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Enhancing Employee Retention Prediction Through Federated Learning and Associative Classification using FedCBA: A Case Study on IBM HR Analytics

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Abstract
Human resources analytics stands out as a critical area for enhancing employee engagement and satisfaction. However, the privacy and security of data related to employee behavior pose a significant barrier in such analyses and applications. To address issues related to data privacy and sharing, the federated learning architecture offers a new approach in the development of employee engagement prediction models. Federated learning preserves data privacy by enabling the processing of data located in different organizations without centralization. Additionally, sharing models contributes to reducing network traffic and energy consumption while also decreasing the carbon footprint. In this study, a federated learning-based relational classification architecture was developed on the IBM HR Analytics dataset to improve employee engagement prediction. During the model training, the duCBA (Data Unaware Classification Based on Association) algorithm was revised, and a new federated learning aggregation algorithms called FedCBA (Federated Classification Based on Association) was used. The experimental results show that the model achieves %87 accuracy and proves the effectiveness of the proposed method. Findings reveal that employees who work overtime, have low environmental and job satisfaction, and have short tenure are likelier to leave their jobs. In contrast, employees with good work–life balance and high satisfaction levels tend to stay. These findings suggest that the proposed method protects data confidentiality and provides tangible insights to improve employee engagement.

Keywords Federated learning · Data privacy · Relational classification · Employee engagement prediction · Human resources analytics

1 Introduction

In today's competitive business world, the success of organizations depends to a large extent on their ability to recruit and retain qualified employees. However, this goal of success has evolved over the centuries as labor management has changed. In the early twentieth century, in the post-industrial revolution era, companies' workforce management focused more on the control of production processes and the management of physical labor. In this period, since physical labor was seen as the most important criterion for employees, employees were only seen as workers for firms. Individual performance and commitment of employees were ignored. However, this situation started to change, especially in the 1970s, with the growth of the information and service sectors. The most important point in this change was that the quality of the labor force and the commitment of the employees began to come to the fore. While this situation triggered the emergence of the concept of talent management, businesses had to focus on developing strategies for the acquisition and retention of talented employees [1].

In the twenty-first century, significant developments in the field of technology have enabled the integration of tech-

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nology into many different fields. The use of data analytics and artificial intelligence (AI) tools in workforce management has become increasingly widespread [2]. The use of data analytics and artificial intelligence tools in workforce management is increasingly widespread, with concepts such as employee engagement, performance management, and attrition becoming critical factors in human resource management. Today, organizations place great importance on managing their employees to maintain market reputation and gain a competitive edge that leads to higher profits. Employees are regarded as the organization's most valuable resource, making it a primary responsibility to address employee issues, provide appropriate solutions, and foster a strong work environment. However, employee attrition remains one of the most serious challenges organizations face. While employee resignation was once considered merely an individual loss, it now significantly impacts overall productivity, customer satisfaction, innovation capacity, and the continuity of company culture. Moreover, recruiting and training new hires entail high costs, disrupt team dynamics, and can cause organizations to lose their competitive advantage [3].

Especially in the information technology sector, workforce structure and work culture have rapidly evolved, with today's employees being much more flexible compared to previous generations. Attrition has become a chronic problem driven by supply and demand dynamics, negatively affecting organizational competitiveness. The emergence of next-generation IT companies and startups has led many employees to leave in pursuit of new skills, making attrition a costly and challenging issue for management to solve. Although organizations are continually refining HR policies, attrition rates continue to rise each quarter [4, 5].

Numerous modeling approaches have been developed to analyze and predict employee turnover tendencies by incorporating a wide range of factors, including job satisfaction, work–life balance, opportunities for career advancement, and compensation. These models aim to uncover underlying patterns and identify key determinants that influence an employee's decision to stay with or leave an organization [3–5]. However, data privacy becomes a critical issue when applying these forecasting models. In decentralized organizational structures or large companies spread across different branches, it is challenging to perform these analyses while maintaining the confidentiality of employee data. While the centralization of sensitive data comes with data security risks, innovative solutions are required to protect the privacy of individuals [6].

Federated learning (FL) is an emerging machine learning paradigm that enables collaborative model training across multiple decentralized devices or servers while keeping the raw data localized [7]. Unlike traditional centralized learning methods, where data must be aggregated into a central repository for model training, FL allows each participating node to train the model locally and only share model updates (e.g., gradients or parameters) with a central server. This approach not only significantly reduces the risk of data leakage but also aligns with growing concerns around data privacy and regulatory compliance [8–10].

In this context, federated learning offers a compelling solution by facilitating privacy-preserving training on distributed data sources [11]. Sensitive information—such as gender, age, salary, or health records—remains on local devices or organizational nodes, thus minimizing exposure and ensuring confidentiality. This is particularly beneficial in domains like human resources (HR) analytics, where employee-related data are both highly personal and legally protected. By leveraging FL, organizations can collaboratively build models for tasks such as employee satisfaction analysis and turnover prediction without needing to pool their data centrally. As a result, federated learning not only enhances data security but also enables more inclusive and accurate models by incorporating insights from diverse, real-world datasets that would otherwise remain siloed due to privacy constraints.

The main problem addressed in this paper is to ensure data privacy in the analysis of employee rates. Employee performance is directly related to workplace productivity. Therefore, employee performance is an important indicator for the sustainability of workplaces. However, AI-based analysis systems do not provide adequate measures for data security and privacy while monitoring this critical process. Therefore, privacy concerns should be addressed when analyzing data such as employee performance and turnover rates.

This paper aims to answer the following research question: What is the impact of a federated learning technique applied to an employee dataset optimized by data preprocessing steps on the prediction of employee attrition while preserving data privacy? In this context, using IBM HR Analytics Employee Attrition [12] dataset, a model is trained with FL architecture and employee attrition trends are predicted. Within the scope of FL architecture, the Federated Classification Based Relationships (FedCBA) algorithm developed in this study was used. FedCBA is an improved version of the previously developed Data Unaware Classification Based on Association (duCBA) [13] federated learning aggregation algorithm. duCBA algorithm is built on the Classification Based on Associations (CBA) [14] algorithm, one of the relational classification methods. When model training is performed with CBA, classified/labeled association rules are obtained. The improvement process is carried out by comparisons based on the performance of association rule algorithms in CBA. In this context, different association rule algorithms such as Apriori, Frequent Pattern Growth (FP-Growth), and Equivalence Class Transformation (Eclat) were evaluated and their performances were analyzed and the algorithm with the highest accuracy was selected. It was determined

which algorithm is more efficient for employee attrition prediction and the relationship between the relevant algorithms and human resources (HR) variables was revealed. The findings make the relationships between these variables more explainable and provide actionable insights that can be used in practice.

The main contributions of this study are as follows:

- Demonstrating the applicability of the federated learning approach by enabling secure model training in distributed systems.
- Analyzing the performance of the federated learning architecture while preserving the privacy of employee data and demonstrating its potential as an effective solution for HR analytics.
- Employing a relational classification technique to derive significant association rules from the dataset, ensuring the results are both usable and understandable for human resources departments.
- Examining the effects of modifiable variables, such as work–life balance, on attrition rates and presenting findings aimed at increasing employee loyalty. Additionally, offering policy recommendations to organizations.

This study addresses a significant gap in the field of human resource management, particularly in employee turnover prediction. Traditional models largely rely on centralized data analysis, which inherently poses risks to data privacy and security. In contrast, our proposed federated learning approach enables the use of distributed data without centralizing it, offering more secure, privacy-preserving, and interpretable insights related to critical factors such as employee satisfaction and work–life balance.

Although there is considerable research on federated learning, most existing studies are limited to classical machine learning or deep learning models [7]. There is a notable absence of work that combines relational classification methods with federated learning to enhance both model interpretability and data privacy, while ensuring compliance with regulations such as the General Data Protection Regulation (GDPR) [15], Turkey's Personal Data Protection Law (KVKK) [16], and The Equal Employment Opportunity Commission (EEOC) [17]. This is precisely where our approach makes a unique contribution.

Our novel federated learning architecture leverages association rule-based classification to predict employee turnover in a distributed and privacy-preserving environment. This enables model training across diverse data sources without the need for centralized data storage, improves the interpretability of models and decisions for HR professionals, and guarantees data privacy and legal compliance.

Consequently, this work introduces an innovative paradigm to both academic research and practical applications in human resources, empowering organizations to develop effective strategies that enhance employee engagement while safeguarding data privacy—thereby achieving sustainable competitive advantages.

The remainder of the article is structured as follows: Sect. 2 provides the background of the topic and an overview of related works. Section 3 outlines the methodology employed in the study. Section 4 presents the experimental results and their analysis. Section 5 summarizes the findings, discusses the advantages and limitations of the proposed method, and offers recommendations for future research. Finally, Sect. 6 interprets the overall results and explores their broader implications.

2 Related Work

This section discusses the components utilized within the scope of the study, including the federated learning architecture, its application in human resources analytics, and the challenges and limitations associated with federated learning. Additionally, the CBA algorithm and its advantages are examined, along with its application in human resources. The section also covers the Apriori, Eclat, and FP-Growth algorithms, emphasizing the role of association rules in federated learning and their application to HR data. Finally, the IBM HR Analytics Employee Attrition dataset and relevant literature are analyzed.

2.1 Federated Learning

Federated learning is a machine learning method that allows data to be analyzed without being centralized. In traditional data analytics, data are collected in a center for model training, while in FL, model training is performed on devices or servers where data sources are located. This method has gained importance, especially in sectors where the need to protect the confidentiality of sensitive data is high. A central server collects model parameters updated locally on each device and combines them to create a global model. This method allows data owners to contribute without having to share their data in a central cloud [18–21].

FL offers serious contributions, especially to data privacy and security. The fact that data remain locally on devices allows data owners to contribute without compromising the security of their data. In areas such as health, finance, and human resources, analyzing sensitive data without transferring it is very advantageous in terms of meeting data privacy and legal compliance requirements.

There are basically four stages in federated learning.

- Determination of clients by the server.
- Sending global model parameters to clients.

- Retraining the model for each request with local data.
- After training, sending local model parameters back to the server and integrating these parameters into the global model.

This entire process is repeated a certain number of times in order to improve the global model. Figures 1 and 2 represent the federated learning architecture [22].

Figure 1 shows a type of federated learning called Cross-Device Federated Learning. In this architecture, clients consist of devices such as smartphones, IoT devices, or edge devices. It is preferred in scenarios where there are many devices for model training, i.e., the number of client devices is high. Figure 2 shows a type of federated learning called Cross-Silo Federated Learning. In this architecture, clients consist of a small number of organizations such as hospitals and banks. The number of clients is limited. Each silo has access to a large amount of local data and more stable computational resources than individual devices in cross-device FL [22].

2.1.1 Federated Learning in Human Resources Analytics

FL presents a transformative approach to human resource analytics by enabling organizations to gain valuable insights while fully preserving employee privacy. FL-based solutions for key HR applications—such as employee satisfaction assessment, performance evaluation, recruitment optimization, and turnover prediction—empower organizations to conduct comprehensive analyses without compromising sensitive data [3].

- *Employee satisfaction*: FL leverages data stored locally on employees' devices to accurately gauge satisfaction and motivation levels. This decentralized approach safeguards personal data, providing management with reliable insights to enhance workplace morale and engagement.
- *Performance evaluation*: By processing performance-related data locally, FL eliminates the need for centralized data collection, thus maintaining confidentiality while enabling precise and fair employee evaluations.
- *Turnover prediction*: FL enables the development of robust predictive models for employee attrition without requiring direct data sharing, helping organizations proactively identify at-risk employees while upholding data privacy standards.

This privacy-preserving paradigm not only strengthens trust between employees and employers but also unlocks the potential for deeper, more actionable human resource analytics.

2.1.2 Challenges and Limitations of Federated Learning

While FL offers significant advantages, it also faces some technical and operational challenges [18–21].

- *Heterogeneous data*: in FL systems, the fact that the data in each data source are not homogeneous is a common challenge. Data can vary greatly in terms of quality, size, and distribution across devices or institutions. This diversity can affect the model's training process and accuracy.
- *Communication costs*: the decentralized operation of FL requires constant updates of model parameters and transmission of these updates to a central server. This can lead to high communication costs, especially in projects with large data and intensive model updates.
- *Model updates*: FL creates technical complexity as it requires each participant to constantly update their model. Model compatibility between participants must be ensured, and the impact of each update on the overall model must be carefully monitored.
- *Collaboration between participants*: ensuring trust and supporting collaboration between different data owners is critical to the success of FL. In addition to technical compliance, legal and ethical compliance is also required in the process of decentralized sharing and analysis of data between participants.

