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Adaptive Type-1 Fuzzy Logic-Based System for Predicting Employee Attrition

Khalid Almohammadi[1] and Saleh Alharbi*[2]

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Abstract: One of the challenges encountered by employers is the loss of skilled and competent employees. Organizations invest significant efforts in talent acquisition and development, and losing employees implies the loss of resources. This predicament requires novel pre-emptive strategies to curb high turnover rates, thereby minimizing attrition. Recent AI-based interventions have emerged as pivotal tools, offering valuable insights and predictive potential to determine the factors underlying employee attrition. Thus, adequately competent talent retention strategies can be formulated and implemented. This paper proposes a novel model based on predictive type-1 fuzzy logic that can learn the likelihood of employee attrition based on employee characteristics as well as the organizational milieu to aid human resources managers in the implementation of robust retention tactics. We validated the efficacy of our model by conducting experiments that included 72 participants at a Saudi university and analyzing the participant responses. The promising outcomes of our proposed system demonstrate the anticipatory power of estimating attrition prediction rates, underscoring the capability of the system to handle attrition. These outcomes are delivered at a lower average error rate and standard deviation, validating our model's capacity to navigate inherent uncertainties while predicting attrition.

Keywords: *Type-1fuzzy logic, employee attrition, attrition prediction rates*

1. Introduction

Rapid technological revolution has led to the rise of artificial intelligence (AI), with immense applications in business. Data analysis provides new knowledge for organizations; hence data is a valuable asset for organizations and is crucial for the implementation of strategic plans. Thus, many organizations are adopting new technologies to boost their efficiency and competitive advantage and ensure accurate decision-making [1]. Businesses are starting to adopt new technologies in different fields. In recent years, organizations have incorporated AI into their processes. Chung et al stated that “AI has already been applied to increase efficiency of improve financial performance in fields such as production management, marketing, purchasing, distribution and human resource management (HRM)” [2]. The scope of AI application in HRM is gradually expanding into areas such as recruitment [1],[2],[3]. Where it is attracting attention of their powerful result on its application of data analysis techniques where it produce valuable result such as using a machine learning when it used for preventing employees attrition [1],[2],[4],[5].

Organizations can adopt AI for processes across different departments to enjoy benefits such as better decision-making [6]. Vardarlier and Zafer indicated that a company’s real asset is its human resources (HR), since the skills and quality of employees translate to competitive advantages [7]. In recent years, companies have been deploying AI to make objective decisions [8]. Thus, companies, by adopting AI in HRM, transform data into knowledge, allowing them to make reasonable predictions, optimize HR activities and solve critical issues [9],[10]. Organizations invest times and money on employee recruitment and training. Thus, when there is a high rate of employees leaving their job, organizations have to spend scarce resources to employ and train new employees. Also, it takes time for new employees to learn on the job and acclimatize to the organizational culture [1],[11].

The process by which an employee leaves an organization is generally faster than the process by which they leave [12]. Loss of employees may result in loss of competitive advantages for organizations; thus organizations need to keep employee attrition in check [12]. Moreover, reasons for attrition should be assessed and addressed. On the other hand, reducing or preventing employee attrition has an impact on organizational management and culture [13]. By using AI applications to understand the data behind employee attrition, organizations can take pre-emptive actions to prevent or reduce employee attrition, whereas in the past organizations could only deal with such issues after an employee has left [2]. Researchers have proposed some methods and models to predict employee attrition [14]. In recent years, many machine learning models that predict employee attrition for different organizations have been built [1],[15].

