Research Article

Analysis of Employee Satisfaction using Artificial Neural Networks: A Case Study in the Information Technology Industry in Sri Lanka

I.U. Hewapathirana* and W.A.S.M.S. Thilakarathna

**ihewapathirana@kln.ac.lk*

Software Engineering Teaching Unit, Faculty of Science, University of Kelaniya, Sri Lanka

Abstract

Job satisfaction is vital to the prosperity of all industries, including the information technology (IT) sector. This research represents the pioneering attempt to employ Artificial Neural Networks (ANNs) for the purpose of examining the factors that affect job satisfaction among IT professionals in Sri Lanka. Data was gathered from a survey of 156 IT professionals and was analyzed statistically to identify seven factors that influence job satisfaction. An ANN was trained to predict job satisfaction using the extracted factors as inputs. The accuracy of the model in predicting job satisfaction was 94.64%. This suggests that ANNs have the potential to identify critical factors for IT employees and target interventions to increase their satisfaction. Additional research on the fitted ANN revealed that working conditions, family-friendly policies, and level of autonomy at work are crucial factors in determining a person's job satisfaction. Employers can use our findings to increase employee satisfaction by implementing appropriate policies. In addition, our ANN model can used to identify employees who are likely to leave and to provide them with customized interventions.

Keywords*: Artificial neural networks, IT industry, Job satisfaction, Sri Lanka*

1. Introduction

Job satisfaction plays a significant role in the overall well-being of employees. IT professionals often face high levels of stress due to tight deadlines, complex problem-solving, and the constant need to keep up with technological advancements. In this regard, satisfaction is critical for the long-term retention, dedication, and loyalty of IT professionals to the organization, as well as the establishment of an inspiring and productive work environment (Moro *et al., 2021*). Furthermore, the IT sector in Sri Lanka is expanding quickly, creating a significant need for skilled IT experts. The current job market is highly competitive, and companies are seeking strategies to both recruit and maintain high-performing employees (Kalyani, 2021). Thus, understanding the factors that contribute to employee satisfaction is a crucial strategy. According to (Yanchovska, 2021) the most significant factors influencing job satisfaction of IT professionals are opportunities to improve professional qualifications, gain new skills and knowledge, become more competitive, and have free time for personal life. (Hettiarachchi, 2014) also states that job satisfaction in terms of salary, promotion, supervision, and work aspects has an impact on job performance, and there are positive connections between job performance and these four factors. (Nan Hu *et al.*, 2004) found that IT professionals are more satisfied if their jobs are more aligned with company strategy and if their jobs give them recommending and decision power. According to the research by (Calisir and Gumussoy, 2007), certain work characteristics, such as job autonomy and task variety, can have a favorable effect on job satisfaction. This, in turn, may enhance an individual's problem-solving capabilities. Overall, organizations capable of addressing these factors are more inclined to possess satisfied employees.

Prior research on the satisfaction of IT employees utilized various statistical techniques to examine the data. For example, both (Mahmood *et al.*, 2000) and (Mehmood and Hussain, 2017) collected data on IT employees from numerous Chinese IT firms from Beijing and used hierarchical linear modeling (HLM) to examine the relationship between the life stress experienced by IT employees and their job satisfaction levels. Data was gathered from a sample size of 110 participants in (Cherukur and Soundariya, 2021) and the collected information was then subjected to analysis through the use of descriptive statistical techniques in the SPSS software. In (Al-Shammari, 2021) confirmatory factor analysis was utilized to develop a six-factor structural equation model for assessing the degree of satisfaction among IT employees in Kuwait.

