Fuzzy Based Model for Mitigating Employee Attrition

Nida Hasib[1][a], Syed Wajahat Abbas Rizvi[1][b] and Vinodani Katiyar[2]
[1] *Amity University Uttar Pradesh, India*
[2] *DSMNR University, Lucknow, India*

Keywords: Model for Mitigating Employee Attrition, MMEA, Risk Code, Risk Metrics, Fuzzy Inference System, FIS.

Abstract: Employee attrition is a major concern for IT firms in today's corporate environment. Aside from the loss of human resources, employee turnover also diminishes the organization's ability to use the expertise and revenue-generating potential of those individuals. This study proposes a fuzzy logic-based phase-wise Model for Mitigating Employee Attrition (MMEA) that evaluates employee attrition at each stage of the software development life cycle using the most pertinent risk measures. The research has made use of the fuzzy inference process power in creating a model based on the anticipated and reduced staff attrition. Using data from sixteen actual software projects, the suggested model's predictive accuracy is confirmed. The MMEA model developed as per the guidelines of the proposed framework may help software professionals to take appropriate corrective measures to predict and reduce employee attrition during software development life cycle for efficient and accurate software development process in IT sector. By giving management of the organization the ability to proactively address attrition-related issues and make long-term strategic decisions that benefit the company, the model effectively maximizes staff retention, according to the research. Our results produced proof that the alternate strategy was valid. As a result, managers and companies may find a more practical tool in the used method for evaluating employee decline.

1 INTRODUCTION

Employee attrition is a significant concern for organizations, leading to substantial losses in IT industry. Each organization's context is unique, so tailored strategies are essential. Employee attrition in the IT industry can be influenced by several factors, including absenteeism, performance, and engagement. By combining predictive models, data insights, and employee development, companies can effectively reduce attrition rates in the software development industry (Hasib et al. 2023).

There are various number of techniques through which employee attrition can be mitigated in software development industry- Data Analytics and Insights, Upskilling and Empowering Managers, Predictive Models Using Machine Learning, Fuzzy logic. Fuzzy is the term used to describe things that are ambiguous or unclear. Fuzzy is the term used to describe the things that we commonly encounter in the real world that are ambiguous or confusing. Fuzzy logic provides tremendously helpful thinking flexibility since we often encounter circumstances in the real world when we are unable to determine whether a condition is true or untrue.

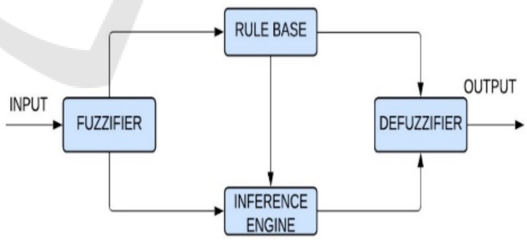


Figure 1: Fuzzy Logic Architecture.

Fuzzy logic is created using fuzzy rules, which are if-then statements that depict the relationship between input and output variables in a fuzzy way as rule base. A fuzzy logic system produces a fuzzy set, which is a collection of membership degrees for each possible

[a] https://orcid.org/0000-0001-8178-422X
[b] https://orcid.org/0009-0006-8064-9388

Hasib, N., Rizvi, S. W. A. and Katiyar, V.
Fuzzy Based Model for Mitigating Employee Attrition.
DOI: 10.5220/0013460500003956
In *Proceedings of the 7th International Conference on Finance, Economics, Management and IT Business (FEMIB 2025)*, pages 105-117
ISBN: 978-989-758-748-1; ISSN: 2184-5891

output value (Yadav and Yadav, 2015), (Nikmanesh, 2023). Figure 1 depicts a fuzzy logic architecture that handles fuzzification and defuzzification.

Figure 2 depicts a comprehensive fuzzy logic system for reliability modelling. Fuzzy logic systems consist of four primary parts: fuzzy rule base, fuzzy inference process, fuzzy membership function (input), and defuzzification (output). The process of converting a clear value into a fuzzy value is called fuzzification. The input and output variables are fuzzified using linguistic variables such as low (L), medium (M), and high (H) based on the available data and related uncertainty. The fuzzy rule base is the fundamental building block of all fuzzy systems.

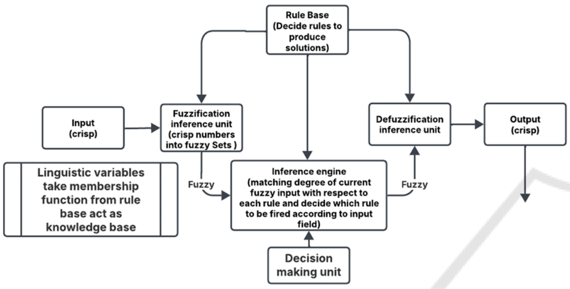


Figure 2: Overview of Fuzzy Logic System for mitigating employee attrition.

The fuzzy rule foundation is made up of historical data, human knowledge expertise, and failure analysis. These rules are implemented in an acceptable and effective manner using the other fuzzy system components.

To sum up, fuzzy logic is a mathematical framework that captures ambiguity and uncertainty in decision-making; it has many uses and permits partial truths. There is an intermediate value in fuzzy logic, nevertheless, that is both partially true and partially false. Thus, utilizing the risk measures that impact employee attrition throughout the SDLC phases, a fuzzy logic based phase-wise employee attrition recognition and mitigation model is presented in this article (Yadav and Yadav, 2015).

The rest of the paper is organized as follows: In section 2, related work is discussed. In section 3, the proposed framework is presented. Section 4 describe implementation of phases of model. Section 5 describe empirical validation of sixteen case studies and predicted result of MMEA, Section 6 and 7 predictive accuracies of MMEA and quantitative comparison with other models. Conclusion and future extensions are presented in section 8.

2 FRAMEWORK FOR MITIGATING EMPLOYEE ATTRITION

In continuation with the highlighted need and significance as discussed in previous section, the researcher has already proposed a structured framework for Mitigating Employee Attrition (Figure 2.) based on biological immune system based artificial immune system conceptual theory as a solution for the identified inadequacies present in earlier employee attrition evaluation studies (Hasib et al., 2023) (Hasib et al., 2024).

The framework described a comprehensive employee attrition quantification process through its eight phases (Conceptualization, Initialization and Recognition, Correlation and Association, Development and Quantification, Analysis and Finalization) as depicted in Figure 3. It has been designed in such a way that both industry personnel and researchers will find it simple to execute. The framework focuses on all phases of the software development life cycle. The researcher thoroughly defined all of the framework's phases, as well as its key attributes, which support its claim to be a better employee attrition framework. (Chauhan and Patel, 2013) (Hasib et al., 2024)

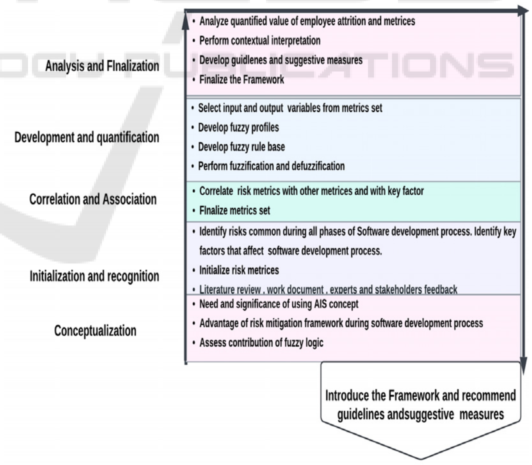


Figure 3: Framework for Mitigating Employee Attrition.

3 FRAMEWORK IMPLEMENTATION

In the proposed mode (MMEA), employee attrition indicator during all the phases of SDLC using eleven risk metrics for recognition and mitigation of employee attrition of IT sectors. The model was developed using a fuzzy inference technique, and risk metrics are evaluated in language terms.

