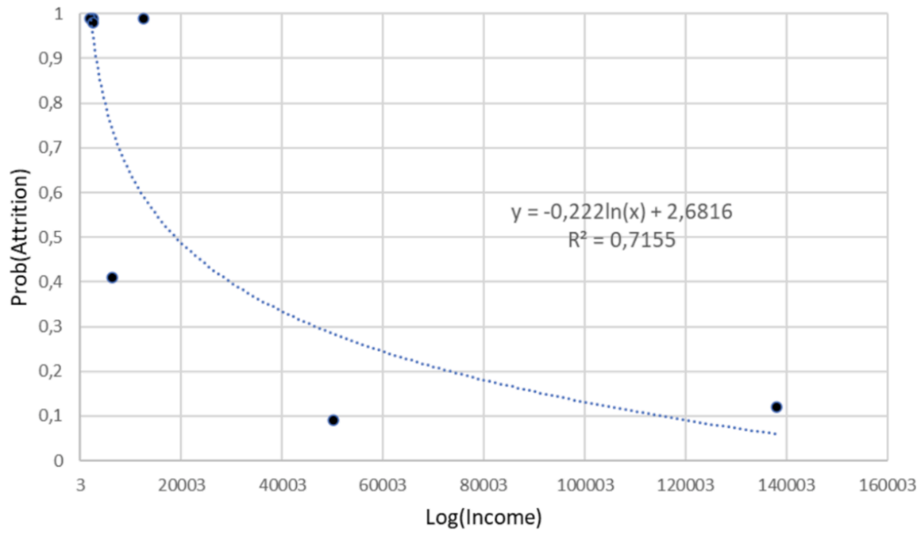

Fig. 9. Relationship between the logarithm of income and the probability of attrition.

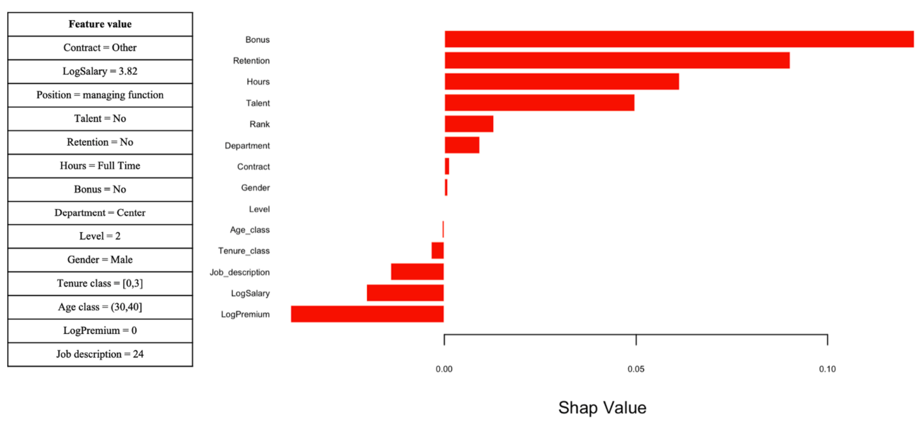

Fig. 10. Detail of the feature value and Shap values of the example.

departments or locations within the same company, adapted for cross-functional roles or different operational contexts. Shifting from this global view to a more detailed one, we found that the analysis can also be applied at the departmental or even at an individual level. This is because factors identified as significant on average may manifest differently within specific departments or different individuals. As Chung et al., (2023) suggested, these differences often arise from the unique workplace environments found in each department or from employees' psychological or subjective factors. Consequently, policies developed at the departmental or individual level may differ from those set at the company level. HR plays a crucial role here in interfacing with functional and divisional managers. HR not only facilitates these analyses but also supports actions aimed at retaining and attracting future employees. This strategic alignment is important not only for HR professionals but also for functional and divisional managers looking to retain their employees or attract new ones.

In transitioning from macro-level insights to micro-level dynamics, the regulatory landscape undergoes transformation. This shift is characterized by variations in policies and practices across departments, reflecting local operational needs and managerial decisions. While global analyses provide a solid foundation, they need to be adapted to fit the diverse operational realities and strategic goals at the department level.