Artificial neural networks (ANNs) represent a category of machine learning algorithms that can find complex patterns from data. The suitability of ANN models for predicting employee satisfaction is noteworthy, particularly when compared to conventional statistical models that are challenged by the complexity of the phenomenon, which can be affected by a variety of factors (Kirby *et al.*, 1998). Several researchers have employed ANN models to predict employee satisfaction with high accuracy. For example, (Rustam *et al.*, 2021) discovered that a deep learning model outperformed other machine learning algorithms for predicting employee job satisfaction using text evaluations from employees of key technology companies. Similarly, (Yao and Zhang, 2021) discovered that an artificial neural network had a faster convergence speed and a superior overall prediction accuracy. (Tian and Pu, 2008a) analysed the factors influencing hotel employee satisfaction in China using an artificial neural network and discovered that professional development opportunities and long-term growth prospects were the most significant contributors to employee satisfaction. These studies indicate that neural networks are a promising technique for predicting employee satisfaction.

Despite the abundance of research on factors influencing job satisfaction among employees, there exists a limited number of studies conducted within the Sri Lankan IT industry. Moreover, to the best of our knowledge, no research in the field have utilized ANNs. The present study aims to address the aforementioned gap in the literature by employing a combination of statistical analysis and artificial intelligence techniques to identify the factors that affected job satisfaction in the field of IT in Sri Lanka.

The remaining sections of the paper are organized as follows. Section 2 outlines the methodology employed in this study, including data collection procedures, design of the research, and a description of the ANN model. Section 3 presents the results and findings of the study, including the identification of key factors influencing job satisfaction among IT professionals in Sri Lanka and the evaluation of the ANN model's accuracy in predicting job satisfaction. Section 4 discusses the implications of the findings, highlighting their significance for employers in the IT industry and offering practical recommendations for enhancing employee satisfaction and retention. Finally, Section 5 concludes the paper by summarizing the key findings, highlighting the contributions of this research, and suggesting directions for future studies in the field of employee satisfaction and the application of ANNs in organizational settings.

2. Material and Methods

In this section, we outline the methodology undertaken to collect data, analyze the collected information, and train the Artificial Neural Network (ANN) model. The two main research questions (RQs) of our study are as follows:

RQ1: What factors influence Sri Lankan IT employees’ job satisfaction?

RQ2: What are the impacts of different demographic factors on Sri Lankan IT employees' job satisfaction?

We collect data for two months by distributing an online questionnaire to employees working on various job roles in the IT sector. Samples were selected based on the convenience sampling method. The questionnaire consisted of three main parts. The first part included questions that collected demographic information of the respondent. The second part consisted of Likert-scale questions. Likert scale ranging from 1 – Extremely Dissatisfied or Strongly Disagree to 5– Extremely Satisfied or Strongly Agree was used. The second part included questions that evaluated the stress level of employees during various phases of project completion, employees' engagement with family and society, and satisfaction towards various aspects such as job title, company culture, salary, type of work conducted, number of benefits, and country of residence. The third part consisted of the final question on overall job satisfaction. This question had only two responses 'yes' or 'no' and was used as the dependent variable when training the ANN.

Overall, we received 159 responses. After validating the responses, we selected 156 responses for the analysis. We performed data coding in Microsoft Excel and convert open-ended responses and text variables into numeric variables. The preprocessed dataset was loaded into the statistical software SPSS. SPSS 22 software was used to perform the descriptive analysis and exploratory factor analysis. Demographic variables in part one of the questionnaire were summarized using counts and percentages and Lickert-scale variables were summarized using means and standard deviations. Prior to performing factor analysis, Lickert-scale validation was assessed using the Cronbach alpha test. Then, the Bartlett Test (Bartlett Test of Sphericity) and the KMO (Keyser – Meyer – Olkin Measure of Sampling Adequacy) tests were first conducted to assess the suitability of the dataset to perform a factor analysis. After that, exploratory factor analysis was performed using maximum likelihood and Varimax rotation (with Kaiser Normalization) and factors that had eigen-value greater than one were retained and analyzed in order to answer RQ1. Then, the extracted factors were used as input variables for the ANN model. This way, employee satisfaction is predicted using continuous-valued input variables. Since employee satisfaction is a psychological emotion with fuzzy characteristics, this is a more accurate method for satisfaction prediction than utilizing the original discrete input variables (Tian and Pu, 2008a). Python programming language was used to train the ANN and obtain predictions. The trained ANN was then further explored and analyzed to answer RQ2.