3.1 Implementing Conceptualization Phase

In terms of the framework, this phase serves as the foundation for the subsequent phases. This is the initial phase in developing a comprehensive solution to a problem. The image illustrates two subtasks: The importance of applying the AIS idea and implementing a risk mitigation framework during software development are discussed in (Hasib et al., 2023) (Hasib et al., 2024). The first two sections of this paper and past research work covered all three conceptual subtasks.

3.2 Implementing Initialization and Recognition Phase

Certain risk issues pose a hazard to every stage of the SDLC, from the project's first examination to its final release. The risk factors that are relevant to every stage of the SDLC are continually changing requirements, time contention, project funding loss, team attrition, data loss, miscommunication. One the key factor that effect software development process most according to literature review is employee attrition. Employee attrition effects and disturb continuous processing of Software development life cycle phases and impact IT sectors/industries in its cost, efficiency and productivity.

There are number of causes of employee attrition in IT industries during software development process. A number of employee attrition reduction frameworks uses risk metrics has been proposed in last two decades. The accuracy of predictions may rise with the selection of risk measures. But the most important factors in lowering employee attrition have to be taken into account. As a result, the researcher obtained a number of risk measures from various available sources through a literature study. As per the comprehensive literature review performed by researcher there are number of variables exist in literature that effects employee attrition in IT sectors (Gupta and Bhatia, 2023), (Rusi and Viollet, 2023). Researcher has taken top most recommended risk metrics that effects most out of number of factors which are reasons of employee attrition in IT industry (Table 1) (Hasib et al., 2025). Those are considered as risk metrics for recognition and mitigation of employee attrition through quantification analysis of our model (MMEA) (Figure 4). The objective of the initialization and recognition phase is to initialize and recognize the effectiveness of factors that are related directly or indirectly to the employee attrition during software development process.

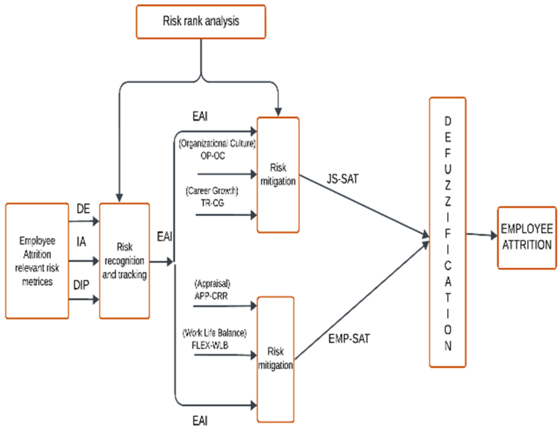


Figure 4: Model for Mitigating Employee Attrition.

Table 1: Risk Code and Metrics.

S.NO.	Risk Code	Risk Metrics
1	DE	Decreased Engagement
2	IA	Increased Absenteeism
3	DIP	Decline in Performance
4	EAI	Employee Attrition Indicator
5	OP-OC	Organization Culture (Openness-Organizational Culture)
6	TR-CG	Career Growth opportunities (Training-Career Growth opportunities)
7	APP-CRR	Appraisal (Appraisal-Compensation, reward, recognition)
8	FLEX-WLB	Work Life Balance (Flexibility-Work Life Balance)
9	JS-SAT	Job Satisfaction
10	EMP-SAT	Employee Satisfaction
11	EMP-ATT	Employee Attrition

3.3 Implementing Correlation and Association Phase

In this step of the framework the researcher has shortlisted eleven metrics out of others form the literature review of different organization dealing with evaluation of employee attrition for betterment of software development process in IT industries (Hasib et al., 2025). Out of these some refer to risk recognition phase and other refers to risk mitigation (Kermani, 2021). All risk metrics are assigned with linguistic values after expert renewal. After that correlation and association process conducted through risk matrix between key risk metrics (employee attrition indicator and employee attrition, job satisfaction, employee satisfaction) with other risk metrics on the basis of if-then analysis. (Figure 5).

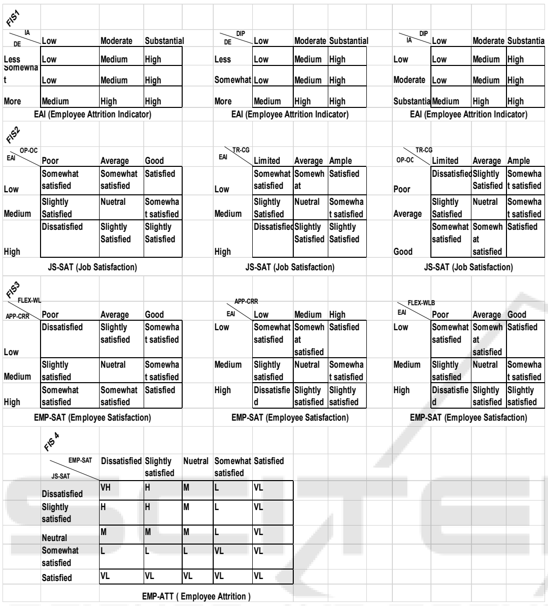


Figure 5: Risk metric analysis in FIS1, FIS2, FIS3, FIS4 using risk matrix.

After rationalizing association and correlation with respect to employee attrition of recognized risk metrics in above section, finally is to freeze metric set which can be mutated according to strategies of organization environmental condition during software development process and employee attrition mitigation accuracy will be maintained.

3.4 Implementing Development and Quantification Phase

Since the actual development of the MMEA occurs during this phase, it is the most important one in the framework. The model is implemented using the Mandani type-1 fuzzy logic toolbox in MATLAB R2024a. The model's fundamental steps include choosing risk metrics (input/output variables), creating a fuzzy profile of these variables, creating a fuzzy rule base, and utilizing a fuzzy inference system (FIS) to recognize and mitigate employee attrition throughout the software development process at all stages.

The forms of membership functions can be polygonal, trapezoidal, triangular, and more. Triangle membership functions are taken into consideration in this study for the creation of fuzzy profiles for a variety of identified input/output variables (Table 2). Due to its simplicity and ease of comprehension, triangular membership functions (TMFs) are frequently employed for the computation and interpretation of employee attrition statistics.

Table 2: Risk metrics range of membership function.

S. NO.	Risk Metrics	Input/ Output metrics	MF range (0-1)
1	DE	Less, Somewhat, More	[-.5 0 .5], [0 .5 1], [.5 1 1.5]
2	IA	Low, Moderate, Substantial	[-.5 0 .5], [0 .5 1], [.5 1 1.5]
3	DIP	Low, Moderate, Substantial	[-.5 0 .5], [0 .5 1], [.5 1 1.5]
4	EAI	Low, Medium, High	[-.5 0 .5], [0 .5 1], [.5 1 1.5]
5	OP-OC	Poor, Average, Good	[-.5 0 .5], [0 .5 1], [.5 1 1.5]
6	TR-CG	Limited, Average, Ample	[-.5 0 .5], [0 .5 1], [.5 1 1.5]
7	APP-CRR	Low, Medium, High	[-.5 0 .5], [0 .5 1], [.5 1 1.5]
8	FLEX-WLB	Poor, Average, Good	[-.5 0 .5], [0 .5 1], [.5 1 1.5]
9	JS-SAT	Dissatisfied, slightly satisfied, neutral, somewhat satisfied, satisfied	[-.25 0 .25], [0 .25 .5], [.25 .5 .75], [.5 .75 1], [.75 1 1.25]
10	EMP-SAT	Dissatisfied, slightly satisfied, neutral, somewhat satisfied, satisfied	[-.25 0 .25], [0 .25 .5], [.25 .5 .75], [.5 .75 1], [.75 1 1.25]
11	EMP-ATT	Very Low, Low, Medium, High, Very High	[-.25 0 .25], [0 .25 .5], [.25 .5 .75], [.5 .75 1], [.75 1 1.25]

FIS 1

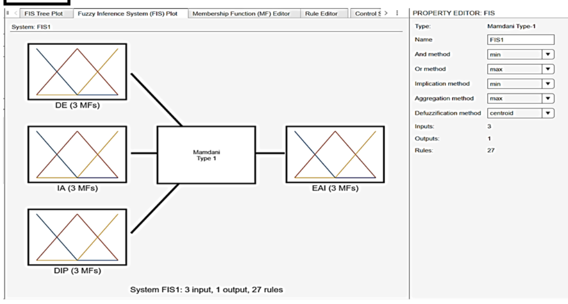


Figure 6: Fuzzy Inference System (FIS 1) plot.