2.2 Classification Based on Association Algorithm: CBA

The Classification Based on Association (CBA) algorithm is a data mining technique that combines classification and association analysis [23–25]. It is particularly useful for classification problems. CBA analyzes the relationships between attributes in datasets and transforms these relationships into classification rules. In this way, it becomes possible to better understand and predict the relationships within the data during the classification process.

One of the key advantages of CBA is its ability to produce more meaningful and interpretable classification models by combining the comprehensive rule discovery capability of association mining with the goal-oriented approach of classification [26].

However, association rule mining can generate a large number of redundant or spurious rules, especially in high-dimensional datasets. To mitigate this issue, the CBA algorithm sets minimum thresholds for support and confidence. In the proposed version of the algorithm [27], Classification Based on Associations Rule Generator (CBA-RG), only the rules that meet the predefined minimum support (minsup) and minimum confidence (minconf) values are generated, and unnecessary rules are eliminated at the very first stage.

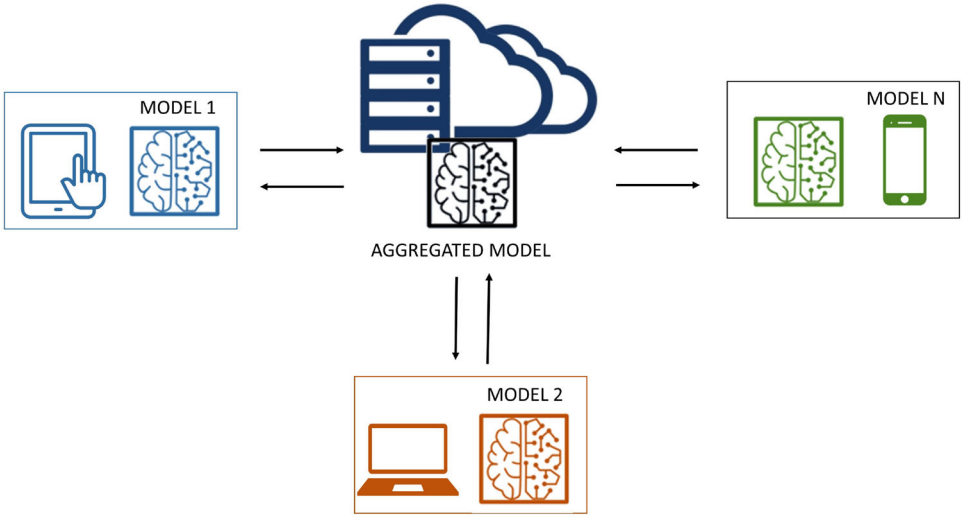

Fig. 1 Cross-device federated learning

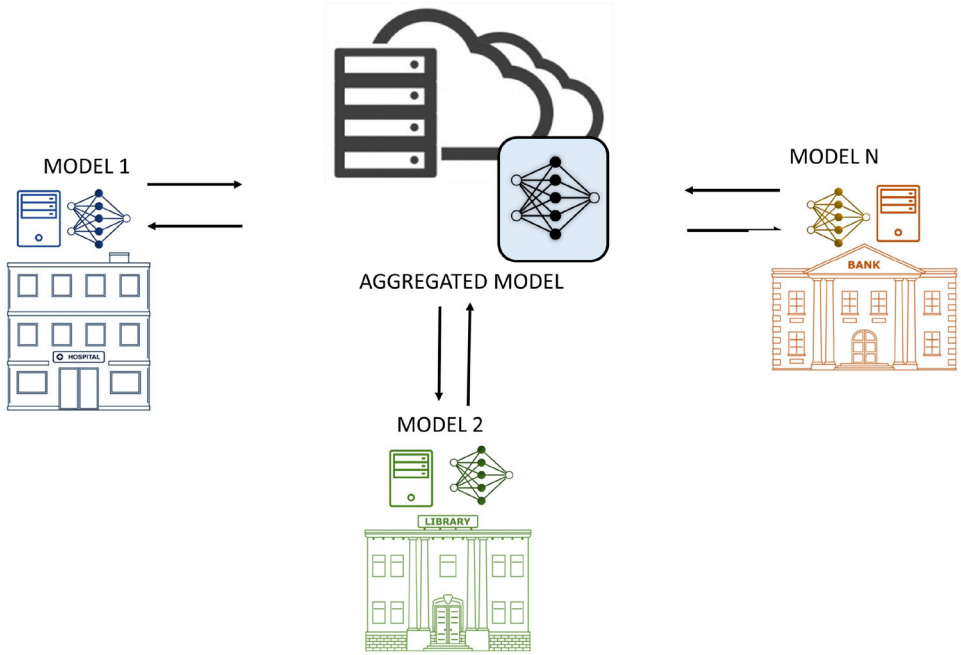

Fig. 2 Cross-silo federated learning

Moreover, the algorithm applies a pruning process to further optimize the generated rule set. In the CBA algorithm, pruning is based on the pessimistic error pruning approach used in the C4.5 algorithm [28]. This method calculates the estimated error rate for each rule, and if the error rate of a rule is higher than that of the same rule with one condition removed, the rule is pruned. In this way, only meaningful rules that contribute to classification performance are retained, helping to prevent overfitting of the model.

CBA algorithm also enhances the reliability of the classifier by selecting the rule with the highest confidence value when multiple rules share the same antecedent. In the literature, additional metrics such as lift or conviction are suggested to evaluate rule quality [29]. However, CBA algorithm does not employ these metrics, as its primary objective is classification rather than association mining.

2.2.1 CBA Algorithm in Human Resources

CBA can be used as a powerful tool in HR analytics. It provides strategic insights to HR departments with rules that relate interactions and characteristics among employees in the analysis of important HR metrics such as employee performance, job satisfaction, and attrition.

- Employee performance: CBA algorithm can define the rules of association between factors that affect employee performance.

- Job satisfaction: CBA algorithm can be used to determine the factors that affect the level of job satisfaction of employees.
- Attrition: CBA offers a powerful analysis method to understand attrition trends.

2.2.2 CBA's Advantages

One of the biggest advantages of CBA algorithm is that the obtained relationships can be easily explained. This explainability visualizes the relationships within the data in decision-making processes and allows the model to understand the rules by which it makes predictions. Especially in a human-focused field such as HR, decision makers can easily see which factors affect employee performance, satisfaction, or attrition by observing the rules produced by CBA. Through explainability, CBA algorithm not only identifies the relationships within the data but also enables decision makers to better understand this information and develop strategies.

As a result, CBA algorithm can be used as a valuable tool in the analysis of important metrics such as performance, job satisfaction, and attrition in the HR field. The explainable structure of CBA facilitates the use of information obtained from data analysis in decision-making processes, making HR strategies more effective.

2.3 Apriori, Eclat, and FP-Growth Algorithms

Apriori, Eclat, and FP-Growth algorithms are important methods used for extracting association rules in data mining [25, 30–32]. These algorithms are used to find and analyze relationships between items in large datasets.

The general comparison of the three association rule algorithms mentioned is given in Table 1 [25, 30–32].

2.3.1 Role of Association Rules in Federated Learning

Association rules enable associations to be made over distributed datasets in FL. In particular, approaches such as duCBA [13] perform rule extraction operations from various datasets using association rules in FL environment. Since FL enables data to be analyzed without being centralized, it can extract rules locally instead of extracting data from different sources.

In this manner, association rules can be used in FL as follows:

- Classification rules can be extracted in distributed data without sharing data.
- FL models can make joint inferences by preserving the confidentiality of the data, and the relevant rules can benefit users without being centralized.
- In areas with sensitive data such as health, finance, human resources, association rules can be used to make effective predictions over data while preserving data confidentiality among participating organizations.

2.3.2 Role of Association Rules in HR Data

Association rule algorithms can be used in the analysis of important issues such as employee satisfaction, turnover prediction, and employee performance in HR analytics.

- Turnover prediction: analysis can be made on the tendency of employees to leave their jobs using association rule algorithms. In this way, it is possible to determine risk factors.
- Employee satisfaction: association rules between factors affecting employee satisfaction can be determined. These factors contribute to HR departments taking strategic steps to increase employee motivation.
- Performance analysis: Apriori, FP-Growth, and Eclat algorithms can be used to determine the factors affecting employee performance. Through these algorithms, performance analysis can be performed and environments can be created that will enable employees to be more successful at work.

As a result, Apriori, Eclat, and FP-Growth algorithms both provide performance in big data analysis and provide insights in areas such as HR analytics. In FL, analysis on distributed data with association rules allows high-performance results to be obtained while preserving data privacy.

2.4 IBM HR Analysis Employee Attrition Dataset and Literature Papers

In 2023, the IBM HR Analysis Employee Attrition dataset [33] was analyzed. This IBM dataset has 1,470 samples and 34 features to analyze employee attrition rates. Various machine learning models such as Logistic Regression, Random Forest, Naive Bayes, Neural Networks, and an ensemble model were tried in the study. The Logistic Regression model showed the best performance with 88% accuracy and 85 AUC-ROC score. Distance between home and work, job satisfaction, and salary stood out among the important factors of employee attrition.

In 2022, the authors emphasized the importance of employee retention, highlighting the cost and time invested by companies in their workforce [3]. To address the issue of high attrition rates, the authors proposed a predictive approach using the IBM HR Analytics dataset. Given the imbalanced nature of the dataset, they employed Adaptive Synthetic Sampling (ADASYN) to balance the classes.

Table 1 Comparison of Apriori, Eclat, and FP-Growth Algorithms

Feature	Apriori algorithm	Eclat algorithm	FP-Growth algorithm
Working principle	Finds frequent itemsets by iteratively generating candidate sets	Finds frequent items quickly with vertical data representation	Searches for frequent elements in the dataset using a frequency pattern tree
Data representation	Uses horizontal data representation	Uses vertical data representation	Data is reconstructed with a frequency pattern tree structure
Performance	May be slow on large datasets, excessive unnecessary processing	Fast on small datasets, memory usage can be problematic on large datasets	Fastest in large datasets
Number of Unnecessary Candidate Clusters	High	Medium	Low
Memory Usage	Low	Medium	High
Application Areas	Suitable for use on small and medium datasets	Fast analysis on small datasets	Offers high performance in large datasets
Installation Complexity	Low	Medium	High
Advantages	Simple and understandable, easy to implement	Offers faster results in some cases due to vertical data structure	Most effective method in terms of performance and speed
Disadvantages	Excessive unnecessary processing, slow on large datasets	Memory usage can be challenging on large datasets	Complex setup, more memory consumption

Subsequently, advanced gradient boosting models, namely XGBoost and CatBoost, were applied to both the original and balanced datasets. In addition, the study introduced a privacy preserving. Additionally, a privacy-preserving solution using federated learning was integrated, employing Logistic Regression and Neural Network models sequentially at the edge nodes. This approach enables different organizations to collaboratively train a shared model without exchanging raw data. For model evaluation, F1-Score and accuracy metrics were used. CatBoost achieved an accuracy of 90% and an F1-Score of 69%, while XGBoost recorded an accuracy of 90% and an F1-Score of 68%. Within the federated learning framework, the Logistic Regression model reached an accuracy of 87%, and the Neural Network model achieved 89% accuracy.

In 2021, data preprocessing and post-processing processes were applied on the IBM HR dataset using a three-stage framework [34]. The study proposed a unique feature selection method called "maxout" to increase the prediction accuracy. Predictions were made using the Logistic Regression model, and validation was done on bootstrapped datasets to increase the stability of the model. The F1-Score was improved with the Maxout feature selection method. The study emphasized factors such as age, job role, and experience in employee attrition.

A study was conducted in 2013 on 309 employee data from a Nigerian educational institution, covering the period between 1978 and 2006 [35]. In the study, Decision Tree models were developed in WEKA and See5 tools to predict future employee attrition, and rule sets were created with these models. Among the important findings, it was determined that factors such as job satisfaction and work–life balance were important attrition indicators. The study did not provide an accuracy metric, and suggested decision rules for human resources applications were emphasized.