2.1 Artificial Neural Networks (ANN)

An artificial neural network (ANN) is a machine-learning model inspired by the structure and function of the human brain. ANNs are made up of interconnected nodes, called neurons, which process information and pass it on to other neurons. The connections between neurons are weighted, and the strength of these weights determines how much information is passed on. Considering the lth layer, the mathematical equation of an artificial neural network model is:

$$y_l = f_l(w_l^T x_l + b_l),$$

where y_l is the output of the layer, f_l is the activation function, w_l is the weight vector, x_l is the input vector, and b_l is the bias term. The activation function is a non-linear function that helps the neural network learn complex relationships between the input and output data. The weight vector and the bias term are parameters that are learned during the training process. The weight vector determines how much weight is given to each input, and the bias term adds a constant offset to the output of the neural network.

The neural network is trained by minimizing the error between the predicted output and the actual output. This is done using a technique called backpropagation. Backpropagation is an iterative process that adjusts the weights and bias terms of the input, hidden, and output layers of the neural network until the error is minimized. Here, the error is the difference between the actual values of the output layer nodes and the values predicted by the network. The relationship between overall employee satisfaction and its factors is nonlinear. Therefore, it is appropriate to use an ANN to estimate employee satisfaction.

3. Results

3.1 Preliminary Analysis

Among the 156 IT employees who participated in the survey, 140 (90%) expressed job satisfaction, whereas 16 (10%) reported job dissatisfaction. Table 1 shows the distribution of the age of the survey respondents according to gender. According to the table, the majority of respondents of this survey were aged below 30, where males aged between 24-28 years were the category with the highest number of responses. Also, our analyses on job experience level (Table 2) show that 67 of the respondents were working as interns. According to Figure 1, more than 80% of the respondents possessed a bachelor's degree. Employees working in various job roles participated in our survey. Among them, most were related to software development and earning less than $5000 per year (Table 3). Table 4 shows the distribution of the respondents' working culture with country of origin. Among our respondents, 146 were from Sri Lanka, 3 from India, 3 from the UK, 1 from Russia, 1 from Ireland, 1 from New Zealand, and 1 from Moldova. The majority of respondents from all countries were working from home while a considerable number of respondents from Sri Lanka were also working hybrid.

Table 1: Gender vs age cross-tabulation

		Age					Total
		19-24	24-28	28-35	35-45	Above 45	
Gender	Male	23	67	7	4	1	102
	Female	7	38	5	3	1	54
Total		30	105	12	7	2	156

Table 2: Job experience level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Internship	67	42.9	42.9	42.9
	Less than 2 Years	34	21.8	21.8	64.7
	2-5 Years	37	23.7	23.7	88.5
	5-10 Years	8	5.1	5.1	93.6
	More than 10 Years	10	6.4	6.4	100.0
	Total	156	100.0	100.0	