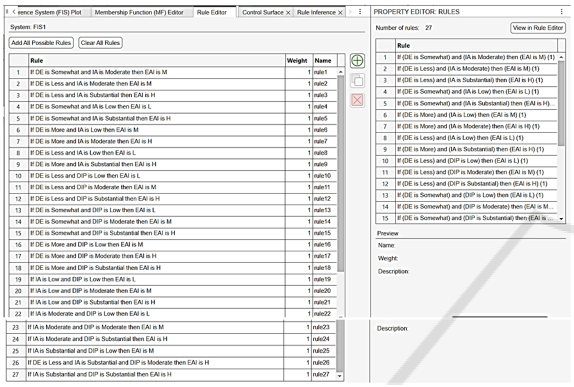


Figure 7: 27 Rules of FIS1.

FIS 2

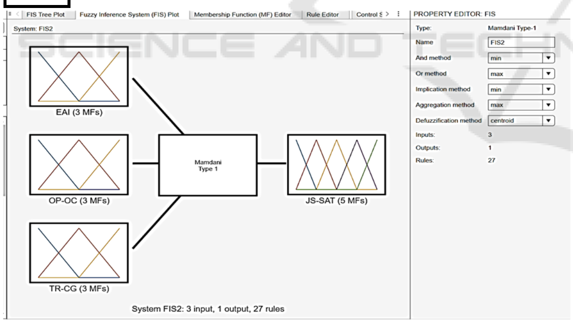


Figure 8: Fuzzy Inference System (FIS 2) plot.

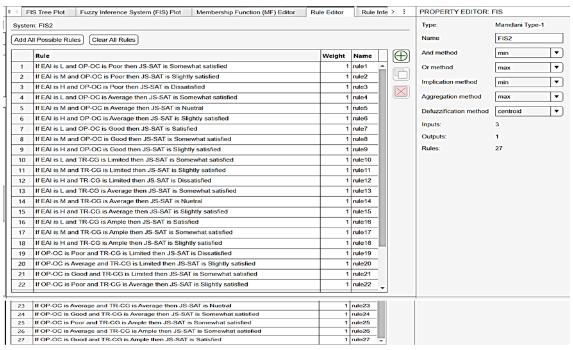


Figure 9: 27 Rules of FIS2.

FIS 3

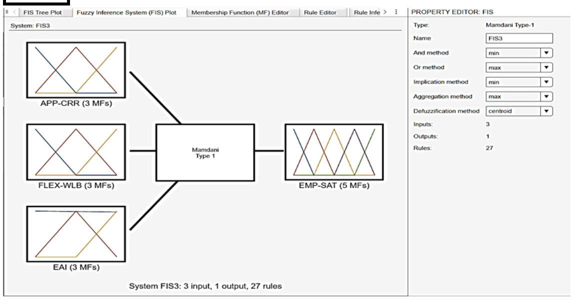


Figure 10: Fuzzy Inference System (FIS 3) plot.

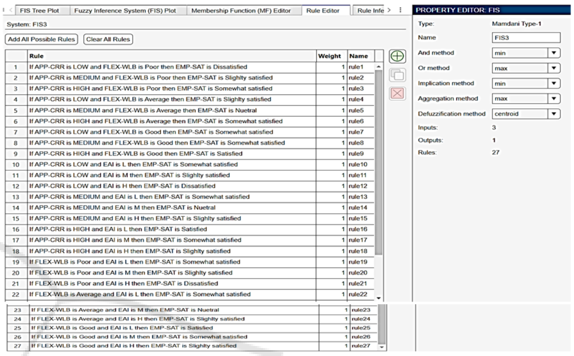


Figure 11: 27 Rules of FIS3.

FIS 4

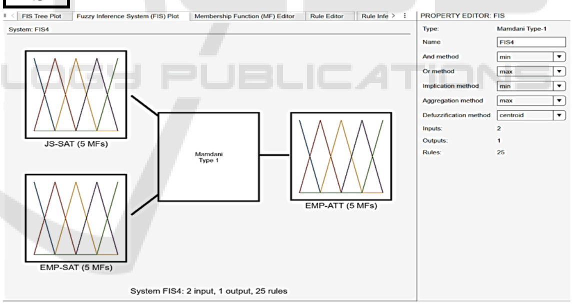


Figure 12: Fuzzy Inference System (FIS 4) plot.

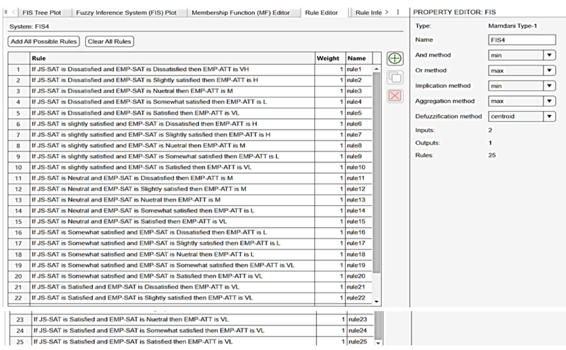


Figure 13: 25 Rules of FIS4.

From the above correlation and association phase, it has been visualized that range of membership function are created between 0-1. As shown in above (Table 2) first eight risk metrics have three MFs ranges and last three risk metrics form the list have five MFs ranges. On the basis of the previous phase, we come to know how much fuzzy rules are to be prepared, 106 fuzzy rules are prepared for dealing with recognition and mitigation of employee attrition using different risk metrics. With reference to these fuzzy rules, fuzzy inferences are reflected with various significant values from organizations work modules document. Employee attrition evaluation performed through these rules and their inferences to recognize level of attrition and try to reduce attrition percentage through manipulating various risk metrics in proposed model based on organization environmental condition. The explanatory process of proposed model is shown above in this section as 4 Fuzzy Inference System (FIS1, FIS2, FIS3, FIS4) which consist of Fuzzy Inference System(FIS) plot; property editor of all FIS consist of -implication method (min), aggregation method (max), defuzzification method (centroid); membership function plot for every metrics showing degree of membership; rule editor showing all possible rules created in every fuzzy inference system; rule inference system. In proposed model FIS 1 consist of 27 rules, FIS 2 consist of 27 rules, FIS 3 consist of 27 rules, FIS 4 consist of 25 rules. In all total 106 rules to solve employee attrition mitigation problem in IT sectors. (Figure 6 to Figure 13) shows all fuzzy profiles of FIS 1, FIS2, FIS3, FIS4 including its fuzzy inference system plot, fuzzy profiles with membership ranges, and fuzzy rules (Ahmed et al., 2013).

3.5 Implementing Analysis and Finalization Phase

Although the developed Model for Mitigating Employee Attrition has been theoretically and empirically validated for accuracy and efficiency even though in order to analyse employee attrition consistency an analysis on special cases (0,0.5,1) of risk metrics during every phase of framework has been presented in (Table 3).

Table 3: Special cases of EAI, JS-SAT, EMP-SAT for employee attrition mitigation.