In 2022, the SAS library dataset with 35 features and 1,500 records was used [36]. Various methods were applied in the study, such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest, and an ensemble model created using a structuring architecture for optimal model selection. The ensemble model showed improvement in terms of accuracy and F1-Score when tuned with optimal hyperparameters. The study drew attention to important factors such as job satisfaction and work–life balance in employee attrition. Federated learning and Apriori Algorithm were not used.

In 2018, a study employing an XGBoost-based machine learning model predicted employee attrition with high accuracy using basic HR data [5]. The model effectively supported workforce retention strategies by anticipating turnover behavior.

In 2018, a study was conducted by applying various methods such as Logistic Regression, Ridge Classification, Lasso Classification, Linear Discriminant Analysis (LDA), Decision Trees, Random Forest, and Naive Bayes to the IBM HR dataset [37]. The study revealed that LDA provided the highest accuracy, Logistic Regression the highest precision, and Ridge the highest recall rate. Among the important factors in employee attrition, elements such as job role, job level, and overtime stood out.

In 2018, the growing interest in machine learning among business leaders highlighted the need for its application in predicting employee attrition [38]. Utilizing a synthetic IBM dataset, three experiments were carried out: first, training imbalanced data using SVM, Random Forest, and KNN models; second, applying the ADASYN technique to address class imbalance, followed by retraining; and third, employing manual undersampling to balance the classes. The KNN model ($K = 3$) trained on the ADASYN-balanced dataset achieved the highest F1-Score of 93%. Furthermore, feature selection reduced the feature set to 12, with the Random Forest model attaining an F1-Score of 90%.

In 2019, a study using the Weka tool on IBM employee data, factors influencing attrition were analyzed through classification and clustering algorithms [4]. K-means clustering was applied, and the algorithm's performance was compared. The findings supported data-driven decision-making in human resource management.

In 2021, the IBM HR dataset was used for machine learning applications and analysis [39]. Both balanced and unbalanced versions of the dataset were examined. In the study, data preprocessing steps, data balancing using ADASYN, and feature selection were added to the deep neural network (DNN) method. 91.16% accuracy was achieved on the unbalanced dataset, and 94.16% accuracy was achieved on the balanced dataset. The study revealed that factors such as overtime, job level, and monthly income were important predictors. Federated learning and Apriori Algorithm were not used.

Employee turnover is a serious problem for organizations and affects the productivity of the company [40]. This research aims to develop a model that can predict whether employees will leave or not. In 2020, machine learning-based classifiers such as support vector machines, decision trees, and random forest algorithms were evaluated on departments with more than 1000 employees. Confusion matrix and classification reports showed that these models were better at detecting the majority class (non-leaving employees) and less sensitive to the minority class (leaving employees). However, the decision tree classifier outperformed others with 99% accuracy. The proposed study can help companies develop strategies to retain their employees.

In 2023, using the IBM HR dataset, nested ensemble learning method was applied, which included models such as Naive Bayes, Support Vector Machine, Random Forest and Logistic Regression, and combined stacking and voting ensemble techniques [41]. The nested ensemble model performed better than individual models, achieving 94.5% accuracy and 98.5 AUC; these results are statistically significant when compared to the base model. Federated learning and Apriori Algorithm were not used.

Yand and Islam determined the important factors affecting employee turnover using Random Forest and K-means Clustering. According to Random Forest, salary, age and number of companies worked are effective factors in turnover decisions [42]. According to K-means Clustering results, older, higher job level, satisfied, and more company experience employees are less likely to leave. However, more in-depth research should be conducted since each individual has different motivations. In the analysis conducted with logistic regression, women's turnover rate was found to be %34.1 lower than men, and married and divorced people's turnover rates were lower compared to singles. In addition, employees who travel frequently tend to leave 2.4 times more than those who do not travel. The turnover rate of Human Resources employees is also high. Among other findings, it was observed that those with 2–4 companies' experience had a lower turnover rate, and people with a doctorate had the lowest turnover rate. When evaluating the model performance, it was determined that Logistic Regression gave better results with an accuracy rate of 88.43%. As a result, it is recommended that companies pay more attention to employee satisfaction and produce special solutions for their Human Resources employees.

A 2019 study analyzed email communication data from a business school [43]. The study used sentiment analysis, word count analysis, and correlation analysis as email features. The study found that increased external communication, decreased internal communication, and lower levels of positive emotion were linked to higher employee attrition risk. The study aimed to help business schools retain faculty.

Arqavi et al. proposed a model with deep learning in 2022 using IBM HR Analytics dataset [44]. The selected dataset in the study was used to compare a six-layer deep learning model, Random Forest, and other machine learning models. The deep learning model achieved 94.52% accuracy, outperforming Random Forest (92.55%). The study identified Stock Option Level, Monthly Income, Job Satisfaction, Job Participation, and Total Years of Work as the most important factors.

In 2020, four advanced machine learning techniques, namely extra tree classifier, support vector machine, logistic regression, and decision tree, were comparatively applied for employee turnover prediction [45]. The applied machine learning techniques achieved 87% accuracy with support vector machine technique, 72% accuracy with logistic regression technique, and 83% accuracy with decision tree technique. Data resampling method was used to balance the dataset. The methods were validated against k-fold validation and previous advanced studies. When 10-fold validation was used, SVM achieved 88% accuracy, LR achieved 4% accuracy, DTC achieved 84% accuracy, and the proposed method achieved 93% accuracy. EEDA application revealed that the main factors causing employee turnover were salary, hourly wage, job level, and age.

In 2020, researchers used machine learning techniques to predict the probability of an employee leaving the company [46]. The data were divided into training and testing phases and evaluated with classification algorithms. The Gaussian Naïve Bayes classifier gave the best results, achieving the highest recall rate (0.54) and a false negative rate of 4.5%. The analysis showed that the factors affecting the departure were salary, age, overtime, and distance from work. These results provide a basis for developing more efficient classifiers that predict employee departures (Table 2).

In the existing literature, various algorithms have been applied to the IBM dataset. However, there is no study that utilizes association rules within a federated learning approach. This study fills an important gap in the literature.

3 Methodology

In this section, the dataset used in the study is explained in detail, followed by the data preprocessing steps performed. In addition, the basic concepts in the study are introduced.

3.1 Dataset

IBM HR Analytics Employee Attrition & Performance is an open-access dataset developed by IBM and synthetically produced. This dataset includes employee information for attrition and performance analysis and is specifically designed to help companies' human resources departments understand employee loyalty and other concerns.

The dataset contains 1470 records and 35 features. Feature names and other information are provided in Table 3.

Additionally, sample data from the dataset are shown in Table 4.

Various analyses can be performed on the dataset, including:

- Turnover analysis: examining factors that influence employees' decisions to leave their jobs.
- Performance and satisfaction analysis: analyzing the relationship between employees' performance and their satisfaction with the workplace.
- Predictive modeling: predicting employee turnover based on satisfaction and other factors using classification algorithms.
- Cluster analysis: grouping employee profiles into specific categories.
- Annual changes and promotion: examining employees' annual changes and promotion statuses within the company.

The IBM HR dataset used in this study includes various quantitative and categorical HR attributes related to employees, such as age, income, job role, and satisfaction levels. However, it does not contain qualitative variables reflecting psychological, cultural, or organizational aspects, such as motivation, leadership style, or company culture. Consequently, the scope of this study is limited to measurable HR data, and the analysis does not incorporate qualitative dimensions of human behavior that might also influence attrition.

3.2 Data Preprocessing

Data preprocessing steps were performed to improve the dataset used in the study. In this section, the procedures performed to deal with various problems such as duplicate, missing or imbalanced dataset that may affect the model performance in the dataset are mentioned. In the dataset, classification was made according to the "Attrition" feature. This attribute is a binary categorical variable and has "No" and "Yes" values. "No" refers to the personnel who are still working in the company, and "Yes" refers to the personnel who left the company. Table 5 and Figure 3 show the class label distribution according to Attrition feature.

Out of the total 1,233 employees in the dataset, 83.89% remain employed, while the remaining 16.11% have left the company. Table 5 illustrates the imbalance within the dataset, with the minority class of employees who have departed accounting for only 16.11% of the total observations.

In this study, to implement the federated learning architecture, the dataset is first divided into training and test datasets. Then, for each client, the dataset is organized to contain an equal amount of data according to the number of clients. This was done to avoid the problem of nonindependent and identically distributed (Non-IID) [47] data. However, the problem of label imbalance in the dataset remains.

Label imbalance refers to situations where the majority class is dominant and the minority class is underrepresented. This can cause the model to focus on the majority class and not learn enough about the minority class. Particularly in distributed learning environments, such as federated learning, the effect of unbalanced datasets can be more pronounced because each client's data may have a different distribution. This can reduce the generalizability of the model, lead to misclassification of minority class instances, and negatively affect the accuracy of the model [48].

To overcome this imbalance, the Random Oversampling method [49] was applied. This method removes the labeling imbalance in the dataset by replicating the instances of the minority class and helps the model to learn both classes efficiently. While synthetic data generation techniques (e.g., SMOTE) are often used for numerical data, they operate by interpolating between samples, which can lead to invalid feature combinations in categorical datasets. In the context of Associative Classification, preserving the authenticity of frequent itemsets is critical; synthetic instances could distort

Table 2 Overview of the related work

Article	Year	Dataset	Used algorithms	Did federated learning used?	Did Apriori used?	Accuracy (or other) results
[3]	2022	IBM HR	Catboost XGboost	No	No	90%
[3]	2022	IBM HR	Logistic regression neural network FedAVG	Yes	No	87–89%
[4]	2019	IBM HR	Decision tree Naïve Bayes K_means Expectation Maximization	No	No	Correct/incorrect classification
[5]	2018	IBM HR	XGBoost	No	No	90%
[33]	2023	IBM HR	Logistic regression, Random forest, ensemble	No	No	88%
[34]	2021	IBM HR	Logistic regression with "max-out" feature selection	No	No	Improvement in F1-score
[35]	2013	Nigerian educational institution data	Decision trees in WEKA and See5	No	No	Unknown
[36]	2022	SAS library dataset	Artificial neural networks, support vector machines, random forest, ensemble	No	No	Unknown
[37]	2018	IBM HR	Logistic regression, linear discriminant, ridge, lasso, decision trees, random forest	No	No	86%

Table 2 continued

Article	Year	Dataset	Used algorithms	Did federated learning used?	Did Apriori used?	Accuracy (or other) results
[38]	2018	IBM HR	SVM random forest KNN	No	No	F1-score: 90%
[39]	2021	IBM HR	Deep neural network with ADASYN balancing	No	No	94% (balanced dataset)
[40]	2020	IBM HR	Support vector machine, decision tree, random forest	No	No	99%
[41]	2023	IBM HR	Nested ensemble (stacking & voting)	No	No	94.5%
[42]	2020	IBM HR	Random forest, logistic regression, K-means	No	No	88.43%
[43]	2019	Business school email data	Sentiment analysis, correlation analysis	No	No	Unknown
[44]	2022	IBM HR	Deep learning (6-layer), random forest	No	No	94.52%
[45]	2022	IBM HR	Extra tree classifier, support vector machine, logistic regression, decision tree	No	No	93%
[46]	2020	IBM HR	Gaussian and Bernoulli Naive Bayes decision tree random forest logistic regression KNN SVM	No	No	Recall: 54%
Our work	2025	IBM HR	CBA (Apriori, Eclat, and FP-Growth)	No	Yes	94%
Our work	2025	IBM HR	CBA (Apriori, Eclat, and FP-Growth) FedCBA	Yes	Yes	87%