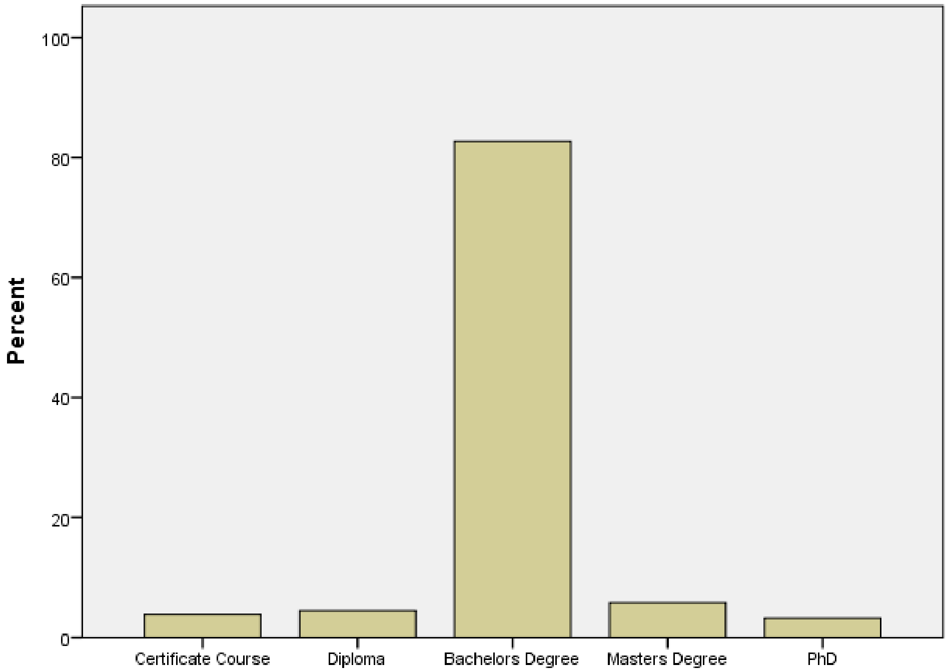

Figure 1: Distribution of educational qualifications

Table 3: Job role vs annual salary crosstabulation

		Annual salary							
		Less than $1000	$1000 - $5000	$5000 - $10000	$10000 - $25000	$25000 - $50000	$50000 - $100000	More than $100000	Total
Job role	IT Supporters	7	0	1	0	1	0	1	10
	Testers	3	2	0	1	1	0	0	7
	Developers	42	26	13	10	3	1	0	95
	Security	1	2	0	0	0	0	0	3
	Designers	4	1	0	1	0	0	0	6
	Data Engineers	5	4	1	3	0	0	1	14
	Others	6	10	2	3	0	0	0	21
Total		68	45	17	18	5	1	2	156

Table 4: Working culture vs country crosstabulation

		Country							Total
		Sri Lanka	India	UK	Russia	Ireland	New Zealand	Moldova	
Working culture	Work from Home	75	2	2	1	0	0	0	80
	Work from Office	17	0	1	0	0	0	0	18
	Hybrid	54	1	0	0	1	1	1	58
Total		146	3	3	1	1	1	1	156

3.2 Factor Analysis

Table 5 contains the means and standard deviations for the 24 independent variables considered for our study. The statistics show that most of the mean scores range around 3 with relatively small standard deviations. This indicates that most employees have medium estimating scores and that the scores are generally concentrated. Most employees disagree about experiencing stress after the project. Also, respondents who were mainly young people aged below 30 years have disagreed on receiving complaints from partner (V5) or society (V9). The results show high agreement on looking for further learning (V24). The respondents are considerably satisfied with the living country (V15) and are similarly interested in moving to another country to try out better opportunities (V13).

After exploring the 24 input variables, the internal consistency and reliability of the Likert-scale questions were assessed by performing Cronbach's alpha tests. Two tests were performed by separating questions into two groups. That is, (i) questions that measure agreement and (ii) questions that measure satisfaction. The results of the tests indicate that the 15 questions employed for assessing employees' level of agreement were properly selected and indicate an adequate level of internal consistency (α = .612). Similarly, the nine questions that assess an individual's satisfaction on various aspects also exhibit a notable degree of internal consistency (α = .678) (Taber, 2018). Next, factor analysis is carried out to identify the hidden factors from these 24 variables. This way, the noise will be removed, and the same information contained within a large number of original input variables will be concentrated on a small number of factors that can be used for further analysis.