5. Conclusion

This study explores employee attrition using a real dataset obtained from an Italian financial company. Through a comprehensive literature review, we identified key factors and motivations related to employee attrition within our dataset. Additionally, we examined various machine learning models commonly used for predicting employee attrition. Four models were evaluated and compared using standard metrics, and Random Forest emerged as the top-performing model. Given the strongly unbalanced dataset, we employed the ROSE method in conjunction with Random Forest to address the class imbalance issue.

Our results indicate that careful data analysis and machine learning techniques can build reliable and accurate employee attrition predictions. Based on SHAP analysis, we also provided sample insights on the main features of some employees leaving the company. These findings (sometimes counterintuitive) are of interest to the HR department of the company which may establish retention plans to mitigate the risk of attrition.

The impact of certain variables is observed within specific categories (such as jobs or departments), which exhibit different behaviors compared to the overall population. In these cases, the variables show varying degrees of significance or distinct directional effects. This analysis does not seek to generalize findings but rather provides a fine-grained perspective that HR should consider when formulating policies, recognizing that a one-size-fits-all approach is not feasible.

Table 8
Gender (%) by full time/part time commitment and type of contract.

	Other		Credit		Managers		Executives		Overall	
	Full-Time	Part-Time	Full-Time	Part-Time	Full-Time	Part-Time	Full-Time	Part-Time	Full-Time	Part-Time
Female	2.5	0.1	69.9	13.3	0.7	0.0	12.9	0.5	86.0	14.0
Male	8.3	0.1	62.2	0.3	5.7	0.1	23.4	0.1	99.4	0.6

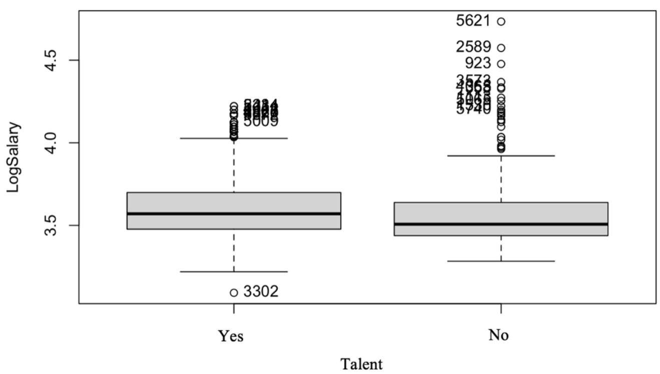

Fig. 11. Logarithm of the Salary given Talent (%).

The results and the fruitful interactions with the HR of the financial company allowed us to understand the impacts and implications of such this kind of business-research collaboration.

The findings suggest that HR analytics can provide results that are traceable to business Key Performance Indicators (KPIs), which are useful for making evidence-based decisions, developing appropriate policies, and monitoring their effects. The HR function often pursues goals that are functional to good business operations but are not directly visible in terms of measurable results. Improving HR measurement and data-driven HR systems is a powerful way to demonstrate the value of the HR function and shift towards a more business and strategic orientation.

Another important finding is that simply applying predictive algorithms is not enough for HR managers or decision-makers to make informed decisions. To understand which variables to intervene on, Feature Importance is useful because it shows which variables are relevant. However, this alone is not sufficient because it does not indicate the direction of the variables, thus not providing information to HR managers on whether to take positive or negative action on a variable. The SHAP algorithm is useful for this purpose. It can also be applied to a single employee (as shown in the example of Job Description 24), which can be very helpful in understanding where to intervene to retain a particular employee. However, algorithms alone are insufficient for decision-making. Expert judgment remains critical, as the current data emphasizes the importance of developing a conceptual understanding of the cause-and-effect relationships derived from data analysis. As we have seen from interpreting causal mechanisms, they may not be obvious and are interpretable only within the specific context from which the data is derived. In fact, if we interpret the values of the graph without knowing how the source data are structured and what they indicate, we could misinterpret the relationship of causality and then draw the wrong conclusions that could lead to counterproductive interventions. For example, interpreting Fig. 6 may lead to the misconception that retention incentives increase attrition. However, understanding the data structure reveals that such incentives actually identify individuals likely to leave, and as the incentives expire, these individuals are indeed more likely to depart. Hence, the company's policy of providing retention incentives is effective in identifying potential departures and managing attrition rates.

Moreover, we have demonstrated that the drivers explaining the phenomenon of attrition can vary depending on the level of detail at which the phenomenon is studied. Because there are no universally valid rules, both the SHAP technique and expert judgment are essential for understanding which factors drive each individual case, and for making the best decision in each individual case. These insights are essential for helping HR managers understand the level of detail in analysis necessary to develop suitable policies for each target variable.