Table 3 Features

Nos	Attribute	Data	Type	No	Attribute	Data	Type
1	Age	Numeric	Ratio	19	MonthlyIncome	Numeric	Ratio
2	Attrition	Textual	Nominal	20	MonthlyRate	Numeric	Ratio
3	BusinessTravel	Textual	Nominal	21	NumCompaniesWorked	Numeric	Ratio
4	DailyRate	Numeric	Ratio	22	Over18	Textual	Nominal
5	Department	Textual	Nominal	23	OverTime	Textual	Nominal
6	DistanceFromHome	Numeric	Ratio	24	PercentSalaryHike	Numeric	Ratio
7	Education	Numeric	Ordinal	25	PerformanceRating	Numeric	Ordinal
8	EducationField	Textual	Nominal	26	RelationshipSatisfaction	Numeric	Ordinal
9	EmployeeCount	Numeric	Ratio	27	StandardHours	Numeric	Ratio
10	EmployeeNumber	Numeric	Nominal	28	StockOptionLevel	Numeric	Ordinal
11	EnvironmentSatisfaction	Numeric	Ordinal	29	TotalWorkingYears	Numeric	Ratio
12	Gender	Textual	Nominal	30	TrainingTimesLastYear	Numeric	Ratio
13	HourlyRate	Numeric	Ratio	31	WorkLifeBalance	Numeric	Ordinal
14	JobInvolvement	Numeric	Ordinal	32	YearsAtCompany	Numeric	Ratio
15	JobLevel	Numeric	Ordinal	33	YearsInCurrentRole	Numeric	Ratio
16	JobRole	Textual	Nominal	34	YearsSinceLastPromotion	Numeric	Ratio
17	JobSatisfaction	Numeric	Ordinal	35	YearsWithCurrManager	Numeric	Ratio
18	MaritalStatus	Textual	Nominal				

Table 4 First 3 records of the dataset

Dataset
41, Yes, Travel_Rarely, 1102, Sales, 1, 2, Life Sciences, 1, 1, 2, Female, 94, 3, 2, Sales Executive, 4, Single, 5993, 19,479, 8, Y, Yes, 11, 3, 1, 80, 0, 8, 0, 1, 6, 4, 0, 5
37, Yes, Travel_Rarely, 1373, Research & Development, 2, 2, Other, 1, 4, 4, Male, 92, 2, 1, Laboratory Technician, 3, Single, 2090, 2396, 6, Y, Yes, 15, 3, 2, 80, 0, 7, 3, 3, 0, 0, 0, 0
49, No, Travel_Frequently, 279, Research & Development, 8, 1, Life Sciences, 1, 2, 3, Male, 61, 2, 2, Research Scientist, 2, Married, 5130, 24,907, 1, Y, No, 23, 4, 4, 80, 1, 10, 3, 3, 10, 7, 1, 7

Table 5 Distribution of attrition dataset

Class label	Number	Volume (%)
No	1233	83.89
Yes	237	16.11
Total	**1470**	**100**

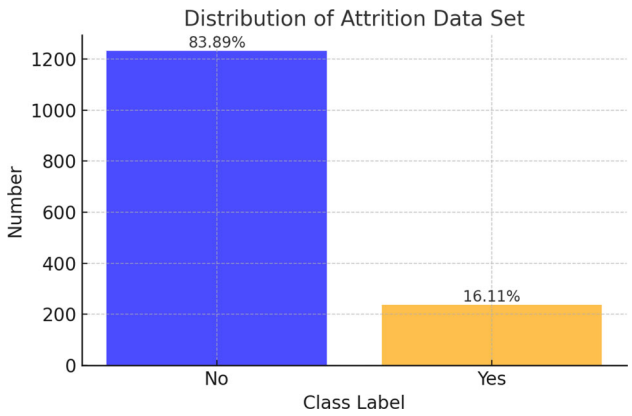

Fig. 3 Distribution of attrition dataset

support values and lead to the extraction of noisy or artificial rules. Therefore, Random Oversampling was chosen to ensure that the mined rules remain interpretable and are based solely on real-world observations. This method is widely preferred in similar studies and was adopted in this study as it is the most suitable approach for the categorical structure of the dataset. After applying RandomOverSampling, the number of samples belonging to the "No" and "Yes" classes was balanced and an equal number of samples were obtained in total. The new number of samples is 2466. The number of features did not change and remained as 35. After sampling, the distribution of class labels according to the Attrition feature in the dataset is shown in Table 6

Following the random oversampling method, the Chi-square test [50] was applied to determine the significant relationships between categorical variables. Chi-square test

Table 6 Distribution of attrition class labels in sampled dataset

Class label	Number	Volume (%)
No	1233	50.00
Yes	1233	50.00
Total	**2466**	**100**

Imbalance ratio: 1.0

was preferred because of its power to test the independence between categorical data in the dataset. This test is especially ideal for assessing whether there is a statistically significant relationship between two categorical variables. The result of the Chi-squared test is given in Fig. 4.

In Fig. 4, the x-axis represents the p-values, and the y-axis the names of the features analyzed. The p-value significance threshold of 0.05 is highlighted using a red line in the graph. According to the results of the Chi-square test, the columns with no significant relationship were identified as "EmployeeCount," "Over18," "PerformanceRating," and "StandardHours," and these columns were removed from the dataset.

In this study, since the CBA algorithm operates on categorical data, we initially attempted to transform continuous numerical variables into categorical intervals through discretization. However, it was observed that this transformation resulted in significant information loss and reduced model interpretability. Therefore, instead of applying a global discretization across the entire dataset, we opted to leverage the internal mechanisms of the pyArc library, which can dynamically generate interval bins for continuous variables during rule mining. This approach allowed us to preserve the detailed information in the dataset while enabling the extraction of meaningful association rules. Additionally, functions provided by the Python pandas library were used to check for missing and duplicate values in the dataset, and it was determined that there were no missing or duplicate records.

In addition, IBM HR Analytics dataset used in this study is a synthetically generated dataset. Compared to real-world HR systems, it should be noted that there may be deviations in the distribution of certain variables and that relationships between variables might be modeled in a more pronounced manner. This may limit the generalizability of the model to real-world scenarios. Therefore, it is recommended that future studies validate the findings using real organizational data.

3.3 Federated Learning

There has been a growing interest in utilizing big data for artificial intelligence models that yield accurate outcomes. This increasing demand and necessity for data have underscored the importance of data privacy and security like never before. One prevailing approach that addresses this concern is known as federated learning [18, 51]. Federated learning, implemented within a client–server architecture, involves training the model using local data on individual clients and transmitting the model to the server instead of the data itself. These models received at the server are then merged to obtain the final model. In other words, the model is conveyed from the client to the server, while the data remain on the client side, ensuring data privacy. Furthermore, this approach reduces communication costs and optimizes power utilization. By eliminating the need to establish a connection and transfer data between the client and server, communication overhead is minimized, resulting in communication savings. Figures 1 and 2 represent the federated learning architecture [22].

In federated learning architecture, model training is conducted on clients, and these local models are trained using various machine learning and deep learning algorithms. The trained models are then aggregated on a central server to create a global model. Federated learning aggregation algorithms have been developed to combine the models trained

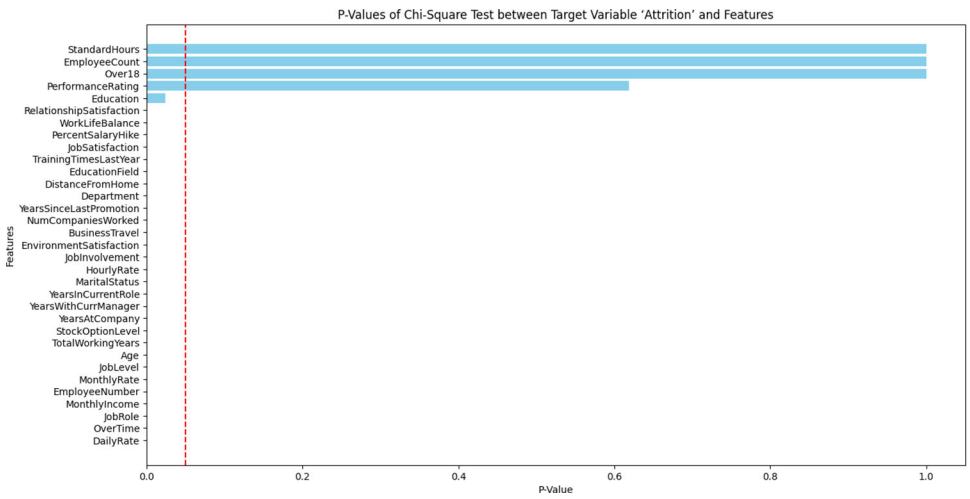

Fig. 4 Chi-square test

on clients at the server [52]. These algorithms are techniques used for merging or updating local models. Among the most commonly used federated learning aggregation algorithms are Federated Averaging (FedAvg) [53], Federated Matched Averaging (FedMA) [54], Federated Stochastic Gradient Descent (FedSGD) [55], Federated Proximal (FedProx) [56], Federated Gradient Aggregation (FedGATE) [57], and Federated Kernel Support Vector Machine (FedKSVM) [58]. In this study, the duCBA [13] algorithm has been chosen as the model aggregation method in the federated learning environment [59]. duCBA is an innovative approach that integrates rule-based models trained with CBA algorithms on local devices by updating the support and confidence values of the rules. Throughout this study, several improvements have been made to the duCBA algorithm, enhancing its performance. This enhanced and optimized version is referred to as FedCBA and is expected to make a significant contribution to the field of federated learning.

FL is a learning paradigm based on processing data locally on client devices without centralizing it, while transmitting only model updates to a central server. However, testing the FL architecture on real devices is not always feasible or practical due to hardware constraints and privacy concerns. Therefore, the development and evaluation of federated learning algorithms often rely on federated learning simulations in the literature.

In simulation-based approaches, a single centralized dataset is artificially partitioned to mimic the federated environment. Each partition is treated as an independent client and is considered as if it originates from a separate data source. In this way, the federated learning architecture can be modeled in a controlled, laboratory setting. This simulation process generally consists of the following stages:

- Data partitioning: IID (Independent and Identically Distributed) scenario: the dataset is randomly and equally divided into partitions, ensuring that the data distribution across clients remains similar. Non-IID Scenario: The data are split heterogeneously among clients; certain clients may predominantly contain specific classes or data characteristics. This setting mimics the real-world heterogeneity typically observed in federated learning.
- Local training: each client trains its local model using only its own data. Upon completion of training, the client sends its model parameters (or gradients) to the central server.
- Model aggregation: the central server integrates updates received from clients through a federated learning aggregation algorithm to construct a global model. One of the most commonly used methods is the FedAvg algorithm; however, in this study, we employ the FedCBA algorithm, which has been developed as an enhancement over the duCBA algorithm.
- Performance evaluation: the performance of the global model is assessed using metrics such as accuracy, loss, and F1-Score. In addition, critical performance indicators for federated learning are monitored, including convergence speed, communication cost, computational time, and memory usage.

The simulation environment offers significant advantages for testing federated learning algorithms under different data distribution scenarios, evaluating their robustness and scalability. It also provides experimental flexibility independent of real devices and enables rapid experimentation with different parameter configurations. In this study, the performance of the proposed FedCBA algorithm was similarly evaluated in a simulation environment, systematically demonstrating its advantages over conventional methods.

Based on the IBM dataset employed in this study, a flowchart has been developed to represent the federated learning processes. In Fig. 5, the process begins with data loading, followed by partitioning the dataset according to the employees' departments. This partitioning results in the creation of three distinct clients: Sales, Research & Development, and Human Resources. This specific partitioning strategy was deliberately chosen to simulate a realistic, Non-IID FL environment. By segregating data based on functional units, the study mimics the heterogeneity found in real-world cross-silo scenarios, where each client exhibits distinct feature distributions and class imbalances. Furthermore, this diversity provides a critical testing ground for the primary motivation of this work: evaluating the proposed framework's capacity to resolve conflicts and effectively aggregate heterogeneous association rules derived from diverse sources. Each client performs local model training using only its respective data. Subsequently, the parameters of the trained local models are transmitted to the central server, where the aggregation is conducted using the enhanced FedCBA algorithm. In the final stage, the performance of the resulting global model is evaluated, thus completing the overall process.

3.4 Data Unaware Classification Based on Associations: duCBA

In this study, the duCBA algorithm, which was previously developed by us, is used. duCBA is a relational classification algorithm based on CBA [27, 60] and is designed as a federated aggregation algorithm specialized for federated learning architecture. In Figure 6, the working architecture of the duCBA algorithm is presented in detail.