Table 5: Summary statistics for independent variables of the study

	Mean	Standard deviation
Experience on stress during a project (V1)	3.26	.866
Experience stress after the project (V2)	1.92	.834
Can focus on other work during a project (V3)	3.27	1.092
Experience stress near project due dates (V4)	3.63	1.030
Received complaints from partner (V5)	2.36	1.249
Missed a family event (V6)	2.69	1.254
Receive family support (V7)	3.58	1.329
Have work after work hours (V8)	3.40	1.259
Received complaint from society (V9)	2.35	1.189
Have missed a social event (V10)	2.51	1.247
Manage time for extra activities (V11)	2.83	1.212
Provide financial contribution for society (V12)	3.03	1.086
Considered moving to another country (V13)	3.62	1.317
Considered working remotely in another country (V14)	3.94	1.154
Satisfaction with currently living country (V15)	3.65	1.212
Satisfaction with company benefits (V16)	3.30	1.161
Satisfaction with amount of workload (V17)	3.12	.977
Satisfaction with value and recognition (V18)	3.28	1.105
Consider salary increase (V19)	2.50	1.242
Satisfaction with salary compared to competitors (V20)	2.96	1.267
Satisfaction with salary for position (V21)	2.90	1.235
Satisfaction with salary to cover expenses (V22)	2.76	1.250
Satisfaction with job position (V23)	3.61	1.105
Looking for further learning (v24)	4.13	1.017

The next step in the analysis was to determine if the samples were suitable for doing factor analysis. Accordingly, the Bartlett Test (Bartlett Test of Sphericity) and the KMO Test (Kaiser-Meyer-Olkin Measure of Sampling Adequacy) are performed. Typically, statistical significance is attributed to levels of 0.01 for the Bartlett test and 0.7 for the KMA test (Peck *et al.*, 2019). For the present study, the samples exhibit a chi-squared value of 0.000 (< 0.01) and a KMO value of 0.732. This is indicative of a correlation between the variables and hence suitable for performing factor analysis. Table 6 displays seven factors that were generated through factor analysis. These factors exhibited eigenvalues exceeding 1.0. The seven components together accounted for 64.16% of the total variance of the samples.

Table 6: Results of the factor analysis

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.457	18.571	18.571	3.374	14.057	14.057
2	3.640	15.167	33.738	2.965	12.353	26.411
3	2.193	9.139	42.877	2.097	8.735	35.146
4	1.533	6.389	49.266	1.980	8.249	43.396
5	1.262	5.258	54.524	1.959	8.161	51.557
6	1.210	5.040	59.564	1.734	7.225	58.783
7	1.104	4.600	64.165	1.292	5.382	64.165

The factor rotation method used was varimax with Kaiser Normalization. After observing the factor loading matrix produced by SPSS, the factors were named after the variables loading above 0.50 or below -0.50 with the corresponding factor. These descriptions are provided in Table 7.

Table 7: Factor descriptions

Factor	Factor Name and Its Related Variables
F1	Monetary and spiritual benefits (V16, V20, V21 and V22)
F2	Leisure time for personal pursuits (V5, V6, V9 and V10)
F3	Opportunities to improve professional qualifications (V23 and V24)
F4	Working conditions (V13, V14, and V15)
F5	Family-friendly policies (V7, V11, and V19)
F6	Support from peers (V1 and V4)
F7	Level of autonomy during work (V2 and V3)

Identifying and assigning names to various factors requires a combination of scientific and creative efforts (Tian *et al.*, 2008). The variables that depict a higher factor load for each variable are selected, and the shared characteristics of those variables are identified and subsequently used to label the factors. Factor 1 is highly loaded on variables V16, V20, V21 and V22 that describe satisfaction with the monetary and other motivating benefits offered by the company. Hence, Factor 1 is named as *monetary and spiritual benefits*. Factor 2 is mainly correlated with V5, V6, V9 and V10 variables which describe the ability to participate in family and social events. Hence, Factor 2 is named as *leisure time for personal pursuits*. Variables V23 and V24 comprises Factor 3 and describe career advancement opportunities, also known as *opportunities to improve professional qualifications*. Factor 4 is highly loaded on V13, V14, and V15. These variables describe a person's perception of his external environment. Thus, we name Factor 4 as *working conditions*. Variables V7, V11, and V19 that demonstrate an individual's involvement with family activities are highly correlated with factor 5. Due to this reason, Factor 5 is named as *family-friendly policies*. Factor 6 comprises V1 and V4 which demonstrate the stressfulness of completing a project. As a team of IT employees usually completes a project, Factor 6 is named as *support from peers*. Finally, Factor 7 is named as the *level of autonomy during work* as it is loaded by V2 and V3 which describes an individual employee's abilities.