	DE	IA	DIP	EAI
Best	**0**	**0**	**0**	**0.163**
Average	**0.5**	**0.5**	**0.5**	**0.5**
Worst	**1**	**1**	**1**	**0.837**
Employee Attrition Indicator at Initialization and Recognition phase				
	OP-OC	**TR-CG**	**EAI**	**JS-SAT**
Best	**1**	**1**	**0**	**0.92**
Average	**0.5**	**0.5**	**0.5**	**0.5**
Worst	**0**	**0**	**1**	**0.08**
Job satisfaction during mitigation phase				
	APP-CRR	**FLEX-WLB**	**EAI**	**EMP-SAT**
Best	**1**	**1**	**0**	**0.92**
Average	**0.5**	**0.5**	**0.5**	**0.5**
Worst	**0**	**0**	**1**	**0.08**
Employee Satisfaction during mitigation phase				
	JS-SAT	**EMP-SAT**	**EMP-ATT**	
Best	**0**	**0**	**0.92**	
Average	**0.5**	**0.5**	**0.5**	
Worst	**1**	**1**	**0.08**	
Employee Attrition during Mitigation phase				

The following stage is to formulate several suggestive measures based on the analysis carried out in the previous step. These actions will serve as suggestions for reducing staff attrition. These recommendations will help control the risk metrics' values and lessen employee churn in the IT industry when software projects are being developed. As a result, the staff members engaged in the software development process' risk recognition and mitigation phase have the following recommendations made for them.

a) Recognize the change in engagement, performance, absenteeism by taking feedback from employees. Target the threshold of 20% of recognized variables. On the basis of last work documents of company recognized variables will be updated according to organization environmental conditions. Value greater than or equal to 25% will undergo mitigation process, as this will impact on the percentage of employee attrition.

b) On the basis of value of DE (Somewhat, More), DIP (Moderate, Substantial), IA (Moderate, Substantial) in recognition phase based on feedback, interview, past work document, strategies are followed according to the fuzzy rules implemented. If

DE, IA, DIP is more than threshold then EAI will be average and worst.
c) Strategies may be changed throughout the software development life cycle on the basis of organization environment feedback.
d) In this study OP-OC, TR-CG, must be changed during phases of the software life cycle towards 100% for better Job Satisfaction and better reduced employee attrition.
e) In this study APP-CRR, FLEX-WLB must be changed during phases of the software life cycle towards 100% for better Job Satisfaction and better reduced employee attrition.
f) JS-SAT and EMP-SAT both are directly proportional to EMP-ATT (Employee Attrition). density.
g) Job satisfaction and employee satisfaction level must be above 25% for better employee attrition.

In the light of above guidelines, the following recommendations are made to the designer in order to mitigate employee attrition for smooth functioning of all phases of software development process. Continuously monitor the effectiveness of the implemented strategies and adjust the FIS and rules as needed to reflect changes in the organization or industry trends.

4 EMPIRICAL VALIDATION OF THE MMEA

In order to statistically validate the proposed model (MMEA), this section of the work calculates the Pearson's correlation coefficient between the actual employee attrition values, which are already known, and the defuzzified (predicted) values using a model that is used in an IT organization's software development process to reduce employee attrition. The researcher contacted reputable and well-established software development companies in Noida and Lucknow to confirm or validate the model's ability to quantify. The researcher then gathered pertinent data during all phases of software development life cycle of 16 software projects that were already implemented and operating (see appendix). The Table 4 indicate actual data quantified from above mentioned dataset and predicted data from proposed research framework.

Table 4: Actual and predicted values.

PROJECTS	ACTUAL	PREDICTED
1	0.4	0.372
2	0.49	0.473
3	0.4	0.366
4	0.45	0.35
5	0.58	0.5
6	0.39	0.322
7	0.313	0.25
8	0.236	0.2
9	0.45	0.3
10	0.55	0.42
11	0.54	0.42
12	0.7	0.6
13	0.6	0.55
14	0.58	0.52
15	0.45	0.42
16	0.43	0.38

In order to validate the proposed model (MMEA), EMP-ATT has been computed using the fuzzy toolbox of MATLAB, for 16 software projects, those are currently in operation. The related real values and their predicted values are shown in the (Table 4). The Pearson's correlation coefficient between anticipated and actual employee attrition has now been calculated to verify the model's capacity to be quantified.

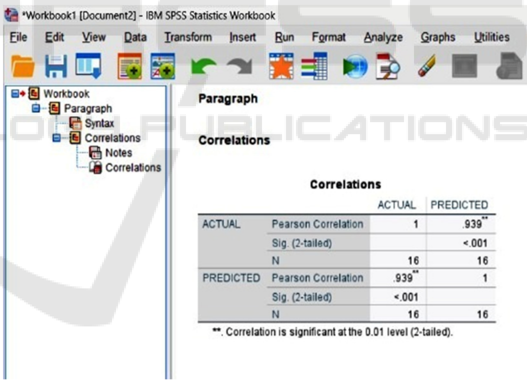


Figure 14: SPSS correlation analysis.

The correlation was calculated using IBM SPSS, and as (Figure 14) illustrates, its value is (0.939). The correlation value makes it clear that there is a substantial association between the employee attrition values that are already known and the attrition that the MMEA predicts and mitigates. As a result, it can be said that the suggested model effectively quantifies staff attrition (Priambodo et al., 2022).

5 RESULTS AND DISCUSSIONS

5.1 Comparison on Employee Attrition Values

Following section is going to briefly describe and quantitatively compare some of those studies on the basis of their relevance with the new Model for Mitigating Employee Attrition (MMEA) in terms of their quantified employee attrition values.

(Archita Banerjee, Rahul Kumar Ghosh, Meghdoot Ghosh, 2017) (Figure 15) contributed to the West Bengal IT sector and developed a model for employee retention. The equation that resulted from the procedure is as follows:

$$Y = 2.897 - 0.864X1 - 0.305X2 + 0.174X3 + 0.630X4 \quad (1)$$

Where, Y denote Possibility of staying in the existing organization, X1 is Uncongenial Organizational Culture, X2 is Insufficient Compensation follows, X3 is Job Satisfaction, X4 is Sociable Organizational Practice

Looking at the table values, it is clear that the MMEA developed in this study predicts and manages the process of reducing employee attrition in the IT industry during the software development process more accurately than the model developed by Archita Banerjee, Rahul Kumar Ghosh, and Meghdoot Ghosh (2017) as (shown in Figure 15).

Quantitative Comparison 1

						Model of this Research	Archita Banerjee, Rahul Kumar Ghosh, Meghdoot Ghosh(2017)
Case study	Projects	OP-OC /Organizational Culture	APP-CRR / Compensation	JS-SAT / Job Satisfaction	EMP-SAT /Organizational Practice	EMP-ATT	Possibility of Employee to stay in organization
1	1	0.65	0.6	0.61225	0.53525	0.38	2.596139
2	2	0.55	0.5	0.52	0.5	0.473	2.67478
3	3	0.4	0.4	0.63	0.54	0.366	2.87922
4	4	0.5	0.6	0.65	0.54	0.35	2.7353
5	5	0.65	0.7	0.5	0.3	0.5	2.3979
6	6	0.65	0.6	0.38	0.7	0.322	2.65952
7	7	0.8	0.75	0.35	0.78	0.247	2.52935
8	8	0.65	0.5	0.65	0.75	0.2	2.7685
9	9	0.45	0.75	0.55	0.7	0.3	2.81615
10	10	0.65	0.45	0.45	0.57	0.42	2.63555
11	11	0.5	0.5	0.46	0.57	0.42	2.75164
12	12	0.65	0.4	0.35	0.4	0.6	2.5263
13	13	0.7	0.6	0.33	0.46	0.55	2.45642
14	14	0.35	0.45	0.49	0.36	0.52	2.76941
15	15	0.65	0.6	0.56	0.38	0.42	2.48924
16	16	0.7	0.45	0.62	0.5	0.38	2.57783

Correlation among risk factors

						Proposed Model	Archita Banerjee, Rahul Kumar Ghosh, Meghdoot Ghosh(2017)	
Case study	Projects	OP-OC /Organizational Culture	APP-CRR / Compensation	JS-SAT / Job Satisfaction	EMP-SAT /Organizational Practice	EMP-ATT	Possibility of Employee to stay in organization	
1	1	0.65	0.6	0.61225	0.53525	0.38	2.60	Archita Banerjee, Rahul Kumar Ghosh, Meghdoot
1	1	0.7	0.75	0.65	0.75	0.203	2.65	Ghosh(2017)- Poosibility of stay increases as job
2	2	0.65	0.6	0.52	0.5	0.473	2.56	Archita Banerjee, Rahul Kumar Ghosh, Meghdoot
2	2	0.7	0.75	0.6	0.6	0.371	2.55	Ghosh(2017)- Poosibility of stay decrease as job

Figure 15: Comparison between proposed model and existing model.