[1] *Computer Science Department, Applied College, University of Tabuk, Saudi Arabia*
Email: kalmohammadi@ut.edu.sa
[2] *Department of Management, Faculty of Business Administration, University of Tabuk, Saudi Arabia*
Email: s.alharbi@ut.edu.sa

This paper employs an innovative approach to predict employee attrition rates using type-1 fuzzy logic. This system takes into account a wide array of characteristics that influence employee attrition and uses both the attributes of the employees as well as the organization for its prediction. These characteristics include demographics like gender, age, commuting distance, current salary, employee satisfaction with the work environment, performance evaluation, and employee satisfaction with their roles and responsibilities. This collection of input data enables the proposed system to discern the employee attrition rate followed by a prognosis grounded on the aforementioned tenets. We subjected 72 respondents to certain empirical pursuits to collate their feedback. The prediction of employee attrition presented by our system features a reduced mean of errors and standard deviation, implying that this approach can deal with the inherent uncertainties of predicting employee turnover rates.

This paper is divided into the following six sections. Section 2 offers an overview of the existing machine learning techniques utilized for predicting employee attrition. Section 3 elucidates type-1 fuzzy logic systems. Section 4 describes the elements underlying the theoretically proposed and practically implemented type-1 fuzzy logic system for predicting employee attrition. Section 5 illuminates the empirical experiments and results. Finally, Section 6 concludes the paper and explores potential for future work.

2. RELATED WORK

2.1 An Overview of Employee Attrition and the Impacts on HR

An organization's human resources (HR) are viewed as its core asset and competitive advantage because they ensure productivity and the achievement of organizational goals. Thus, when organizations retain their skilled employees, they ensure sustained quality performance [16],[17]. Business environments are rapidly and continuously changing. Moreover, organizations encounter various issues related to human resources, which can have negative effects if not properly addressed. Thus, organizations that can effectively manage their human resources often enjoy sustained optimum performance [18]. Organizations that fail to improve the working conditions of their employees may see low levels of productivity and performance [2].

Fallucchi et al (2020) defined attrition as "[the process of] an employee resigning or retiring from a company" (p.2) [1]. Chung et al (2023) stated that "the problem of employee attrition is considered a key issue in all organizations because it adversely affects organizational performance" [2]. A direct effect on businesses of employees leaving their job is the interruption of ongoing tasks as the company would need time to hire and train new employees (Yedida et al 2018). Therefore, to sustain their competitive advantages, organizations must minimize employee attrition. Management must identify and address factors that lead to employee attrition in order to maintain high levels of performance and productivity [19],[20]. To address issues related to employee attrition, organizations should follow two steps. First, an organization must define its critical functions. Second, it must identify employees who seem likely to leave and establish strategies to retain employees.

Previous studies have shown the impacts of employee attrition on organizations' performance [21]. Mozaffari et al (2023) found that a high attrition rate depletes an organization's finances and knowledge base as well as employees' engagement level, which in turn affects the attainment of organizational goals [23]. Rombaut and Guerry (2018) observed that "companies with a high voluntary turnover rate have significantly lower performances than their rivals" (p.96) [4]. Some authors have argued that highly motivated and satisfied employees show greater loyalty and are more productive [1]. Others have suggested that organizations should only retain motivated and happy employees as they are more productive, creative and willing to contribute to sustained improvement in organizational performance [16],[17].

Businesses often experience dynamic changes. An organization's human resources (HR) are viewed as the backbone to sustained competitive values, thus business leaders have a vital role in ensuring that organizations utilize the full potential of employees. Managers must adopt the right approach to minimize employee turnover. Decision must be based on data and facts. Businesses are incorporating analytics into HRM processes to make accurate decisions. As Rombaut and Guerry (2018) stated, "a different approach to HR analytics is needed" (p.97), thus companies can use data meaningfully to improve HR practice, for example to make predictions [2]. Angrave et al (2016) emphasized the need for HR professionals to "develop better methods and approaches" that could boost performance [22].

In our proposed study, we adopt correlated system inputs and outputs from previous researches which consider inputs that affect employees leaving their organization with the related cause, which is the attrition rate. Factors used in this study are adapted from [1],[2],[4],[23],[24],[25],[26] ; they are relevant to the Saudi culture and workplace environment. These factors include demographics like gender, age, commuting distance, current salary, employee satisfaction with the work environment, performance evaluation, and employee satisfaction with their roles and responsibilities. Our system is flexible and can accept more inputs, as will be seen in Section 3.