Once extracted, the loadings of the seven factors, F1–F7, were used as inputs to build an ANN to forecast employee job satisfaction. The process of fitting a neural network and obtaining predictions is accomplished using the Python programming language within the Google Colab environment. Libraries Scikit-learn, TensorFlow and Keras were mainly used for this analysis.

3.3. Artificial Neural Network (ANN) Model

As discussed in Section 3.1, the preliminary analysis shows that our dataset depicts a high class-imbalance. That is, there are 140 (90%) examples in the satisfied class while only 16 (10%) examples belong to the not-satisfied class. To address the class imbalance, we first oversample the minority class using the Synthetic Minority Oversampling Technique (SMOTE) technique (Elreedy and Atiya, 2019). The basic idea of the SMOTE procedure is to interpolate between adjacent minority class instances to generate new minority class examples and increase the number of minority class examples in the dataset (Fernandez *et al.,* 2018). After performing oversampling, the dataset now comprises an equal proportion of examples (50:50) from each class. The dataset was then divided for training and testing. The split was performed such that 90% of the samples were assigned to the training set, while the remaining 10% were allocated to the testing set. This splitting was done with stratification to preserve the proportional representation of different classes in both subsets.

According to the findings in (Tian and Pu, 2008a), a three-layer ANN architecture is most suitable for predicting employee satisfaction. Thus, a three-layer back propagation network was constructed based on a carefully designed architecture. The input layer consisted of seven nodes corresponding to the seven factors with Hyperbolic Tangent (Tanh) activation function. The hidden layer consisted of 128 nodes with the Tanh activation function. The output scope of Tanh is (-1, +1). The output layer consisted of a single node with a sigmoid activation function to obtain a binary output scope between 0 and 1. The Adaptive Moment Estimation (Adam) optimisation algorithm, which efficiently updates the model's weights and biases was selected during the training process. Hyperparameter tuning with 5-fold cross-validation was performed to decide the best learning rate, batch size, and number of epochs for the model. The optimal parameter combination was a learning rate of 0.1 with batch size 64 when the ANN trained for 30 epochs.

After the hyper-parameter tuning, the ANN model with the best hyperparameters was applied on the whole training dataset. The results show a training accuracy of 89.71%. Next, the test dataset was introduced to the trained ANN and the testing accuracy was 94.64%. Thus, the predictive validity of the ANN model is exceptional and can be further utilised for obtaining insights into IT employees' job satisfaction.

The means of the factor scores for the samples in the dataset can be considered as an unbiased estimator of the population of factor scores (Tian and Pu, 2008b). Let μ_n denote the mean for the nth Factor, F_n. Then, the means of the seven factors can be denoted as $\mu = [\mu_1, \mu_2, \mu_3, \mu_4, \mu_5, \mu_6, \mu_7]$. This vector can be calculated by aggregating the factor scores based on the required demographic variable. Then, the resulting mean vector can be used as an input to the trained ANN model to measure the probability of employee satisfaction (p). Table 8 provides the corresponding results.

Table 8: Predictions for overall satisfaction by demographic variables

Variable	Category	$\boldsymbol{\mu_1}$	$\boldsymbol{\mu_2}$	$\boldsymbol{\mu_3}$	$\boldsymbol{\mu_4}$	$\boldsymbol{\mu_5}$	$\boldsymbol{\mu_6}$	$\boldsymbol{\mu_7}$	$\boldsymbol{p = 0}$	$\boldsymbol{p = 1}$
Age	Male	-0.0559	-0.0886	0.0509	0.0914	0.0769	-0.1119	0.0399	0.0013	0.9987
	Female	0.1056	0.1674	-0.0961	-0.1727	-0.1452	0.2113	-0.0754	0.0248	0.9752
Education	Certificate	0.0792	-0.1141	0.4439	0.0207	-0.1253	0.0286	0.0045	0.0009	0.9991