According to the figure, the duCBA algorithm works in two stages. In the first stage, model training with CBA is performed on each client (Client 1, Client 2, Client 3,..., Client n). The second stage is to aggregate the models (Model 1,

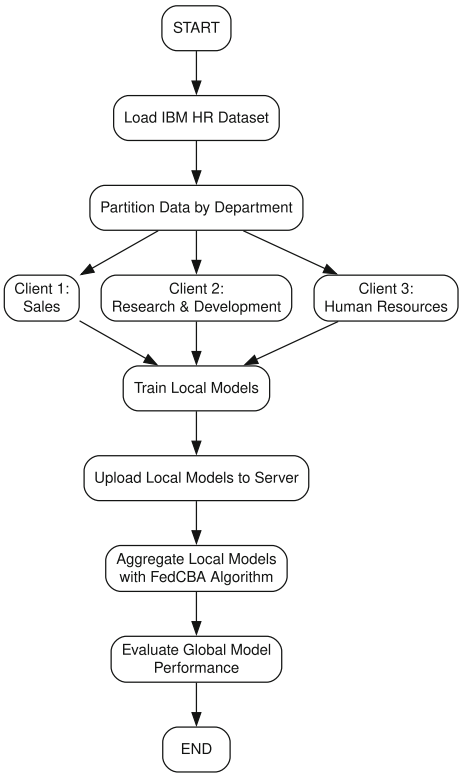

Fig. 5 Flowchart illustrating the federated learning simulation process using the IBM HR dataset, where each department is treated as a separate client and aggregated using the FedCBA algorithm

Model 2, Model 3,..., Model n) sent from the clients to the server and obtain the final/global model.

According to the figure, clients can be modeled as mobile devices, computers, IoT devices, or physical or virtual units representing different domains such as hospitals and banks. These various client types can be identical or different from each other. They can be located in the same or different locations. However, the same application is run on the devices and the trained models are with the same parameters and variables for each device. And each client represents different data sources within the scope of federated learning architecture. The model is trained using the CBA algorithm with local data generated on the client. CBA is a relational classification algorithm. At the end of the model training with CBA, labeled association rules, one of the supervised data mining methods, are created. Support and confidence [61, 62] parameters are used while creating the rules. The models trained with local data on the clients are saved and then sent to a common server accessible by the clients. In the second phase, the aggregation of the models arriving simultaneously from each client to the server is performed. In fact, aggregating the models on the server means aggregating the rules that come with the models. When aggregating the models, all incoming rules are checked and then aggregated. When aggregating the rules, the support and confidence values of the rules are updated and reordered. For the same rules with the same labels from different models, the support and confidence values are updated since the frequency of occurrence of the rule on the whole data will change. For the same rules with different labels, the frequency of occurrence is checked first, and then, the rule with the higher confidence value is retained. After the update process, each rule is ranked according to the new confidence and support values. If the confidence value is the same, a second ranking is done according to the support value. If the support values are also the same, the first

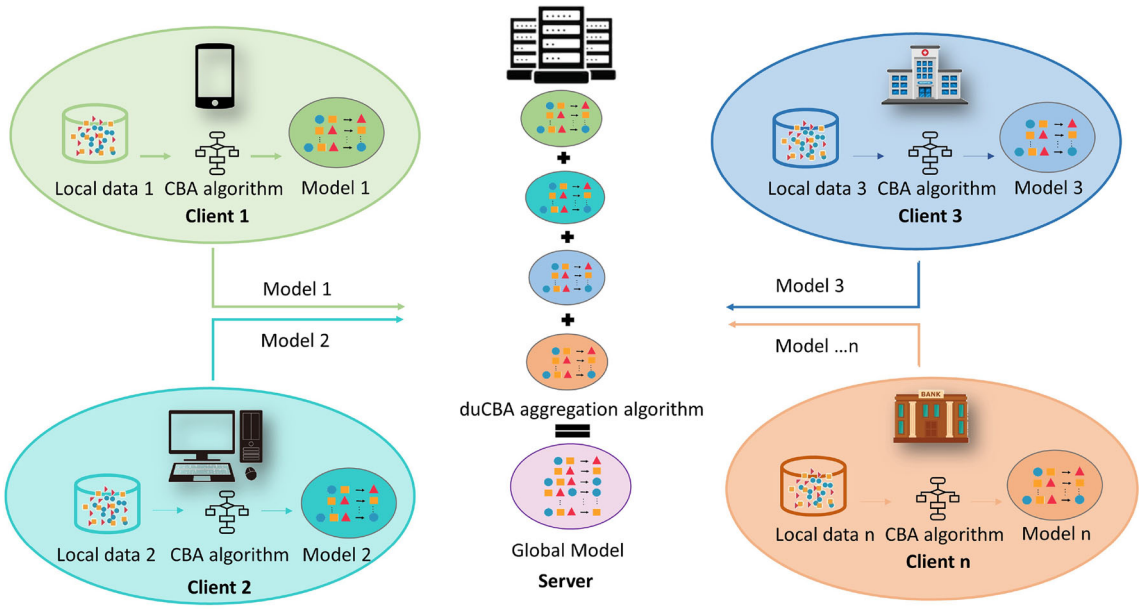

Fig. 6 duCBA study architecture

rule is placed first. The new rule list obtained constitutes the final/global model.

The pseudocode of the duCBA model is provided in Algorithm 1. This code executes the duCBA algorithm adapted for an FL scenario.

Algorithm 1 Federated Aggregation Algorithm: duCBA

Input: Training data D, test data D_{test}, support threshold s, confidence threshold c, number of buckets n_b, number of test runs T

Output: Average accuracy and training time
Load CSV data D
Define target variable for classification
Split D into training set D_{train} and test set D_{test}
Divide D_{train} into n_b partitions $\{D_{train}^{(i)}\}$
for $t = 1$ to T **do**
  Initialize empty duCBA model M
  Initialize $length_of_data_train \leftarrow 0$
  for $i = 1$ to n_b **do**
    Start timer
    Convert partition $D_{train}^{(i)}$ to transaction format $T_{train}^{(i)}$
    if $i == 1$ **then**
      Train M on $T_{train}^{(i)}$ using duCBA
    else
      Train a temporary model M' on $T_{train}^{(i)}$
      Update M by merging M' into M using `update_cba_model()`
    end if
    Evaluate accuracy of M on D_{test}
    Log confusion matrix and classification report
    Log training time
    Increment $length_of_data_train$ by $|T_{train}^{(i)}|$
  end for
end for
Compute and report average accuracy and training time

The objective is to extract duCBA rules from distributed client data in an FL environment, build a unified model, and evaluate the performance of the resulting model on test data.

The workflow begins by loading the data (for example, the Sales_train.txt file). The target variable (Attrition) is defined. The data are then split into training and test sets. The training data are divided into a number of partitions equal to the value of the variable number_of_bucket, which in a federated learning context corresponds to the number of clients. Reflecting the distributed nature of data in real corporate environments, each department (Sales, Research & Development, and Human Resources) was treated as a separate client. Consequently, the dataset was divided into three partitions to simulate this decentralized structure.

From each partition, a TransactionDB object is created. Model training begins with the first partition. For each subsequent partition, a temporary duCBA model is trained. This temporary model is then merged into the main model using the update_cba_model function, performing the aggregation process.

Once all partitions have been processed, the unified model is evaluated on the test dataset, and the accuracy is calculated. Finally, the average accuracy and training times are reported.

The update_cba_model function in the duCBA class of the pyarc library is a critical component for federated learning. This function performs the model aggregation process.

The update_cba_model pseudocode, written to perform the aggregation process, is provided in Algorithm 2.

Algorithm 2 Pseudocode of Function update_cba_model(new_model)

For each rule r' in new_model:
  $matched \leftarrow false$
for each rule r in current model **do**
  if r and r' have same antecedent and consequent **then**
    Update support and confidence by weighted average
    $matched \leftarrow true$
  else if only antecedent matches but consequent differs **then**
    Compare rule frequencies
    Keep rule with higher frequency
    Update support and confidence accordingly
    $matched \leftarrow true$
  end if
end for
if $matched == false$ **then**
  Add r' as a new rule to current model
end if
Re-sort all rules by priority
Update sample size N of the model

Model aggregating with duCBA means aggregating the models trained with CBA on the clients. This is done by aggregating the rules generated in each model. The CBA algorithm works by creating rules on the data and two basic values are calculated to measure the validity of these rules. These are support and confidence. Support shows how frequently a rule is found. Confidence refers to the accuracy rate of a rule [61].

$$\text{Supp}(X \Rightarrow Y) = \frac{\text{Freq}(X, Y)}{N} \tag{1}$$

$$\text{Confidence}(X \Rightarrow Y) = \frac{\text{Freq}(X, Y)}{\text{Freq}(X)} \tag{2}$$

Equations (1) and (2) denote the respective measures of support and confidence. X is the left-hand side of the rule (lhs) and Y is the right-hand side of the rule (rhs), i.e., the label of the rule. N is the total number of samples in the dataset used in model training. Frequency (Freq) indicates the frequency of occurrence of X and Y. In the equation, Support Supp is abbreviated as Confidence Conf.

The support values of the same rules with the same labels ($X \Rightarrow Y$) on three different clients are given in Eq. (3) and

confidence values in Eq. (4), respectively.

$$\text{Supp}_i = \frac{\text{Freq}(X_i, Y_i)}{N_i}, \quad i = 1, 2, 3 \tag{3}$$

$$\text{Conf}_i = \frac{\text{Freq}(X_i, Y_i)}{\text{Freq}(X_i)}, \quad i = 1, 2, 3 \tag{4}$$

The new support and confidence values obtained by aggregating $X \Rightarrow Y$ rules from different clients are calculated as in Eqs. (5) and (6), respectively. This aggregation process is repeated for the same rules with the same labels from different clients.

$$\text{Supp}_{\text{agg}} = \frac{\sum_{i=1}^{n} \text{Supp}_i \cdot N_i}{\sum_{i=1}^{n} N_i} \tag{5}$$

$$\text{Conf}_{\text{agg}} = \frac{\sum_{i=1}^{n} \text{Supp}_i \cdot N_i}{\sum_{i=1}^{n} \frac{\text{Supp}_i \cdot N_i}{\text{Conf}_i}} \tag{6}$$

According to Algorithm 2, rules are processed by comparison. If the same lhs $\rightarrow$ rhs rule exists in both models, the support and confidence values of these rules are updated according to Eqs. (5) and (6). If the lhs is the same but the rhs differs, the rule with the higher frequency is preferred. If there is no match, the new rule is added to the model.

The conflict resolution mechanism in the FedCBA algorithm extends beyond merely selecting the consequent with the highest frequency. It incorporates a confidence recalibration process that penalizes rules with high inter-client disagreement. As defined in Eq. (7), when the server encounters matching antecedents with conflicting consequents (e.g., $X \Rightarrow Y_{winner}$ vs. $X \Rightarrow Y_{loser}$), it selects the consequent with the highest global frequency. However, the new confidence score ($Conf_{new}$) is calculated by dividing this frequency by the total global frequency of the antecedent, which includes the counts of the conflicting rules:

$$\text{Confnew} = \frac{\text{Freq}(X, Y\text{winner})}{\text{Freq}(X, Y_{\text{winner}}) + \text{Freq}(X, Y_{\text{loser}})} \tag{7}$$

Equation (7) ensures that the final confidence metric reflects the global consensus. Even if a rule is selected as the winner, its confidence score is lowered in proportion to the severity of the conflict observed across distributed clients. This serves as an implicit filtering mechanism, ensuring that only rules with high global agreement are prioritized in the final classification model.

3.5 Apriori, Eclat, and FP-Growth Algorithms

CBA algorithm is one of the relational classification methods. This algorithm first extracts association rules and then performs the classification process. Its main purpose is to discover labeled association rules and use these rules in the classification process. The CBA algorithm uses the Apriori [63] algorithm by default to extract association rules. In this study, in addition to the default Apriori algorithm, the FP-Growth [63] and Eclat [63] algorithms were also integrated into the CBA algorithm, and the performances of these different association rule mining methods were analyzed and compared.

The Apriori algorithm is one of the most basic algorithms for association rule inference [64]. This algorithm uses downward closure to identify frequent itemsets. That is, for an itemset to be frequent, all its subsets must also be frequent. Apriori iteratively generates candidate itemsets, performs support calculation on these clusters and selects the clusters that meet the minimum support value. Its advantage is that; it is understandable and applicable. However, it can create many unnecessary candidate items in large datasets, which reduces the performance of the algorithm.

Eclat algorithm is another algorithm used to extract association rules [65]. This algorithm stores items in vertical data format and can detect frequent item sets faster. Through vertical data representation, the process of extracting rules among data is accelerated. This algorithm performs less unnecessary operations than Apriori and is especially effective in smaller datasets. However, Eclat algorithm can be intensive in memory usage, which can lead to limited performance in large datasets.