Finally, an implication of this is the possibility that collaboration between academics and practitioners can be very helpful in improving attrition predictions, which become increasingly important in the post-COVID-19 era. For this reason, a strong link between the HR department and IT department or data scientists is fundamental to developing new data-driven HR policies and monitoring the effects of such strategies achieved over time.

Although our contribution may not initially appear entirely novel, it highlights the risks of relying solely on an approach that considers only variables while assuming their direction. HR departments have a limited budget, which makes it essential to avoid allocating resources to variables that do not produce results. Different environments may assign varying weights and directions to these variables, so our paper shows that focusing only on drivers and their impacts, without considering their direction, is neither an effective nor an efficient approach. Thus, HR actions should effectively target various groups of variables, such as Person-Job Fit, Organizational Attachment and Psychological Attachment. Our research illustrates that in HR, the significance of a variable is not the only consideration; often, decisions are ineffective or even counterproductive without the insights provided by SHAP. Many studies conducted in the past year have used analyses without SHAP, and although some have applied this method, they have not done so in this specific context. Our findings demonstrate that results can be counter-intuitive, highlighting the need to understand both the significance and direction of variables to make informed HR decisions.

This study has several limitations. Firstly, we focused on a single case study in Italy, although the company's size and data volume allowed for meaningful generalizations. The asynchronous nature of data collection within the company prevented investigating time dependence due to privacy policies. Furthermore, certain constructs considered important in the literature were not included in our predictive models due to data limitations. Moreover, the impact of COVID-19 on attrition behavior and motivations necessitates exploring additional datasets. From a technical standpoint, we did not test two methods suggested in the literature: XGBoost, suitable for larger datasets, and neural networks, prone to overfitting (Lantz, 2019). Future research should incorporate these algorithms to potentially enhance the current findings.

Table 9
Talent rates by Age and Tenure.

	Tenure						Age					
	[0, 3]	**(3, 10]**	**(10, 20]**	**(20, 30)**	**(30, 47]**	**Overall**	**[18, 25]**	**(25, 30]**	**(30, 40]**	**(40, 50]**	**(50, 65]**	**Overall**
No	16.1	14.7	37.5	20.0	11.7	100	3.1	20.5	26.0	30.1	20.3	100
Yes	27.9	40.7	24.6	4.7	2.1	100	4.4	63.3	22.9	4.7	4.7	100

Table 10
Literature framework with details of the models analyzed, the performance measurements used and the results.

Authors	Topic	Evaluation Method	Models		Values of Criteria (%) AUC on Train	AUC on Test	Accuracy on k-fold validation	Accuracy on Train	Accuracy on Test	Precision on Test	F1 score on Test	True Positive Rate on Test	True Negative Rate on Test	Recommended
Saradhi & Palshikar, 2011	Conduct a case study for building and comparing predictive employee churn models and propose a value model for employees	Three datasets: (1) resigned and released, (2) only resigned, (3) only released. 80:20 random split into train and test sets	SVM (1)						80.0			81.2	79.7	SVM
			SVM (2)						82.0			80.0	82.2	
			SVM (3)						84.1			77.8	85.1	
			Random Forest (1)						83.5			53.6	91.9	
			Random Forest (2)						92.3			50.0	97.5	
			Random Forest (3)						88.8			47.2	95.0	
			Naïve Bayes (1)						74.0			55.1	79.3	
			Naïve Bayes (2)						79.0			63.3	81.0	
			Naïve Bayes (3)						77.6			44.4	82.6	
Alduayj & Rajpoot (2018)	Conduct three main experiment to predict employee attrition, using synthetic data created by IBM Watson	On an unspecified split of train and test set	Unbalanced data	Linear SVM					86.9	81.4	37.1	24.0		Quadratic SVM
				Quadratic SVM					87.1	66.2	50.3	40.5		
				Cubic SVM					84.1	50.8	45.8	41.8		
				Gaussian SVM					86.5	78.8	34.3	21.9		
				Random Forest					85.6	75.0	26.9	16.4		
				K Nearest neighbours (K = 1)					82.7	27.5	7.9	4.6		
				K Nearest neighbours (K = 3)					83.7	25.0	0.8	0.4		
			Synthetic data	Linear SVM					78.2	76.3	77.9	79.5		Cubic, Gaussian, Random Forest and k Nearest Neighbours
				Quadratic SVM					87.9	83.9	88.1	92.7		
				Cubic SVM					92.6	87.9	92.7	98.1		
				Gaussian SVM					91.2	88.5	91.2	94.1		
				Random Forest					92.6	95.0	92.1	89.3		
				K Nearest Neighbours (K = 1)					96.7	93.9	96.7	99.7		
				K Nearest Neighbours (K = 3)					92.9	87.7	93.1	99.2		
				K Nearest Neighbours (K = 5)					90.4	84.3	90.9	98.7		
				K Nearest Neighbours (K = 10)					87.2	80.4	88.0	97.0		
Punnoose & Ajit (2016)	Compare XGBoost technique against six historically used classifier, using data from HRIS of a global retailer	Dataset split 80:20 into train and test set	Random Forest (XGBoost)		88.0	86.0								XGBoost
			Logistic Regression		66.0	50.0								
			Naïve Bayes		64.0	59.0								
			Random Forest (Depth controlled)		79.0	51.0								
			SVM (Radial Basis Function)		68.0	52.0								
			Linear discriminant analysis		74.0	52.0								
			k Nearest Neighbours		52.0	50.0								