	Diploma	-0.0035	0.0858	-0.0349	0.0419	0.0706	-0.0516	-0.0777	0.0079	0.9921
	Bachelor’s	-0.3616	-0.4578	-0.259	-0.1938	-0.5769	-0.0508	0.1231	0.0000	1.0000
	Masters	0.099	0.1766	-0.4827	-0.1551	0.3171	0.427	0.4463	0.0107	0.9893
	PhD	0.8177	-0.6617	-1.5826	-0.804	0.525	1.0879	1.7109	0.0365	0.9635
Experience	Internship	-0.0003	0.0311	-0.0232	-0.1531	-0.2189	-0.0063	-0.1456	0.0058	0.9942
	<2	0.0538	-0.0771	0.1916	0.0919	0.0586	0.3032	-0.3242	0.0327	0.9673
	2-5	-0.0167	0.0147	0.1129	0.3227	0.492	-0.2493	0.3562	0.0001	0.9999
	5-10	-0.4749	0.0863	-0.6844	-0.1217	-0.4523	-0.1269	-0.2886	0.0007	0.9993
	10<	0.2606	-0.0699	-0.3662	-0.3833	-0.1913	0.0353	0.9907	0.0002	0.9998
Job Role	IT support	0.2938	-0.1276	-1.2288	-0.6954	0.06	0.1186	0.2996	0.1902	0.8098
	Tester	-0.2378	0.6604	-0.4463	0.0529	-0.0574	0.0441	0.0278	0.1088	0.8912
	Developer	-0.0176	-0.0647	0.1702	0.0921	0.0772	-0.0728	-0.0266	0.0012	0.9988
	Security	-0.3094	-0.17	0.4417	-1.2324	0.6342	-0.1355	-0.0154	0.0001	0.9999
	Design	-0.1715	-0.5299	-0.0922	-0.1184	-0.1849	-0.526	-0.5239	0.0009	0.9991
	Data	0.6072	0.4204	-0.5259	0.245	-0.3824	0.1474	-0.0322	0.0144	0.9856
	Other	-0.2928	0.0287	0.2779	-0.0565	-0.1416	0.3297	0.1417	0.0264	0.9736
Working Culture	Home	0.0397	0.1778	-0.0847	-0.0896	-0.1147	-0.0703	0.0414	0.0171	0.9829
	Office	-0.166	-0.1475	-0.2552	-0.086	-0.5816	-0.1211	-0.3006	0.0007	0.9993
	Hybrid	-0.0033	-0.1994	0.196	0.1503	0.3387	0.1345	0.0363	0.0001	0.9999
Annual Salary	<1K	-0.3457	-0.002	-0.0896	-0.1482	-0.1066	-0.0934	-0.1193	0.0006	0.9994
	1K-5K	0.2135	-0.0609	0.1723	0.1442	0.0312	0.0104	-0.0015	0.0012	0.9988
	5K-10K	0.1365	0.215	0.0827	0.3301	0.2971	0.1822	0.2075	0.0007	0.9993
	10K-25K	0.228	-0.2416	-0.026	0.0239	0.1239	0.0987	-0.1637	0.0061	0.9939
	25K-50K	0.8734	0.1904	-0.1542	-0.1446	-0.1491	-0.5576	0.7391	0.0026	0.9974
	50K-100K	1.4553	1.3705	0.6697	-0.8072	-1.0011	1.4729	0.3132	0.0001	0.9999
	100K<	0.8256	0.6223	-1.2485	-0.4631	0.154	1.1642	1.7942	0.0630	0.9370

According to the results in Table 8, it is apparent that regardless of the value of the demographic variable, the probability of employee satisfaction is high. Thus, it is justifiable to claim that demographic variables do not have a considerable effect on employee satisfaction.