FP-Growth algorithm was developed to overcome the performance problems of the Apriori algorithm. This algorithm stores data in a Frequent Pattern Tree data structure to identify frequent item sets. FP-Growth operates by splitting the dataset into chunks and extracting frequent patterns on these chunks. Unlike Apriori, instead of generating all candidate clusters, it provides a significant improvement in memory usage and processing time. Despite having high performance on large datasets, FP-Growth algorithm's setup process is complex and requires more memory usage on certain datasets.

The CBA algorithm uses the Apriori algorithm by default to extract association rules. In this study, in order to improve the performance of the CBA algorithm and improve the duCBA algorithm, three different association rule algorithms (Apriori, FP-Growth and Eclat) are applied to the integration with the CBA algorithm, respectively. By integrating each association rule algorithm with the CBA algorithm, respectively, the impact of the integration on duCBA is analyzed in detail. In this integration process, the contributions of each algorithm to CBA and their effects on the classification performance of duCBA were analyzed in detail. In addition, the potential of each algorithm to improve the classification performance was compared, and the superior performance of each algorithm was determined.

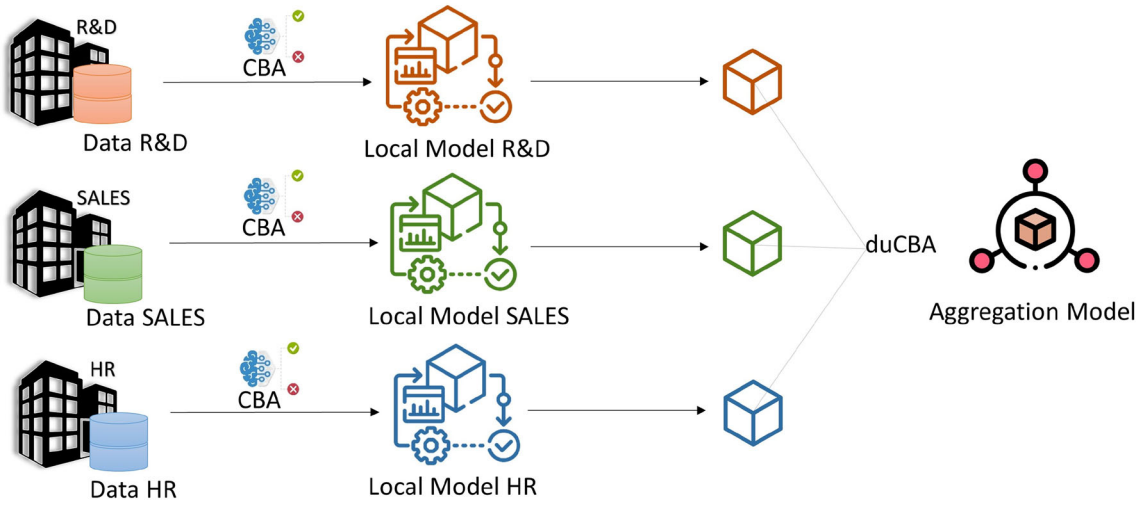

Fig. 7 Three client federated learning architecture

4 Experimental Results

In this study, the reasons for employee attrition are analyzed. Within the scope of the dataset, the variables affecting attrition were evaluated in an interpretable manner using a relational classification method. For this purpose, the CBA algorithm, which generates classification-based association rules, was employed. The default method used by the CBA algorithm for generating association rules is Apriori. However, in this study, other association rule mining algorithms, namely Eclat and FP-Growth, were also integrated into the CBA algorithm, and their performances were compared accordingly. The study further evaluated and compared model performances on both balanced and imbalanced datasets.

Additionally, to ensure the confidentiality of employee data, an artificial intelligence-based application was developed using a federated learning architecture. Federated learning architecture operates on the principle that model training processes performed locally on clients are transferred to a central server, where these models are aggregated to create a final, global model. In this study, the federated learning architecture was simulated on a single computer by creating a local development environment. In this environment, the dataset was partitioned into 80% training and 20% testing sets. To implement a federated learning scenario aligned with real-world conditions, the training data were segregated based on department labels (Sales, Research & Development, and Human Resources), where each department was treated as if it were a distinct client. The test set was constructed by drawing an equal amount of data from each department to ensure a balanced evaluation.

The experiments were conducted on a computer equipped with an 11th Generation Intel i5-1135G7 processor and 16 GB DDR3 memory. Python was chosen as the programming language. The duCBA algorithm was utilized as the federated aggregation algorithm. In the implementation of this algorithm, the pyArc module was used to extract association rules. As the CBA algorithm is designed to use association rules for classification and the main priority in this study was accurate classification performance, only the support and confidence measures were considered, while other metrics such as lift and conviction were not employed. Accordingly, the thresholds for support and confidence in the pyArc module were set to 0.01 and 0.2, respectively.

Figure 7 shows the general flow of the application process developed within the scope of the study. According to Fig. 7, the number of clients is assumed to be 3, and the training set used for the study is randomly divided into 3 equal parts. Using each of these parts, three models were trained separately on the client side. The trained models consist of labeled rules. The models were transferred from each client to the server, and these models were aggregated to obtain a global model. Aggregating the models means merging the rules coming from the clients. This aggregation process on the server was carried out using the formulas developed and presented in the methodology section.

As shown in Fig. 7, the CBA method was used for model training on clients. In the first stage, to examine the performance differences of class labels on unbalanced (Table 5) and balanced (Table 6) datasets, model training was performed on datasets without and with RandomOversampling. In the model training process, Apriori, the default algorithm of the CBA method, was used. Then, the results of the two datasets are compared and evaluated.

Both datasets (balanced/unbalanced) were first split into 80% training and 20% testing. The models were then trained on the training dataset. The performance of the models was evaluated using the test dataset and the performance metrics obtained are presented in Table 7, the confusion matrix is

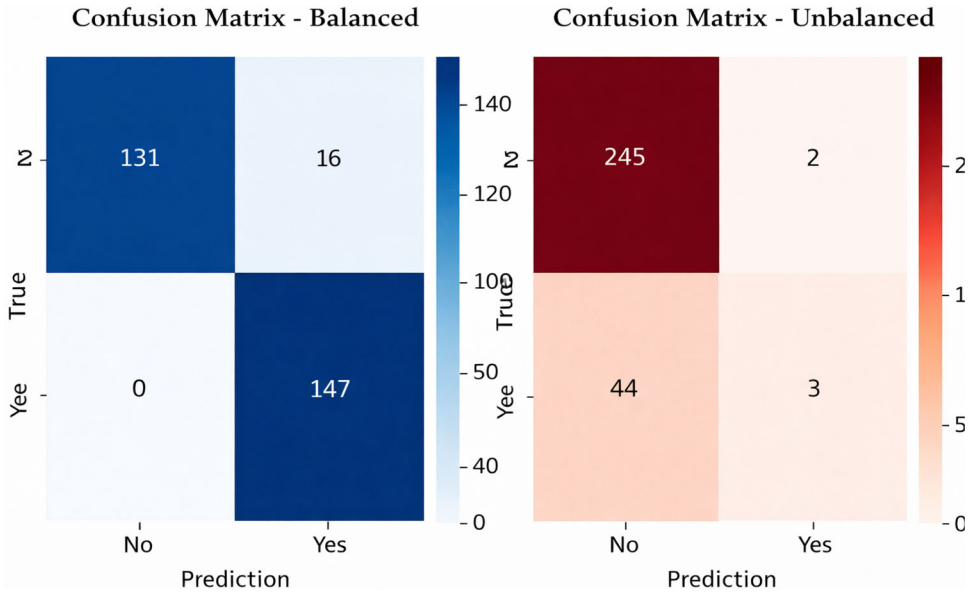

Fig. 8 Confusion matrix of balanced and unbalanced datasets

Table 7 Performance metrics for"Yes" and "No" classes in balanced and imbalanced datasets

Dataset	Class	Precision (%)	Recall (%)	F1-score (%)
Balanced	No	100	90	94
Balanced	Yes	90	100	94
Imbalanced	No	85	99	91
Imbalanced	Yes	60	6	12

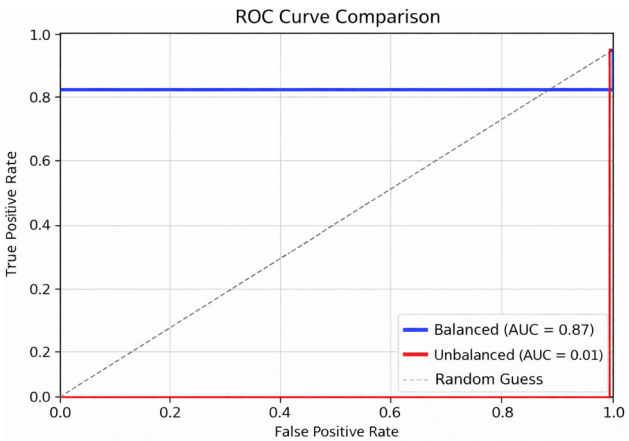

Fig. 9 ROC curve and AUC score of balanced and unbalanced datasets

shown in Figure 8, and the graph showing the ROC curve and AUC score of both datasets is shown in Figure 9.

According to Table 7 and Fig. 8, on the balanced dataset, the model performed reasonably between the "No" and "Yes" classes. On the unbalanced dataset, the model overlearned, i.e., it memorized the weighted class "No." It has serious difficulty in predicting the "Yes" class correctly.

Figure 9 compares the performance of a model trained on balanced and unbalanced datasets using the ROC curve. The

Table 8 Comparison table for imbalanced dataset

Paper	Model	Accuracy (%)	F1-score (%)
[3]	Catboost	90	69
	XGboost	90	68
[38]	Linear SVM	87	37
	KNN (K=1)	83	8
	Random Forest	86	27
Ours	CBA	85	50

graph shows that the model performs well on the balanced dataset (AUC = 0.87) but performs poorly on the imbalanced dataset (AUC = 0.01).

As shown in Table 8, the CatBoost and XGBoost models achieved 90% accuracy on the imbalanced dataset; however, their F1-Scores remained at around 68–69%, indicating a tendency toward the majority class. The Linear SVM, Random Forest, and KNN models produced lower F1-Scores, with KNN achieving an F1-Score of only 8%, revealing its limited ability to detect the positive class. Although the CBA model yielded a lower overall accuracy of 85%, it achieved an F1-Score of 50%, demonstrating a more balanced performance in detecting the minority class compared to some other models.

As shown in Table 9, the performance of all models improved on the balanced dataset. CatBoost, XGBoost, and Random Forest achieved accuracy and F1-Scores between 92 and 94%. The KNN model produced an F1-Score of 97% on the balanced dataset, obtaining high results in contrast to its low performance on the imbalanced dataset. Linear SVM demonstrated lower performance compared to the other models, with 78% accuracy and F1-Score. The CBA model

Table 9 Comparison table for balanced dataset

Paper	Model	Accuracy (%)	F1-score (%)
[3]	Catboost	94	94
	XGboost	93	93
[38]	Linear SVM	78	78
	KNN ($K = 1$)	97	97
	Random forest	92	92
Ours	CBA	94	94

Table 10 Average accuracy values for association rules algorithms

Association rules algorithm	Average accuracy (%)
Apriori	84
Eclat	83
FP-Growth	87

Table 11 Average precision values for association rules algorithms

Association rules algorithm	Average precision (%)
Apriori	84
Eclat	84
FP-Growth	87

Table 12 Average recall values for association rules algorithms

Association rules algorithm	Average recall (%)
Apriori	84
Eclat	84
FP-Growth	87

achieved 94% accuracy and 94% F1-Score on the balanced dataset, obtaining results equivalent to the CatBoost model.

After it was determined that no overfitting occurred due to the experiments with the balanced dataset, the analyses continued to compare the association rules. Firstly, the Apriori algorithm, used by default for model training with CBA, was used and association rules were obtained. Then, similar steps were applied for Eclat and FP-Growth algorithms and the effect of each algorithm on the overall performance was analyzed, respectively.

As a result of the study, the performance of the Apriori, Eclat, and FP-Growth algorithms, which were used to extract association rules, was evaluated using accuracy, precision, recall, and F1-Score [66] metrics, and their training times were compared. To minimize the influence of random factors and to obtain more reliable average values, each algorithm was run three times, and the average results were calculated. The results obtained are given in Tables 10, 11, 12 and 13.