Satpal, Rajbir Singh and Manju Dhillon (2019) provided a model for the constructs that exist in the literature, but only selected dimensions of both constructs are utilized to generate inferences that assist companies in identifying factors that influence attrition intentions. The equation which emerged after the process was as

$$\text{Attrition Intentions (C)} = 4.884 + 0.215 \times \text{HR Factors} + 0.201 \times \text{Personal Factors} + 0.218 \times \text{Job Related Factors} + 0.166 \times \text{Organizational Factors}. \quad (2)$$

The study attempts to investigate and establish a relationship between a number of characteristics that may contribute to retention risks. The study also aims to draw attention to the shift in tactics used to lower staff attrition.

Now looking at the table values it can be easily inferred that the MMEA developed in this research predict and manage the process of mitigation of employee attrition in IT industry during software development process quiet accurately than the model developed by (Satpal and Dhillon, 2019) as (shown in Figure 16).

Quantitative Comparison 2

						Model of this Research Existing Model	Satpal, Rajbir Singh and Manju Dhillon (2019)
Case study	Projects	APP-CRR/ HR factors	FLEX-WLB / Personal factors	JS-SAT / Job related factors	EMP-SAT/ Organizational factors	EMP-ATT	Turnover Intentions
1	1	0.6	0.75	0.61225	0.53525	0.38	5.386072
2	2	0.65	0.65	0.52	0.5	0.473	5.35076
3	3	0.5	0.54	0.63	0.54	0.366	5.32702
4	4	0.75	0.58	0.65	0.54	0.35	5.39317
5	5	0.45	0.45	0.5	0.3	0.5	5.23
6	6	0.6	0.35	0.38	0.7	0.322	5.28239
7	7	0.55	0.65	0.35	0.78	0.247	5.33868
8	8	0.4	0.67	0.65	0.75	0.2	5.37087
9	9	0.72	0.65	0.55	0.7	0.3	5.40555
10	10	0.82	0.55	0.45	0.57	0.42	5.36357
11	11	0.65	0.45	0.46	0.57	0.42	5.3091
12	12	0.85	0.25	0.35	0.4	0.6	5.2597
13	13	0.58	0.85	0.33	0.46	0.55	5.32785
14	14	0.65	0.75	0.49	0.36	0.52	5.34108
15	15	0.6	0.6	0.56	0.38	0.42	5.31876
16	16	0.58	0.6	0.62	0.5	0.38	5.34746

Impact of risk factors on employee attrition and Turnover Intentions in organization with correlation among risk factors

						Proposed Model	Satpal, Rajbir Singh and Manju Dhillon (2019)	
Case study	Projects	APP-CRR/ HR factors	FLEX-WLB / Personal factors	JS-SAT / Job related factors	EMP-SAT/ Organizational factors	EMP-ATT	Turnover Intentions	
1	1	0.6	0.75	0.61225	0.725	0.372	5.4175705	**Satpal, Rajbir Singh and Manju Dhillon (2019)**- Turnover Intention increases as job related factor increases vice versa
1	1	0.7	0.8	0.7	0.8	0.288	5.4807	**MMEA model** - Employee attrition increases as job satisfaction increases vice versa
2	2	0.65	0.65	0.52	0.5	0.473	5.35076	**Satpal, Rajbir Singh and Manju Dhillon (2019)**- Turnover Intention increases as job related factor increases vice versa
2	2	0.68	0.7	0.6	0.55	0.388	5.393	**MMEA model** - Employee attrition increases as job satisfaction increases vice versa

Figure 16: Comparison between proposed model and existing model.

Deepesh Mamtani and Dr. Bharti Malukani (2023) suggested a model that focuses on making precise predictions about employee attrition, needing a suitable dataset for training and validation reasons. The implemented machine learning methods are thoroughly examined, and the results are compiled.

The major goal of this work is to create and apply a prediction model that can effectively forecast staff attrition inside a corporation. Proposed model for employee attrition is expressed in equation which emerged after the process of logistic regression is

$$\text{lnactive\%} = -3.7*\text{satisfaction\_level} + 0.20 * \text{evaluation\_score} + 0.170 * \text{number\_of\_years} + 0.18 \tag{3}$$

The study seeks to investigate and establish a link between numerous elements that may be responsible for retention risk. Furthermore, the study attempts to highlight the shift in techniques used and evolving with the concept of employee engagement to reduce staff attrition. Looking at the table values, it is clear that the MMEA developed in this study predicts and manages the process of reducing employee attrition in the IT industry during the software development process more accurately than the model developed by (Mamtani and Malukani, 2023), as (shown in Figure 17).

Quantitative Comparison 3						
					Model of this Research	Deepesh Mamtani, Dr.
Case study	Projects	FLEX-WLB/	JS-SAT / Satisfactio	EMP-SAT/ No. of years	EMP-ATT	Inactive %
1	1	0.75	0.61225	0.53525	0.38	-1.8443325
2	2	0.65	0.52	0.5	0.473	-1.529
3	3	0.5	0.63	0.54	0.366	-1.9592
4	4	0.52	0.65	0.54	0.35	-2.0292
5	5	0.55	0.5	0.3	0.5	-1.509
6	6	0.45	0.38	0.7	0.322	-1.017
7	7	0.35	0.35	0.78	0.247	-0.9124
8	8	0.65	0.65	0.75	0.2	-1.9675
9	9	0.62	0.55	0.7	0.3	-1.612
10	10	0.52	0.45	0.57	0.42	-1.2841
11	11	0.44	0.46	0.57	0.42	-1.3371
12	12	0.39	0.35	0.4	0.6	-0.969
13	13	0.38	0.33	0.46	0.55	-0.8868
14	14	0.45	0.49	0.36	0.52	-1.4818
15	15	0.44	0.56	0.38	0.42	-1.7394
16	16	0.43	0.62	0.5	0.38	-1.943

Impact of risk factors on employee attrition and Turnover intentions in organization with Correlation among risk factors							
					Proposed Model	Deepesh Mamtani, Dr.	
Case study	Projects	FLEX-WLB/	JS-SAT / Satisfactio	EMP-SAT/ No. of years	EMP-ATT	Inactive%	
1	1	0.5	0.61225	0.54	0.372	-1.9943325	Deepesh Mamtani, Dr. Bharti Malukani (2023)- Inactive% decreases as satisfaction level increases vice versa
1	1	0.6	0.7	0.6	0.16	-2.308	MMEA model - Employee attrition decreases as job satisfaction increases vice versa
2	2	0.65	0.52	0.5	0.473	-1.529	Deepesh Mamtani, Dr. Bharti Malukani (2023)- Inactive% decreases as satisfaction level increases vice versa
2	2	0.72	0.6	0.55	0.388	-1.9465	MMEA model - Employee attrition decreases as job satisfaction increases vice versa

Figure 17: Comparison between proposed model and existing model.