2.2 An Overview of the Machine Learning Techniques Used to Predict Employee Attrition

Conventionally, the process of evaluating employee turnover relied extensively on retrospective examination, exit interviews, and surveys for a comprehensive interpretation of the factors underlying employee departures. Besides providing valued insights, these methods often grapple with constraints to delivering timely and anticipatory information. Furthermore, they are inherently reactive, responding to the challenges after their manifestation, rather than preemptively curbing turnover. Acknowledgement of these shortcomings reveals the need to adopt more nuanced predictive analytics techniques. These techniques offer a proactive and empirically grounded approach to understanding and curbing employee turnover [27]. Numerous research studies advocate for the development of a data-driven framework. This section reviews related work on employee attrition by employing data-driven approaches using machine learning techniques.

The study acquaints us with the notion of predicting employee attrition rates via machine learning-based classification algorithms such as k-nearest neighbors, extreme gradient boosting, ad boosting, decision tree, neural networks, and random forests [28],[12]. The ad boost model, random forest regressor, decision tree, logistic regressor, and gradient boosting classifiers were employed for predictive tasks [29]. This study proposes the adoption of a machine learning pipeline that enables the prediction of employee turnover [30] [31]. The outcomes reflect the analysis of certain tenets, such as years of work experience, educational background, gender, and department, which influence employee attrition. Machine learning frameworks like naive Bayes, random forest, decision tree, support vector machine, and k-nearest neighbors were implemented using the Python programming language [32]. A logistic regression algorithm was used to predict employee turnover [33]. Some researchers have evaluated the causal factors underlying employee attrition, focusing solely on logistic regression models with little attention to enhancing the precision of the framework.

A few researchers have employed a range of frameworks for precise prediction of employee attrition [34]. Other studies use a broad variety of machine learning techniques to determine the causal factors forcing an employee to depart from an organization [13], [1]. However, most of these methodologies introduce constraints of knowledge portrayal, implying the inability of such AI techniques to develop fair models depicting human behavior. Hence, it is virtually not feasible to rely on the black-box features of these AI techniques since they pose considerable interpretational barriers to users. In our recommended approach, we leverage white-box learned models in conjunction with fuzzy logic which are easy to comprehend and analyze even for non-expert users.

2.3 Type-1 Fuzzy Logic Systems Methodology

As one of the burgeoning advances in data processing technologies, fuzzy systems have garnered global recognition and are widely being used in a variety of commercial and technological domains, including digitization, administration, knowledge drilling, image signal processing, and pattern recognition [35,36]. In these domains, the knowledge pertaining to the environmental factors and the users reflects uncertainty, vagueness, and imprecision, thus rendering its quantification through conventional mathematical frameworks impossible. The architecture of fuzzy logic systems allows the creation of reliable controllers that operate well even in the face of noise and uncertainty characteristic of real-world settings. Additionally, fuzzy logic systems enable the representation of fuzzy logic data in a clear, adaptable, and human-readable manner. Type-1 fuzzy logic systems are used in applications that employ clear, accurate type-1 fuzzy sets.

Fuzzy logic, which can mimic the rational thought process of humans, has gained in popularity and efficiency as a user-modeling approach after its invention by Zadeh in 1965 [37]. Given that assertions in fuzzy logic might be incomplete facts that fall anywhere between absolute truth and absolute falsehood, fuzzy logic can be considered an augmentation of standard set theory [38]. The four steps encapsulated in a fuzzy logic system (FLS) include the fuzzifier, rule base, inference engine, and defuzzifier, as illustrated in Figure 1 [38]. Rules can be derived through numerical data or by experts. Fuzzy logic systems may be considered as a mapping from the crisp inputs to the crisp outputs after the rules have been established, which may be numerically expressed as y = f (x) [38]. The elements impacting the projection of employee turnover may be summarized by an FLS. An FLS-based modeling structure designed for expert analysts simplifies the rationale behind its use for designers and end users, making it easy to comprehend and adapt.