According to the results presented in Tables 10, 11, 12, and 13, the Apriori algorithm performed 84% on average in all performance metrics. The Eclat algorithm achieved results

Table 13 Average F1-score values for association rules algorithms

Association rules algorithm	Average F1-score (%)
Apriori	84
Eclat	83
FP-Growth	87

ranging from 82 to 85%. The FP-Growth algorithm showed the best performance with results ranging from 85 to 88%. Tables 10, 11, 12, and 13 are expressed visually in Fig. 10 .

Three different algorithms (Apriori, Eclat, FP-Growth) were trained sequentially in this study. Average training times are given in Table 14. It is expressed visually in Fig. 11. Based on the results presented in Figure 11, the average training time of the Apriori algorithm is 29.46 s. The Eclat algorithm, although advantageous in terms of memory, has a highly variable training time of 31.01 s and has the longest training time. This indicates that the algorithm is efficient in memory utilization but inconsistent in training time. The training time of the FP-Growth algorithm varies between 19 and 33 s, and the average training time is 25.30 s. This algorithm performed the best by providing a shorter training time than the other algorithms.

The FP-Growth algorithm offers a more effective performance compared to other algorithms, especially in large datasets, with advantages in terms of processing time and memory consumption. Thanks to its high accuracy rate and short training time, it stands out as an efficient alternative for large-scale datasets. However, it should be noted that this algorithm requires more memory usage during implementation.

Replacing the Apriori method, which is used by default in the CBA algorithm, with the FP-Growth algorithm makes it possible to extract faster and more accurate association rules. The integration of the FP-Growth algorithm into the CBA algorithm has also resulted in significant improvements in the duCBA algorithm, increasing classification accuracy and overall efficiency.

The superiority of FP-Growth in processing speed and its success in accuracy rate allows duCBA algorithm to perform better in federated learning environment. In this context, the new method developed as a result of the integration of the changes made in the CBA algorithm into duCBA is called FedCBA. FedCBA, as a CBA approach supported by the FP-Growth algorithm, is designed to provide higher efficiency and accuracy in a federated learning environment. This development not only addressed the data privacy and distributed processing needs in the federated learning environment, but also allowed for superior performance in classification tasks.

As shown in Table 15, different models and aggregation algorithms were compared on the same dataset within the federated learning environment. In the study conducted by

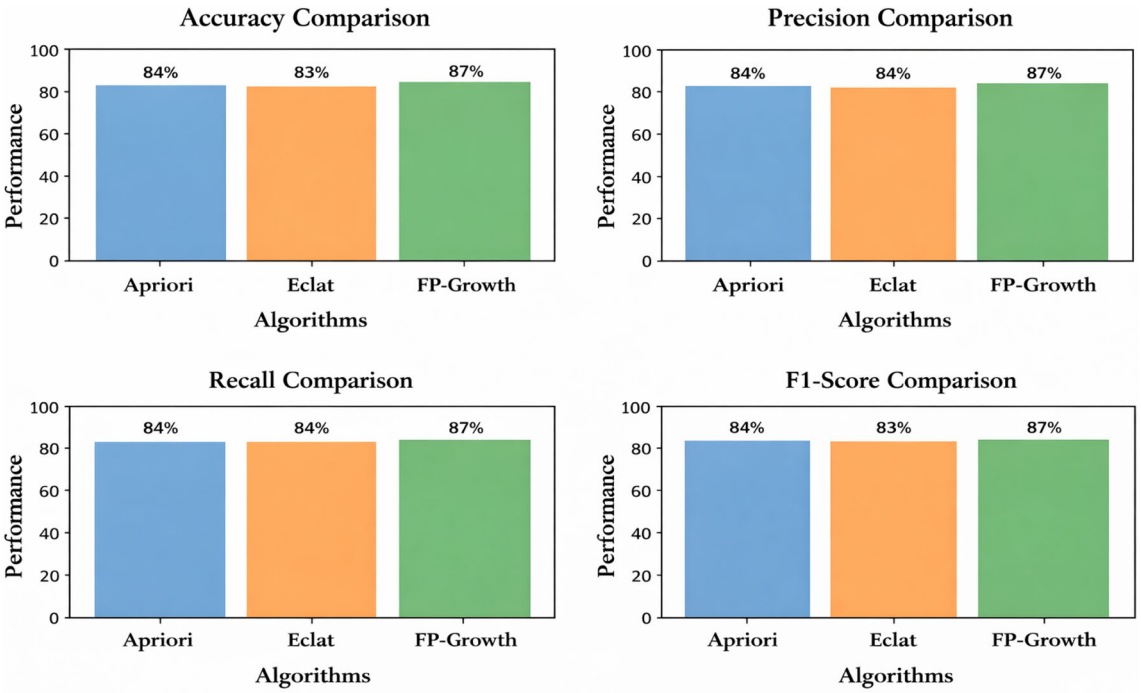

Fig. 10 Performance metric of 3 different algorithms (Apriori, Eclat, FP-Growth) in federated learning architecture

Table 14 Average training time for association rules algorithms

Association rules algorithm	Average training time (seconds)
Apriori	29.46
Eclat	31.01
FP-Growth	25.30

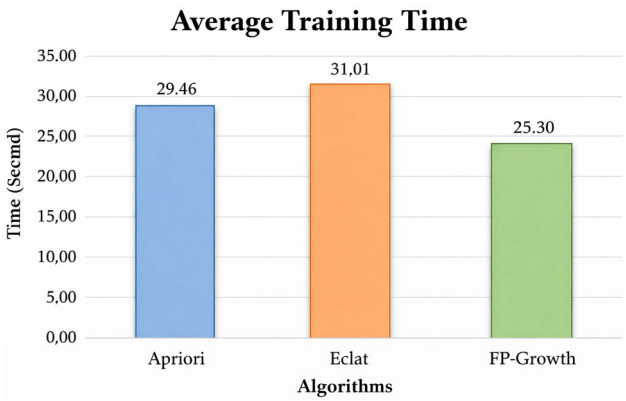

Fig. 11 Average training times of 3 different algorithms (Apriori, Eclat, FP-Growth) in federated learning architecture

[3], Logistic Regression and Neural Network models were trained using the FedAVG algorithm, achieving accuracy rates of 87 and 89%, respectively. In this study, the CBA model reached an accuracy rate of 87% when using the Fed-CBA algorithm. The results indicate that the CBA model can achieve accuracy levels comparable to those of models trained with traditional aggregation methods in a federated learning setting. Moreover, due to its interpretability advantage, the CBA algorithm has the potential to serve as an alternative approach for federated learning applications.

As shown in Table 16, a performance comparison was conducted to empirically demonstrate the contribution and cost of employing a federated architecture, by evaluating the CBA algorithm executed in a local (centralized) environment and our proposed FedCBA approach implemented within a federated learning setting. On the balanced dataset, the centralized CBA algorithm achieved an accuracy of 94%, while the federated FedCBA obtained an accuracy of 87%, indicating approximately a 7% performance loss due to decentralization. Similarly, on the imbalanced dataset, CBA achieved an accuracy of 85%, whereas FedCBA maintained a very close performance with 84% accuracy. Despite

Table 15 Performance comparison of federated learning models on the IBM dataset

Paper	Model	Aggregation algorithm	Accuracy (%)
[3]	Logistic regression	FedAVG	87
	Neural network	FedAVG	89
Ours	CBA	FedCBA	87

Table 16 Performance comparison of CBA and FedCBA using FP-Growth algorithm on balanced and imbalanced datasets

Metric	Model	Balanced	Imbalanced
Accuracy (%)	CBA	94	85
	FedCBA	87	84
F1-score (%)	CBA	94	50
	FedCBA	87	52
Recall (%)	CBA	93	57
	FedCBA	87	53
Precision (%)	CBA	94	72
	FedCBA	87	80
Training Time	CBA	25.37	0.41
	FedCBA	18.76	0.17

these slight losses, the FedCBA model operated significantly faster in terms of training time on both balanced and imbalanced datasets and produced better F1-Scores than CBA, particularly on the imbalanced data. Therefore, the limited performance loss arising from decentralization may be considered acceptable in light of the substantial advantages offered by federated learning in preserving data privacy and enabling inter-institutional collaboration.

Federated Proximal Optimization (FedProx) [67] is an extension of the classical Federated Averaging (FedAvg) algorithm, proposed to address the challenges arising from *statistical and system heterogeneity* in federated learning environments. In real-world federated settings, client devices often differ significantly in terms of data distribution (Non-IID data), data volume, computational capacity, and communication reliability. Under such conditions, the assumptions of homogeneous local updates required by FedAvg are frequently violated, which may lead to unstable convergence or even divergence of the global model.

FedProx introduces a *proximal regularization term* into the local optimization objective in order to restrict excessive deviation of local models from the current global model. Specifically, for a client k at communication round t, the local objective function is defined as [67]:

$$\min_{w} \; F_k(w) + \frac{\mu}{2}\|w - w^t\|^2, \tag{8}$$

where $F_k(w)$ denotes the local empirical risk at client k, w^t is the global model received from the server at round t, and $\mu > 0$ is the proximal coefficient controlling the strength of the regularization.

The proximal term plays a critical role in limiting the divergence of local updates caused by heterogeneous data distributions and unbalanced local training. This formulation enables FedProx to tolerate variable amounts of local computation across devices and to incorporate partial or inexact local solutions without compromising convergence guarantees. Consequently, FedProx is particularly well-suited for federated learning scenarios involving Non-IID data distributions and heterogeneous client resources, where traditional FedAvg may fail to converge reliably.

FedProx does not assume identical data distributions across clients. Instead, it explicitly accounts for statistical heterogeneity by constraining local optimization trajectories, thereby improving robustness and stability in Non-IID federated learning environments.

Within the scope of this study, the proposed FedCBA method is compared against FedProx as a strong and widely accepted baseline for federated learning under heterogeneous and Non-IID data distributions. While FedProx addresses heterogeneity through optimization-level regularization, FedCBA follows a fundamentally different paradigm by adopting a *rule-based relational classification* mechanism instead of gradient-based model aggregation.

The comparison between FedCBA and FedProx is therefore not intended as a direct architectural replacement, but rather as an analytical investigation of two complementary approaches to handling heterogeneity in federated learning. FedProx mitigates divergence by constraining local gradient updates, whereas FedCBA inherently reduces sensitivity to Non-IID data by operating on interpretable association rules learned locally at each client.

By evaluating both methods under identical data partitions and experimental conditions, this comparison aims to isolate the contribution of rule-based aggregation in FedCBA and assess its effectiveness relative to a well-established optimization-based federated learning method such as FedProx.

In the experimental evaluation, FedProx is implemented as a baseline federated learning method to assess its performance under heterogeneous client data distributions. A multi-layer perceptron (MLP) architecture is employed as the local model on each client, consisting of fully connected layers with nonlinear activation functions. This choice reflects a commonly used and computationally efficient model for tabular classification tasks in federated settings.

The federated learning process is conducted over multiple communication rounds, where in each round the server distributes the current global model to all participating clients. Each client performs local training using its private dataset by minimizing the FedProx objective function, which includes the proximal regularization term controlled by the parameter μ. After completing local updates, clients transmit their updated model parameters back to the server, where they are aggregated using weighted averaging.

In our experiments, the number of federated communication rounds is set between 5 and 20 to analyze convergence behavior over time. The proximal coefficient μ is fixed throughout the training process to ensure consistent regularization strength across rounds. This experimental design

Table 17 Performance comparison of FedProx and FedCBA under imbalanced data distribution

Metric	FedProx	FedCBA
Accuracy (%)	81.97	84.00
F1-score (%)	50.47	52.00
Recall (%)	58.70	53.00
Precision (%)	44.26	80.00

allows for a fair comparison between FedProx and the proposed FedCBA method, ensuring that performance differences arise from methodological distinctions rather than from discrepancies in model architecture or training configuration.

As shown in Table 17, FedCBA slightly outperforms FedProx in terms of overall accuracy and F1-Score under an imbalanced data distribution. While FedProx achieves a higher recall, indicating a stronger ability to identify positive instances, this improvement comes at the cost of a considerably lower precision. In contrast, FedCBA demonstrates a substantially higher precision, suggesting that the rule-based aggregation mechanism is more effective in reducing false positive predictions in highly imbalanced federated settings. These results highlight the trade-off between recall oriented and precision-oriented learning behaviors and indicate that FedCBA provides a more reliable and interpretable solution when false alarms are costly.