5.2 Measures of Predictive Accuracy

Along with validating a model, guaranteeing its predicted accuracy is a vital component of any models development. Any improvement in the accuracy of employee attrition prediction can have a major impact on the quality of the software product under development. The literature shows that the most popular measures are Magnitude Square Error (MSE), Mean Magnitude of Relative Error (MMRE), Balanced MMRE, Mean Absolute Percentage Error (MAPE), and Prediction at level n (Pred(n)). The researcher used MATLAB fuzzy toolbox to forecast and reduce employee attrition of software projects that are part of the data set by calculating job satisfaction and employee satisfaction during the software development process. Table 5 displays the actual and expected employee attrition values for each of the 16 projects and predictive accuracy of the model through these values.

The MMRE number is highly encouraging, falling significantly below the acceptability criterion of 0.25. Conte et al recommend MMRE ≤ 0.25 accepted as a prediction accuracy for prediction model. The Balanced Mean Magnitude of Relative Error (BMMRE) and Mean Absolute Percentage Error (MAPE) are the next important accuracy metrics to calculate after the MMRE as shown in Figure 18. It is evident from the figures of the several accuracy metrics that the Model for Mitigating Employee Attritions has a reasonably accurate prediction ability. Consequently, the model may be applied to precisely predict, quantify, and reduce employee attrition across the software development process and life cycle. Given that the errors are less than half the difference between two output outcomes, the model's validation showed satisfactory validity.

PROJECTS	ACTUAL	PREDICTED	ERROR	ABS OF ERROR	Square of error	MRE	BMRE	%ERROR
1	0.4	0.372	0.0280	0.0280	0.0008	0.0700	0.0753	7.0000
2	0.49	0.473	0.0170	0.0170	0.0003	0.0347	0.0359	3.4694
3	0.4	0.366	0.0340	0.0340	0.0012	0.0850	0.0929	8.5000
4	0.45	0.35	0.1000	0.1000	0.0100	0.2222	0.2857	22.2222
5	0.58	0.5	0.0800	0.0800	0.0064	0.1379	0.1600	13.7931
6	0.39	0.322	0.0680	0.0680	0.0046	0.1744	0.2112	17.4359
7	0.313	0.25	0.0630	0.0630	0.0040	0.2013	0.2520	20.1278
8	0.236	0.2	0.0360	0.0360	0.0013	0.1525	0.1800	15.2542
9	0.45	0.3	0.1500	0.1500	0.0225	0.3333	0.5000	33.3333
10	0.55	0.42	0.1300	0.1300	0.0169	0.2364	0.3095	23.6364
11	0.54	0.42	0.1200	0.1200	0.0144	0.2222	0.2857	22.2222
12	0.7	0.6	0.1000	0.1000	0.0100	0.1429	0.1667	14.2857
13	0.6	0.55	0.0500	0.0500	0.0025	0.0833	0.0909	8.3333
14	0.58	0.52	0.0600	0.0600	0.0036	0.1034	0.1154	10.3448
15	0.45	0.42	0.0300	0.0300	0.0009	0.0667	0.0714	6.6667
16	0.43	0.38	0.0500	0.0500	0.0025	0.1163	0.1316	11.6279
					0.1018	0.1489	2.9642	238.2530

MSE(Mean Square Error)	0.006363625	
RMSE(Root Mean Square Error)	0.079772332	
MMRE/MPE(Mean Magnitude of relative error/Mean percentage error)	0.009306758	
BMMRE(Balanced MMRE)	0.185262887	
MAPE(Mean Absolute percentage error)	14.89081323	
PREDICTION AT LEVEL 0.25 Pred(0.25)	93.75	93.75% of predicted EMP-ATT value by EAMM have MRE's less than or equal to 0.25

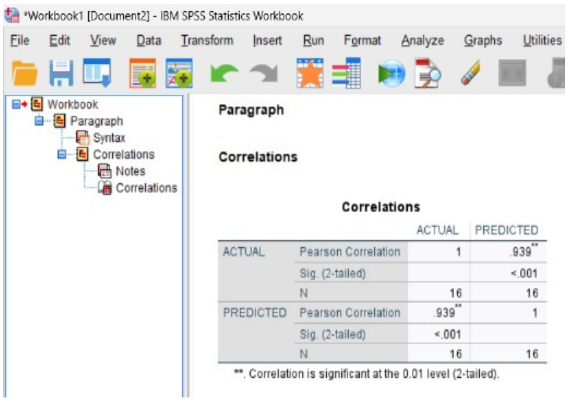
Figure 18: Measures of Predictive Accuracy for MMEA Model.

Looking at the values of various accuracy measures, it is evident that prediction ability of the Employee Attrition Mitigation Model is quiet accurate. Therefore, it can be concluded that the model can be used to accurately predict, track and mitigate employee attrition during software development life cycle during software development process. The errors validated by the model exhibited satisfactory validity, as they are less than half the distance between two output results (Nikmanesh,2023).

5.3 Comparison on Correlation Coefficient

The researcher has computed the Pearson's Correlation Coefficient between the predicted values of employee attrition (through the proposed model; Archita Banerjee, Rahul Kumar Ghosh, Meghdoot Ghosh (2017); Satpal, Rajbir Singh and Manju Dhillon (2019); Deepesh Mamtani, Dr. Bharti Malukani (2023)) and the actual values of the employee attrition. Looking at the values of following table it can be easily noticed that the proposed model in this research has a very High Positive Correlation, While the research work done by Archita Banerjee, Rahul Kumar Ghosh, Meghdoot Ghosh(2017) has High Negative Correlation, and the work done in the same area by Satpal, Rajbir Singh and Manju Dhillon (2019) has a Moderate Negative Correlation, and research study by Deepesh Mamtani, Dr. Bharti Malukani (2023) produces Moderate Positive Correlation (Figure 19 –Figure 22).

Proposed Model Pearson's Correlation Coefficient Measure



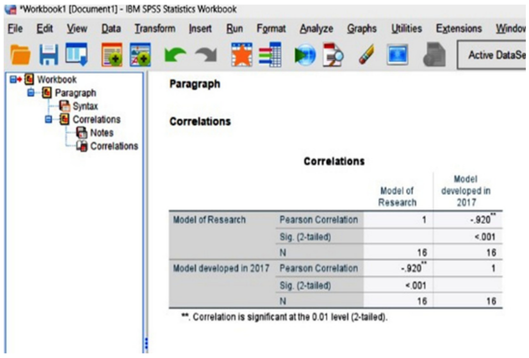
Correlations

		ACTUAL	PREDICTED
ACTUAL	Pearson Correlation	1	.939**
	Sig. (2-tailed)		<.001
	N	16	16
PREDICTED	Pearson Correlation	.939**	1
	Sig. (2-tailed)	<.001	
	N	16	16

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 19: Correlation analysis of proposed model.

Archita Banerjee, Rahul Kumar Ghosh, Meghdoot Ghosh (2017) Pearson's Correlation Coefficient measure (Banerjee et al., 2017)



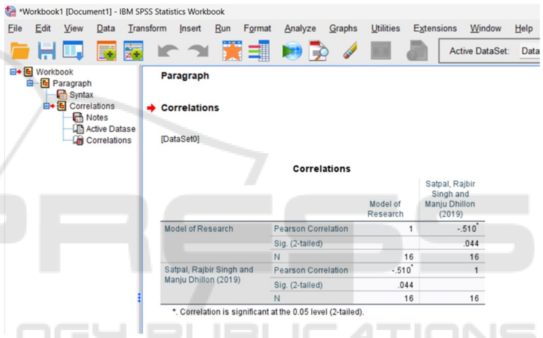
Correlations

		Model of Research	Model developed in 2017
Model of Research	Pearson Correlation	1	-.920**
	Sig. (2-tailed)		<.001
	N	16	16
Model developed in 2017	Pearson Correlation	-.920**	1
	Sig. (2-tailed)	<.001	
	N	16	16

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 20: Correlation analysis of model developed in 2017.