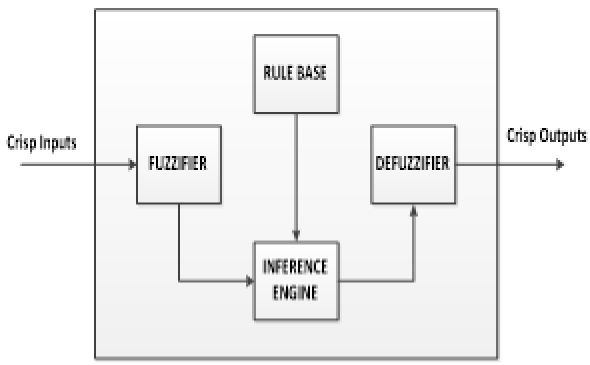

Figure 1: Overview of a Fuzzy Logic System (adapted from [39])

3. THE PROPOSED ADAPTIVE TYPE -1 FUZZY LOGIC-BASED SYSTEM FOR PREDICTING EMPLOYEE ATTRITION

Our system is designed to predict the attrition rate of employees by analysing employee attributes and the overall work environment. Data collection by our system involves amassing information from employees based on various factors prevalent in and related to the workplace. Data analysis is facilitated by a fuzzy logic membership system tailored to input and output variables. System learning is based on an unsupervised one-pass technique [40], [41], [42]. The system retrieves employee departures data and assesses employee attributes along with the conditions prevalent in the workplace at that time to identify the possibility of employee attrition. This analytical finding is then exploited to develop an informed framework that captures the situational behavioral disposition on the basis of the variables and predicts employee turnover. Notably, the system considers the behavioral patterns of employees, reflecting their likely intent of attrition, for generating output data based on their individual profiles and the prevalent organizational environment. In simpler terms, the system first collects employees' data, including their possibility of quitting their jobs. Thereafter, it analyzes this information to acknowledge patterns that link employee attributes and turnover. The resultant output is utilized to create an eloquent framework based on these behavioral patterns in order to predict possible employee attrition in future by manipulating datasets of multiple input and output data deuce, represented as follows [40], [41], [42]:

$$x^{(t)}; y^{(t)} \qquad (t = 1,2,\ldots,N), \qquad (1)$$

In our empirical studies performed in a workplace setting, we employed 8 input variables describing employee attributes and an output variable that reflects the possibility of employees quitting the job. By setting fuzzy rules, we developed a model that correlates the input and output variables without dependence on any mathematical framework. This enhances the flexibility of the system in adapting each rule individually, impacting only specific parts of the whole eloquent model developed by the proposed system. Subsequent to the collection of input and output databases, it is imperative to categorize employee input/output variables using the fuzzy membership functions. This approach quantifies the values of raw input and output variables, translating them into easy-to-grasp tags like low/very low and high/very high. This permits the system to process data in a more nuanced manner by using the intricately designed membership functions.

To derive the rules that describe the behavioral patterns of employee attrition, the pre-established sets of membership functions are combined with the employee input/output data. Our system's technique of extracting rules from input data relies on a refined and expanded variant of the Mendal–Wang method [40], [41]. This is recognized as a one-pass method based on the extraction of fuzzy rules from a set of data that is being analyzed. The antecedent and consequent fuzzy rule sets split the output and input fields into fuzzy regions. The system generates rules across multiple sets of input and output data, emphasizing the link between $x = (x_1, \ldots, x_n)^T$ and $y = (y_1, \ldots, y_k)^T$. The representation typically adopts this format [40], [41], [42]:

$$If\ x_1 is\ A_1^{(l)} and.. x_n\ is\ A_n^{(l)}\ Then\ y_1 is\ B_1^{(l)} and..\ y_k\ is\ B_k^{(l)} \qquad (2)$$

where l=1,2,...,M. M represents the number of rules and l denotes the rules index. The V fuzzy sets are outlined for every input x_s, with $A_s^q, q = 1,\ldots,V$ simultaneously, while the W fuzzy sets $B_c^h, h = 1,\ldots,W$ are outlined for every output y_c.