(continued on next page)

Table 10 (*continued*)

Authors	Topic	Evaluation Method	Models	Values of Criteria (%)									Recommended
				AUC on Train	AUC on Test	Accuracy on k-fold validation	Accuracy on Train	Accuracy on Test	Precision on Test	F1 score on Test	True Positive Rate on Test	True Negative Rate on Test	
Fallucchi et al. (2020)	Analyse a real dataset provided by IBM analytics and identify the main causes that influence attrition	Dataset split 70:30 into train and test set	Naïve Bayes (Gaussian)				78.2	82.5	38.6	44.6	54.1	84.5	Naïve Bayes (Gaussian)
			Naïve Bayes (Bernoulli)				83.1	84.5	45.9	37.9	33.1	92.7	
			Logistic Regression				86.5	87.5	66.3	44.5	33.7	96.2	
			K Nearest Neighbours				84.2	85.2	55.1	15.0	9.0	99.4	
			Decision Tree				79.2	82.3	35.6	35.1	36.1	91.0	
			Random Forest				85.0	86.1	65.8	19.4	13.2	99.1	
			SVM				85.1	85.9	80.8	16.6	9.6	99.4	
			Linear SVM				85.8	87.9	66.5	35.8	24.7	97.8	
Alao & Adeyemo (2013)	Analyse complete records of employees of one of the Higher Institutions in Nigeria, identifying employee related attributes that contribute to the prediction of employee's attrition	On an unspecified split of train and test set	CART (C4.5)		78.4				61.3	63.6	67.0	85.7	CART (C4.5)
			CART (REPTree)		74.9				55.3	57.9	61.8	84.4	
			CART (Basic)		77.7				57.9	60.8	64.1	86.3	
El-Rayes et al. (2020)	Develop tree-based binary classification models to predict the likelihood of employee attrition based on firm cultural and management attributes	Dataset split randomly 80:20 into train and test set	Linear Regression	65.0									Random Forest and Decision Tree
			Logistic Regression	65.0									
			Decision Tree	70.0									
			Random Forest	73.0									
Ribes et al. (2017)	Illustrating the similarities between the problem of customer churn and employee turnover and developing an example of employee turnover prediction model	Dataset split 80:20 into train and test set	Linear discriminant analysis		75.0						74.0	33.0	Tree based ones
			SVM (Radial Basis Function)		80.0						76.0	31.0	
			Random Forest		95.0						96.0	19.0	
			Tree bagging		94.0						94.0	22.0	
Esmaieeli Sikaroudi et al. (2015)	Applying different data mining methods on real data of manufacturing plant to predict employee turnover	k-fold cross validation	Multy-layer perceptron			82.0							Decision Trees
			Probabilistic Neural Network			76.0							
			SVM			75.0							
			CART			80.0							
			k Nearest Neighbours			75.0							
			Naïve Bayes			89.0							
			Random Forest			90.0							

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1:. Overview of the predictive model

Table 10 illustrates in detail the predictive models that have been analyzed by the authors, which performance measures were used to evaluate them and the results they obtained.

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