Satpal, Rajbir Singh and Manju Dhillon (2019) Pearson's Correlation Coefficient measure (Satpal and Dhillon, 2019)



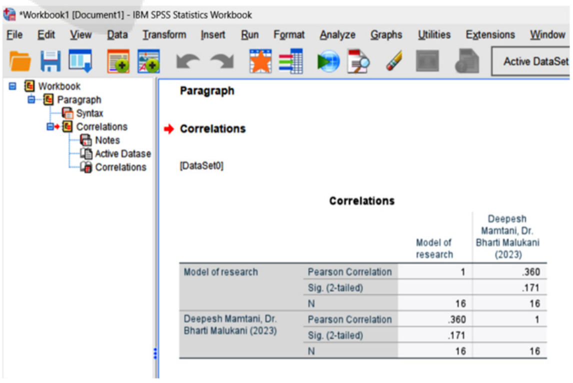
Correlations

		Model of Research	Satpal, Rajbir Singh and Manju Dhillon (2019)
Model of Research	Pearson Correlation	1	-.510*
	Sig. (2-tailed)		.044
	N	16	16
Satpal, Rajbir Singh and Manju Dhillon (2019)	Pearson Correlation	-.510*	1
	Sig. (2-tailed)	.044	
	N	16	16

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 21: Correlation analysis of model developed in 2019.

Deepesh Mamtani, Dr. Bharti Malukani (2023) Pearson's Correlation Coefficient (Mamtani and Malukani, 2023)



Correlations

		Model of research	Deepesh Mamtani, Dr. Bharti Malukani (2023)
Model of research	Pearson Correlation	1	.360
	Sig. (2-tailed)		.171
	N	16	16
Deepesh Mamtani, Dr. Bharti Malukani (2023)	Pearson Correlation	.360	1
	Sig. (2-tailed)	.171	
	N	16	16

Figure 22: Correlation analysis of model developed in 2023.

Table 5: Correlation levels of proposed model with other models.

S. No.	Employee Attrition Model	Pearson's Correlation Coefficient	Correlation level
1	Archita Banerjee, Rahul Kumar Ghosh, Meghdoot Ghosh(2017) (Figure 20)	-920	High Negative
2	Satpal, Rajbir Singh and Manju Dhillon (2019) (Figure 21)	-510	Moderate negative
3	Deepesh Mamtani, Dr. Bharti Malukani (2023) (Figure 22)	0.360	Low positive
4	Proposed Model(MMEA) (Figure 19)	0.939	High Positive

Therefore, it can be concluding that the model (MMEA) of this research is better than the three existing models, on the basis of quantitative values (Table 5).

6 CONCLUSION AND FUTURE EXTENSION

This study could serve as the basis for future research for risk mitigation in software organizations. The framework is quite prescriptive in nature, and will definitely facilitate industry professionals and researchers to recognize and reduce employee attrition during software development life cycle process of software development in IT industry. Consideration of the employee attrition indicator along with employee attrition effected by other risk factors on the basis of its value is an edge over other studies those are based on only prediction and considering employee data because ignoring or overlooking indicator factors and only concentrating on making the risk metrics will not seem good enough.

The MMEA model developed as per the guidelines of the proposed framework in analysis and finalization phase in section 4 may help software professionals to take appropriate corrective measures right from starting phase and continuing towards other phases on the basis of immune theoretical concept of primary measures and secondary measures to help designers as well as developers to predict and reduce employee attrition during software development process in the software development life cycle with an improved efficiency and quality level. The research has utilized the strength of fuzzy inference process in building model. The assessment and amendment of the framework further strengthens it practicality as well as viability by keeping the doors of improvement open for any of the earlier phases. In most of the cases, developed models only provide quantitative values but neither provides suggestions on how to make improvement, nor the precautions on how to avoid abnormalities. Therefore, to fill this gap research has provided the suggestive measures and recommendations based on the results and contextual interpretations.

Apart from the above, reassessment of previously developed or underdevelopment employee attrition models could be done as per the guidance proposed as well as recommendation in this study (Gupta, 2022), (Wardhani and Lhaksmana, 2022), (Udechukwu and Mujtaba, 2007). Beside this, as far as further research is concern, the model may open fresh avenues for the researchers, doing research on employee attrition estimation as well as dealing with strategies to overcome employee attrition. Validating and testing the suggested risk mitigation procedure against other common risk factors occur during Software development life cycle in an actual setting is one way to conduct additional.

ACKNOWLEDGEMENTS

I would like to express my special thanks of gratitude to Dr. Wajahat Abbas Rizvi as well as Dr. Vinodani Katiyar who helped me to do this wonderful research work, which also helped me in doing a lot of Research and I came to know about so many new things I am really thankful to them.

Secondly I would also like to thank my family and friends who helped me a lot in finalizing this study within the limited time frame.

REFERENCES

H Shihadeh, T. (2014). Risk Factors in Software Development Phases. *European Scientific Journal*, *10*, 213–231.

Raza, A. (2022). Predicting Employee Attrition Using Machine Learning Approaches. *Applied Sciences*, *12*(13).

Banerjee, A. (2017). A Study on the Factors Influencing the Rate of Attrition in IT Sector Based on Indian Scenario. *Pacific Business Review International*, *9*, 10–19.

Satpal, S., & Dhillon, M. (2019). Impact of Factors Affecting Employee Retention on Attrition Intentions: In Indian IT Sector. *International Journal on Emerging Technologies*, *10*(4), 273–282.

Mamtani, D., & Malukani, B. (2023). Predictive Model for Employee Attrition Risk Assessment. *European Economic Letters (EEL)*, *13*(1s), 358–364.

Yadav, H. B., & Yadav, D. K. (2015). A Fuzzy Logic Based Approach for Phase- Wise Soft-Ware Defects Prediction Using Software Metrics. *Information and Software Technology*, *63*, 44–57.

Nikmanesh, M. (2023). Employee Productivity Assessment Using Fuzzy Inference System. *Employee Productivity Assessment Using Fuzzy Inference System. Information*, *14*.

Ahmed, I. (2013). Employee Performance Evaluation: A Fuzzy Approach. *International Journal of Productivity and Performance Management*, *62*, 718–734.

Sharma, M. K. (2022). Employee Retention and Attrition Analysis: A Novel Approach On Attrition Prediction Using Fuzzy Inference and Ensemble Machine Learning. *Webology*, (2).

Urs, N. S. (2014). Exploring the Dynamics of Job Satisfaction and Employee Engagement in IT/ITes Industries. *Journal of Applied Management and Investments*, *3*(1).

Kannan, M., & Vivekanandan, K. (2012). *Study on Attrition among New Entrants in Soft-Ware Testing Professionals*.

Demirel, Z., & Çubukçu, C. (2021). Measurement of Employees on Human Resources with Fuzzy Logic. *EMAJ: Emerging Markets Journal*, *11*, 1–7.

Gupta, Santosh & Bhatia, Dr. Nitesh. (2023). A Decade of Trend in the Employee Turnover Intention Study in India: A Systematic Review and Recommendation. FIIB Business Review. 10.1177/23197145231158907.

Bukohwo, E. M. (2015). Risk Model for Software Development Personnel. *Proceedings of the International Multi Conference of Engineers and Computer Scientists*, *1*.

Jiang, R. (2015). A Novel Risk Metric for Staff Turnover in a Software Project Based on Information Entropy. *Software Project Based on Information Entropy: Entropy*, *17*, 2834–2852.

Díaz, G. (2023). Analysing Employee Attrition Using Explainable AI for Strategic HR Decision-Making. *Mathematics*, *11*.

Gupta, S. K. (2022). A Review of Employee Attrition Models and Their Role in Evolution of Attrition Literature. *The Indian Journal of Labour Economics*, *65*(1), 185–214.

Govindaraju, N. (2018). Addressing Employee Turnover Problem: A Review of Employee Turnover Core Models. *International Journal of Innovative Science and Research Technology*, *11*, 516–527.

Srivastava, P. R., & Eachempati, P. (2021). Intelligent Employee Retention System for Attrition Rate Analysis and Churn Prediction: An Ensemble Machine Learning and Multi-Criteria Decision-Making Approach. *Journal of Global Information Management (JGIM)*, *29*(6), 1–29.