The method of single output rules is emphasized for streamlining the ensuing notation as the concept may be easily extended to rules containing numerous outputs [42]. The multiple stages of extracting rules can be illustrated as follows:

Step 1: Concerning a fixed pair of input–output $\left(x^{(t)}; y^{(t)}\right)$ in the dataset (1) (t=1,2,...,N), the membership values $\mu_{A_s^q}(x_s^{(t)})$ are calculated for every membership function q = 1,...,V as well as for every input variable s =1,...,n, thereby determining $q^* \in \{1,\ldots,V\}$ as reflected in the equation below:

$$\mu_{A_s^{q*}}(x_s^{(t)}) \geq \mu_{A_s^q}(x_s^{(t)}) \qquad (3)$$

Apparently, the following rule is deemed to be developed by $\left(x^{(t)}; y^{(t)}\right)$ [40], [41], [42]:

$$If\ x_1^t\ is\ A_1^{q^*}, \ldots, and\ x_n^t\ is\ A_n^{q^*},$$
$$then\ y\ is\ centered\ at\ y^{(t)} \qquad (4)$$

Every input variable x_s has a corresponding fuzzy set $A_s^q, q =, 1, \ldots V$ characterizing it, thereby making it easier to produce the maximum number of rules (V^n), where n depicts the total number of input variables. Nevertheless, taking into account the dataset, out of V^n possibilities, only the rules containing an overriding zone with a minimum of one data point will be produced. As a consequence of executing Step 1, a single rule is created based on every input–output data combination. For every single input, a fuzzy set achieving an enhanced membership value in the IF section of the rule is selected. Both Equations (3) and (4) demonstrate this.

Nonetheless, this does not depict the ultimate rule which will be set in the following step.

Moreover, the computation of the rule weight can be done according to the equation [40], [41], [42]:

$$w^{(t)} = \prod_{s=1}^{n} \mu_{A_s^q}(x_s^{(t)}) \qquad (5)$$

The rule weight $w^{(t)}$ is based on the establishment of the strength of the points $x^{(t)}$ regarding the fuzzy areas accommodating the rule.

Step 2: To determine the rules produced via N data by using Equation (3), Step 1 is performed repetitively on every t datapoint from 1 to N. The considerably large number of data points will lead to the production of multiple rules by implementing Step 1. All the resultant rules have the same IF section and are recognized as conflicting rules (rules with similar antecedent membership functions but different consequent values). In this step, the rules that are determined to have identical IF elements are combined to form a single rule.

As a result, the N rules are split into groups, each group including all of the rules that share the same IF section. In the event that M groups are thought to exist, group l will include Nl rules as explained below [40], [41], [42]:

$$if\ x_1\ is\ A_1^{(q^l)},\ \ldots,$$
$$and\ x_n\ is\ A_n^{(q^l)}, then\ y\ is\ centered\ at y^{(t_u^l)} \qquad (6)$$

where N_l and t_u^l are the data points indices in regard to group. The rules' weighted average in the conflict group is then calculated as follows [40], [41], [42]:

$$av^{(l)} = \frac{\sum_{u=1}^{N_l} y^{(t_u^l)} w^{(t_u^l)}}{\sum_{u=1}^{N_l} w^{(t_u^l)}} \qquad (7)$$