5 Discussion

In Discussion section, several aspects of this study are addressed, including the interpretation of the obtained results, the implications of the identified association rules in relation to employee attrition and retention, and the evaluation of the performance of different federated learning models and algorithms. This section also discusses the advantages and limitations of applying federated learning, CBA, and association rule mining in distributed environments. Finally, potential directions for future research are outlined, considering both technical improvements and broader applications in various domains.

5.1 Interpretation of Findings

In this study, the factors affecting the turnover of employees were analyzed in line with the inferred relationship rules. The first 5 rules obtained in relation to the tendency to quit (Attrition=Yes) and retention (Attrition=No) are given in Table 18. According to Table 18 and other rules obtained, the important findings are as follows:

- Factors associated with increased tendency to leave (Attrition = Yes):
  - Short tenure with current manager and low job level: employees who have worked with their current managers for a short period (YearsWithCurrManager = 0) and hold low job levels (JobLevel = 1) are observed more frequently among those who tend to leave. The presence of overtime work (OverTime = Yes) appears to strengthen this association.
  - Low job satisfaction and marital status: employees with low job satisfaction (JobSatisfaction = 2), working in the sales department (Department = Sales), who are single (MaritalStatus = Single), and working overtime (OverTime = Yes) were identified in rules linked to higher attrition. However, it is essential to note that MaritalStatus and OverTime might be influenced by other latent factors such as age, income level, or organizational culture, and should not be considered purely deterministic predictors.
  - Medium education level and work–life balance: employees with medium education levels (Education = 3), low job levels (JobLevel = 1), short tenure with their managers (YearsWithCurrManager = 0), and average work–life balance (WorkLifeBalance = 3) are also associated with increased attrition risk.
- Factors Associated with retention (Attrition = No):
  - High job satisfaction and moderate job level: employees in the research and development department (Department = Research and Development) with moderate job levels (JobLevel = 2) and high job satisfaction (JobSatisfaction = 4) appear more likely to stay.
  - No overtime and balanced work–life: employees who do not work overtime (OverTime = No), have moderate job levels (JobLevel = 2), maintain an average work–life balance (WorkLifeBalance = 3), and report high job satisfaction (JobSatisfaction = 4) are more frequently observed among those who remain with the organization.
- General findings:
  - Overtime's impact: working overtime (OverTime = Yes) is frequently associated with higher attrition, particularly among employees with lower job levels. Conversely, not working overtime and maintaining work–life balance are characteristics observed among retained employees.
  - Role of job satisfaction: higher job satisfaction (JobSatisfaction = 4) consistently appears in rules linked to employee retention, while lower job satisfaction increases the likelihood of attrition.

Table 18 First 5 Rules Obtained in Relation to The Tendency to Quit and Retention (Attrition = Yes or No)

Rule ID	Rule	Attrition	Support (%)	Confidence (%)
1	YearsWithCurrManager = 0, JobLevel = 1, OverTime = Yes, StockOptionLevel = 0	Yes	4.56	100
2	JobLevel = 2, Department = Research & Development, JobSatisfaction = 4	No	3.49	100
3	JobSatisfaction = 2, Department = Sales, MaritalStatus = Single, OverTime = Yes	Yes	3.44	100
4	Education = 3, JobLevel = 1, YearsWithCurrManager = 0, OverTime = Yes, WorkLifeBalance = 3	Yes	3.19	100
5	OverTime = No, JobLevel = 2, WorkLifeBalance = 3, JobSatisfaction = 4	No	2.83	100

- Tenure with current manager: employees who have worked zero years with their current managers are more frequently observed among those who leave, suggesting the employee–manager relationship as a potential retention factor.
- Departments and travel: higher turnover tendencies were observed among employees in the Sales department and those who travel frequently (BusinessTravel = Travel_Frequently). Meanwhile, employees in the Research and Development department are more represented among those who stay.
- Marital status considerations: while rules indicate that single employees (MaritalStatus = Single), especially those working overtime, may have a higher tendency toward attrition, it is critical to interpret these findings with caution. Such variables might reflect broader socioeconomic or personal circumstances not directly measured in the dataset.

Overall, while these rules provide valuable insights into patterns related to attrition and retention, they should be understood as statistical associations rather than definitive causal relationships. The relatively low support levels (mostly between 2 and 5%) indicate that these patterns may apply to specific subgroups rather than the entire workforce.

5.2 Advantages and Limitations of Federated Learning, CBA, and Association Rules

FL is an innovative approach that enables the development of machine learning models through collaboration among distributed devices or institutions without the need to transfer data to a central server [68]. This privacy-oriented approach can become even more effective when data mining methods such as CBA and association rules are applied within a federated learning environment.

With the federated aggregation algorithm we have developed, we not only address the problem of employee attrition prediction but also examine association analyses based on the CBA algorithm, which performs classification using association rules. In this respect, our algorithm is not limited to the dataset used in our study and can be easily adapted to different sectors and problem domains. For example:

- In the healthcare sector, different hospitals can develop a joint disease diagnosis model without sharing patient data.
- In the financial sector, banks or financial institutions can collaboratively train models for credit risk assessment or fraud detection without the need for centralized data collection.
- In the education sector, different schools or universities can work together to solve problems such as predicting student performance or identifying the risk of early school dropout.

CBA and association rules offer significant advantages in federated learning in terms of data privacy, security, and distributed modeling. Federated learning prevents privacy breaches by keeping data on local devices and allows the aggregation of datasets from different devices or institutions [69]. This diversity enables the extraction of strong patterns and insights, particularly in understanding user behavior. Moreover, computations performed on local devices reduce reliance on central systems and allow for more efficient use of resources. For example, association rules can be applied for real-time spending analyses, user recommendation systems, or sector-specific predictive models [64].

However, federated learning also introduces several operational and theoretical limitations for CBA and association rules. The distributed data structure may negatively affect the generalizability of rules derived from some devices or institutions due to insufficient or imbalanced data samples [70]. Therefore, in our study, we conducted experiments on both imbalanced and balanced datasets to evaluate the generalizability of our architecture, and the results have been added to the Results section. Additionally, network bandwidth requirements and computational load can limit system

performance, especially in scenarios involving large volumes of data. Conflicting or inconsistent rules from different devices or institutions can create complexities in optimizing the central model. Data imbalance and concurrency issues can further exacerbate these limitations [56].

Although the FedCBA aggregation algorithm effectively combines association rules from multiple clients, its efficiency can be challenged when dealing with millions of rules. The current implementation performs pairwise comparisons of rules to identify duplicates or conflicts based on their antecedents and consequents. However, this comparison process scales quadratically as the number of rules increases, leading to potential computational bottlenecks.

To improve scalability, several strategies can be adopted:

- Hash-based deduplication: by computing hash values for rule antecedent consequent pairs, identical rules can be efficiently detected and merged without exhaustive pairwise scanning. This reduces the computational complexity from $O(n^2)$ to approximately O(n) [71, 72].
- MapReduce framework: for huge rule sets, distributed processing frameworks like MapReduce can parallelize rule merging tasks across multiple nodes. Each mapper processes a subset of rules to emit key–value pairs, where keys are hashes of rule antecedents and consequents. The reducer then aggregates rules with matching keys, updating support and confidence values accordingly [73].

Future work aims to integrate such techniques into the FedCBA architecture to support big data scenarios, ensuring the method remains efficient and scalable.

In this study, the IBM HR dataset was initially split into 80% training and 20% testing data. Subsequently, the training data were divided into three subsets corresponding to the departments (Sales, Research&Development, Human Resources) to simulate a federated learning environment. To maintain the department-specific separation essential for this scenario, conventional cross-validation or random splitting was not applied. A limitation of this study is the reliance on a single dataset, which may restrict the generalizability of the results to other contexts such as different industries, countries, or remote work settings. Furthermore, due to the department-based partitioning, it was not possible to validate the model across different datasets or using random splits. Although this design accurately reflects a federated learning setup, it limits the opportunity to evaluate the transferability of the model to other data sources.

However, the fl architecture also has some significant limitations. Although it offers an effective solution for preserving data privacy, fl can be vulnerable to model inversion attacks [74], where malicious actors attempt to reconstruct training data from model outputs. Furthermore, data poisoning attacks [75] pose a serious risk to fl systems; malicious clients may send incorrect or manipulated data to mislead the global model and degrade its performance. Due to the distributed nature of fl, biases present in local clients can propagate and be amplified in the global model, which is another significant disadvantage [76]. Therefore, when implementing fl, it is essential to consider these security vulnerabilities and bias-related issues and to develop appropriate countermeasures [77]. Indeed, there are existing studies focusing on enhancing resilience against such attacks through model protection techniques, various privacy-preserving methods, and secure model aggregation, and further research and development in these areas remain necessary.

5.3 Future Research Directions

The improved FedCBA algorithm developed in this study, which is based on relational classification, offers significant opportunities in federated learning in terms of both privacy and efficiency in data mining processes. Future research is expected to focus on developing more adaptive and less computationally intensive versions of this algorithm [13, 56]. In addition, the integration of privacy-preserving techniques such as differential privacy, homomorphic encryption, and secure multi-party computation into federated learning association rules stands out as an important research area [68, 78, 79].

Furthermore, it is necessary to develop stronger model weighting and aggregation strategies to address issues such as data imbalance, inter-node heterogeneity, and low-quality data [53]. Current trends include the expansion of federated learning for applications such as AI-powered recommendation systems, dynamic spending analyses, and real-time data processing [70].

In this context, it is important to increase interdisciplinary research so that approaches such as the improved FedCBA aggregation algorithm developed in this study, which is based on relational classification, can operate in energy-efficient architectures and be utilized more optimally on edge devices. Furthermore, to validate the environmental impacts of federated learning architectures, it is necessary to conduct measurements and comparisons involving metrics such as energy consumption, computation time, and carbon emissions [80, 81]. Future research in this direction will help to demonstrate the tangible contributions of federated learning technology to sustainability.

6 Conclusion

This study demonstrates that the federated learning architecture offers an innovative and effective solution to overcome data privacy challenges in human resources analytics. The federated learning approach enables decentralized data

processing by preserving data privacy and fostering inter-organizational collaboration, presenting significant potential, particularly in the development of employee retention prediction models. Experiments conducted on the IBM HR Analytics dataset have shown that the proposed FedCBA aggregation algorithm operates successfully with high accuracy rates. The experimental findings confirm that a secure and effective approach is feasible in human resources analytics.

The proposed FedCBA aggregation algorithm is not limited to the dataset used in this study. On the contrary, it has the potential to be applied in various sectors and problem domains. This is because the algorithm is fundamentally based on association rule mining. This method enables the development of interpretable and explainable predictive models by discovering relationships among variables. The primary focus of this study is to integrate association rule mining with the FL architecture, producing models that both preserve privacy and ensure interpretability. To assess the generalizability of our architecture, tests have been performed on both imbalanced and balanced datasets.

The findings of the study reveal that the FedCBA aggregation algorithm, enhanced by the FL architecture, is an effective method for solving complex human resources problems such as employee retention prediction. Considering the increasing legal regulations on data privacy and the necessity to protect sensitive information related to employee behavior, the practical applicability of this approach is of great importance. This study paves the way for the development of reliable and interpretable predictive models in the field of human resources analytics.

Based on the findings obtained within the scope of this study, the following strategies are recommended for implementation in human resources management:

- Reducing overtime: more flexible working hours or effective shift planning should be developed for employees who work overtime. Such measures can improve work–life balance and help reduce employee turnover rates.
- Enhancing job satisfaction: regular feedback meetings and surveys should be conducted to understand the concerns of employees with low job satisfaction levels. These processes aim to develop solutions tailored to employee needs and to increase overall satisfaction levels.
- Manager training: training programs and mentorship opportunities should be offered to improve employee–manager relationships. Strong employee–manager relations are a critical factor in increasing employee loyalty.
- Personalized solutions: special programs and activities should be designed to address the work–life balance needs of specific groups, particularly single employees. These personalized solutions can meet the expectations of diverse employee groups and enhance job satisfaction and engagement.

In conclusion, this study makes significant contributions both theoretically and practically in the fields of human resources analytics and federated aggregation algorithms. Future research aims to further explore the potential of federated learning architecture by applying it to larger datasets, different algorithms, and various sectoral contexts. In this regard, the study offers new research opportunities within the disciplines of human resources management and data science.

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