El-Rayes, N. (2020). Predicting Employee Attrition Using Tree-Based Models. *International Journal of Organizational Analysis*, *28*(6), 1273–1291.

Priambodo, Bagus & Jumaryadi, Yuwan & Rahayu, Sarwati & Ani, Nur & Ratnasari, Anita & Salamah, Umniy & Putra, Zico & Otong, Muhamad. (2022). Predicting Employee Turnover in IT Industries using Correlation and Chi-Square Visualization. International Journal of Advanced Computer Science and Applications. 13. 10.14569/IJACSA.2022.0131210.

Wardhani, F. H., & Lhaksmana, K. M. (2022). Predicting Employee Attrition Using Logistic Regression with Feature Selection. Sinkron: Jurnal Dan Penelitian Teknik Informatika, 6, 2214–2222.

Priya, V. K., & Harasudha, H. H. (2017). A Study on Employee Attrition with Reference to Lanson Toyoya, Chennai. Chennai. Man in India, 97, 115–124.

Udechukwu, I. I., & Mujtaba, B. G. (2007). Determining the Probability That an Employee Will Stay or Leave the Organization: A Mathematical and Theoretical Model for Organizations. Human Resource Development Review, 6(2), 164–184.

Eyupoglu, S. Z. (2017). Job Satisfaction: An Evaluation Using a Fuzzy Approach. Procedia Computer Science, 120, 691–698.

Thirupathy, A., & Dhayalan, C. (2016). Employee Retention and Turnover Using Motivational Variables at India. Int. J. Res. Granthaalayah, 4(8), 1–9.

Purohit, M. (2016). A Study On-Employee Attrition in IT Sector with Special Emphasis on Wipro and Infosys. IOSR Journal of Business and Management, 18(4), 47–51.

Singh, R., & Satpal, M. (2018). Factors Affecting Employee Retention in Indian IT Sector.

Abhyankar, A. (2021).: Indian IT Industry: High Attrition Rates and Employee Retention Strategies. Webology, Vol 18, No.1, 2023-2029

Teotia, S. (2023). Factors Affecting Employee Retention: An Analysis of It Sector in Delhi-NCR (pp. 94–98). Noble Science Press.

Harikumar Pallathadka, V. H. (2022). Attrition in Software Companies: Reason and Measures. Materials Today: Proceedings, 51, 528–531.

Saraf, V., & Peshave, D. M. A. (2020). An Analysis on Employee-Attrition in IT Industry. Mukt Shabd Journal.

Rusi, X., & Viollet, B. (2023). Factors Affecting Employee Attrition: A Systematic Literature Review. Economic Restructuring for Sustainable Development.

Singh, K., & Singh, R. (2019). A Study on Employee Attrition: Effects and Causes. International Journal of Research in Engineering, 2(8), 2581–5792.

David, S. (2015). Attrition in IT Sector. International Journal of Core Engineering and Management (IJCEM), 2(1), 74–92.

Kermani, A. G. (2021). Human Resource Risk Management Framework and Factors Influencing IT. Propósitos y Representac-Iones, 9.

Popescu, S. (2020). A Structured Framework for Identifying Risks Sources Related to Human Resources in a 4.0 Working Environment Perspective. 511–527.

Chauhan, V. S., & Patel, D. (2013). Employee Attrition: A Factorial Study of IT Industry. Journal of Strategic Human Resource Management, 2(1).

Saher, N. (2015). The Impact of Employees Attrition at the Productivity of a Software. International Journal of Natural and Engineering Science, 9(3), 23–37.

Rizvi, S. W. A., Singh, V. K., & Khan, R. A. (2017). Early stage software reliability modeling using requirements and object-oriented design metrics: fuzzy logic perspective. International journal of computer applications, 162(2), 44-59.

Patil, R. S. (2011). Human Resource Challenges & Practices in IT Industry. In Proceedings of the 5th National Conference (pp. 10–11).

Prasad, A., & Kamalanabhan, P. (2010). Human Resource Excellence in Software Industry in India: An Exploratory Study. International Journal of Logistics Economics and Globalization, 2(4), 316–330.

Flouris, T., & Yilmaz, A. K. (2010). The Risk Management Framework to Strategic Human Re-Source Management. International Research Journal of Finance and Economics, 36(1), 25–45.

Alqahtani, Haya & Almagrabi, Hana & Alharbi, Amal. (2024). Employee Attrition Prediction using Machine Learning Models: A Review Paper. International Journal of Artificial Intelligence & Applications. 15. 23-49. 10.5121/ijaia.2024.15202.

George, S. (n.d.). Predicting Employee Attrition Using Machine Learning Algorithms. 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N).

Almohammadi, K. (2024). Adaptive Type-1 Fuzzy Logic-Based System for Predicting Em-Ployee Attrition. International Journal of Intelligent Systems and Applications in Engi-Neering, 12(21s).

Shete, M. (2021). Prediction of Employee Attrition Using Machine Learning Approach. Inter-National Journal for Research in Applied Science and Engineering Technology, (9).

Bormah, A., Taylan, O. Productivity Forecasting of Employees Performance Using Machine Learning and Adaptive Neuro-Fuzzy Inference System. International Journal of Science, Engineering and Technology. 11.

Arslankaya, Seher. (2023). Comparison of performances of fuzzy logic and adaptive neuro-fuzzy inference system (ANFIS) for estimating employee labor loss. Journal of Engineering Research. 11. 100107. 10.1016/j.jer.2023.100107.

Hasib, N., Rizvi, S. W. A., & Katiyar, V. (2023). Artificial Immune System: A Systematic Literature Review. Journal of Theoretical and Applied Information Technology, 101(4), 1469–1486.

Hasib, Nida, Rizvi, S. W. A., & Katiyar, V. (2024). Conceptual framework for risk mitigation and monitoring in software organizations based on artificial immune system. In Lecture Notes in Networks and Systems. Lecture Notes in Networks and Systems (pp. 25–37). doi:10.1007/978-981-97-7423-4_3

Hasib, N., Rizvi, S. W. A., & Katiyar, V. (2023). Biological immune system based risk mitigation monitoring system: An analogy. International Conference on Artificial Intelligence, Blockchain, Computing and Security ICABCS 2023, Volume 1 (pp. 760-767). CRC Press. DOI.10.1201/9781003393580-113.

Hasib, N., Rizvi, S. W. A., & Katiyar, V. (2023). Risk Mitigation and Monitoring Challenges in Software Organizations: A Morphological Analysis. International Journal on Recent and Innovation Trends in Computing and Communication, 11(8), 172–185. https://doi.org/10.17762/ijritcc.v11i8.7943.

Hasib, N., Rizvi, S. W. A., & Katiyar, V. (2025). A Review of Risk Factors Affecting Employee Attrition in IT Sector. 5th International Conference on Paradigms of Communication, Computing and Data Analytics (PCCDA 2025), 18 Jan – 20 Jan, Pt. Lalit Mohan Sharma Campus, Rishikesh, Sri Dev Suman Uttarakhand University, Uttarakhand, India. (Accepted and preseted)(Unpublished).

APPENDIX

The questionnaires used for conducting the qualitative exploratory study and quantitative descriptive study are listed in this section.

Appendix A1	Qualitative Exploratory Study(In-depth Interviews/Work Document)
Appendix A2	Quantitative Descriptive Survey -Risk Factor Ranking
Appendix B1	▪ Pre-Intervention Questionnaire for Validation of Employee Attrition Mitigation Framework in Software Development Projects during SDLC
Appendix B2	▪ Post Intervention Questionnaire for Validation of Employee Attrition Mitigation Framework in Software Development Projects during SDLC
▪ Part I	1) Outcome Assessment of the Framework in Terms of Predicted Value
▪ Part II	2) Qualitative Reviews