In this light, the N_l rules are subsequently merged into a single rule, with the following arrangement [40], [41], [42]:

$$If\ x_1\ is\ A_1^{(l)}, \ldots, and\ x_n\ is\ A_n^{(l)}, then\ \ y\ is\ B^{(l)}$$
(8)

where the output fuzzy set B^l is chosen on the following basis: out of the W output fuzzy sets $B^1 \ldots B^w$, B^{h^*}can be determined as follows [40], [41], [42]:

$$\mu_{B^{h^*}}\ (av^{(l)}) \geq \mu_{B^h}\ (av^{(l)}) \qquad (9)$$

For $h = 1,2,\ldots,W,\ B$ is selected as B^{h^*}. As reflected above, the proposed system manages data pairs of input–output variables and generates several outputs. It is acknowledged that Step 1 is unique with respect to the number of outputs that are linked to every rule, while Step 2 offers a simple proliferation that aims to allow rules to include multiple outputs, wherein the computations described in Equations (7) and (9) are performed repetitively for every output.

The suggested system can recognize and gain insights into employee attrition and attributes with the help of the extracted membership functions and the fuzzy rules retrieved from input and output data of employees In light of this, the algorithm can then predict likely attrition. This system utilizes singleton fuzzification, product ramification, and center of sets defuzzification [40], [41], [42]. The correlation of a precise input vector with a precise output vector $y = f(x)$ can be accomplished according to the formula given below:

$$y(x) = f_s(x) = \frac{\sum_{l=1}^{M} y^1 \prod_{i=1}^{n} \mu F_i^l\ (x_i)}{\sum_{l=1}^{M} \prod_{i=1}^{n} \mu F_i^l\ (x_i)}$$
(10)

where *M* represents the number of rules prevalent in the rule base and y^{-l} depicts the centroid of the *lth* fuzzy output.

4. EXPERIMENTS AND RESULTS

A representative group of 72 employees of Saudi Arabia's Tabuk University were chosen for this study. The survey sought the employees' feedback on their likelihood of quitting their jobs. During the collection of system inputs, the employees examined various parameters like job satisfaction based on their duties and responsibilities, performance review, and demographics such as gender, age, commute distance, current wage, and work environment satisfaction. The rate of employee turnover was captured by the system as the output. Following data collection, type-1 fuzzy frameworks were developed, and fuzzy sets were produced to represent the uncertainty corresponding to every employee's viewpoint about a specific linguistic tag and its impact on the attrition rate and the relative inputs [40], [41], [42]. To build the fuzzy model, the study participants were asked to represent various linguistic variables according to their individual perspectives for subsequent analysis with the help of [40], [41], [42]. d Type-1 fuzzy sets were extracted along with; the rules were

If the gender is male and the age is middle-aged adult and the commuting distance is long trip and the salary is low and the employee's level of contentment regarding the work environment is low and the performance evaluation is high and job satisfaction derived from their roles and responsibilities is moderate, then the likelihood of leaving the job is high.

The average error of the type-1 fuzzy logic system was 0.61 and the average standard deviation was 0.81, as reflected in the test outcomes of the predicted output following the training of the suggested framework. These results point towards precise modeling of the attrition behavior of employees by the type-1 system. The use of the type-1 fuzzy logic system led to enhanced behavioral modeling of employee attrition.

5. CONCLUSION

This paper uses type-1 fuzzy logic to predict employee attrition rates. The approach is dependent on the distinctive attributes of the organization as well as of the employees and considers a broad spectrum of factors that impact employee attrition tendencies. These attributes encompass employee demographics such as age, gender, commute distance, and present remuneration, as well as organizational factors such as employee satisfaction with the workplace environment, performance reviews, and the sense of fulfillment employees get from their roles and responsibilities. By gathering this input data, the suggested system may determine the rate of employee turnover and then generate a potential prediction outcome based on the previously established principles. We collected input from 72 respondents. Our system's projection of employee turnover exhibits a low standard deviation and mean of errors, demonstrating its effectiveness in navigating the uncertainties intrinsic to the prediction of employee attrition rates.

In a future study, our current system will be augmented with a type-2 fuzzy logic system enriched with additional inputs and outputs; this augmented system will then be compared with the currently proposed type-1 system. Furthermore, we will leverage our models to gauge employee attrition by conducting additional realistic assessments.

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