Furthermore, the impact of each factor on employee satisfaction level can be assessed. Here, the mean of the factor of interest is set to 1 while keeping all others 0 and used as an input to obtain predictions from the trained ANN. For example, if the interested factor is F1, μ is set as$[1,0,0,0,0,0,0]$. The corresponding results are given in Table 9.

Table 9: Change of employee satisfaction with factors

Factor	F1	F2	F3	F4	F5	F6	F7
Input	1	0	0	0	0	0	0
	0	1	0	0	0	0	0
	0	0	1	0	0	0	0
	0	0	0	1	0	0	0
	0	0	0	0	1	0	0
	0	0	0	0	0	1	0
	0	0	0	0	0	0	1
Output ($\boldsymbol{p = 1}$)	0.9872	0.8836	0.9994	0.9999	0.9999	0.8663	0.9999

Based on the results presented in Table 9, it can be observed that F4, F5 and F7 have the highest impact on employees' overall satisfaction, as evidenced by their output probability value of 0.9999, the largest among the six output values. Similarly, it is understood that the implementation of F6 yields minimal enhancement in employee satisfaction. The sequence of six factors that have the greatest impact on the overall level of satisfaction is as follows: (i) F4, F5, F7, (iv) F3, (v) F1, (vi) F2 and (vii) F6.

4. Discussion

The main objective of this study is to identify the key factors that impact the level of satisfaction among information technology employees. Furthermore, a secondary objective is to develop a reliable and accurate artificial neural network (ANN) model for evaluating the influence of demographic variables and the identified factors on employee satisfaction. The study utilised 156 observations to attain the objectives. The preliminary analysis followed by advanced statistical testing and model fitting revealed interesting findings.

Exploratory factor analysis revealed seven factors that mainly affect the job satisfaction of IT employees. These include monetary and spiritual benefits (F1), leisure time for personal pursuits (F2), opportunities to improve professional qualifications (F3), working conditions (F4), family-friendly policies (F5), support from peers (F6), and level of autonomy during work (F7).

Considering the seven identified factors, the Artificial Neural Network (ANN) model was carefully constructed to forecast IT employees' job satisfaction and measure the impact of the identified factors and demographics on job satisfaction. The findings indicate that the factors with the greatest impact on IT employee satisfaction are working conditions (F4), family-friendly policies (F5), and level of autonomy during work (F7). It is essential for companies to understand that addressing these significant factors. It will not only benefit employee satisfaction, but also contribute to overall productivity, retention rates, and the company's reputation as an employer in the competitive IT industry. For example, companies should create a comfortable and conducive working environment for their IT employees. This may include providing ergonomic workstations, appropriate lighting, peaceful surroundings, and a clean and organized workspace. By prioritizing and investing in better working conditions, companies can enhance employee satisfaction and overall well-being. Furthermore, in recognition of the importance of work-life balance, companies should adopt family-friendly policies to support their IT employees. This may involve offering flexible work schedules, remote work options, parental leave policies, childcare assistance, and other family-centric benefits. Providing a supportive and accommodating work environment for employees with families can significantly contribute to their job satisfaction and help attract and retain top talent. Empowering IT employees with a higher level of autonomy in their work can lead to increased job satisfaction. Companies should encourage employees to take ownership of their projects, provide opportunities for innovation and decision-making, and allow for a certain degree of independence in their roles. By fostering autonomy and empowering employees, companies can tap into their expertise, boost motivation, and create a sense of fulfillment in their work.

The results of our analysis also indicated support from peers (F6) to be the factor with least impact on employee satisfaction. Even though F6 may not have emerged as a comparatively impactful factor for this case study, fostering a supportive and collaborative work environment remains valuable. It is important for companies to recognize that emphasizing collaboration, strengthening support systems, and focusing on leadership support, can create a positive workplace culture that enhances employee satisfaction, engagement, and overall organizational success.

The results of our study indicate that demographic factors do not have a substantial impact on the level of job satisfaction among employees. It is important to exercise caution when interpreting the results of this study and generalizing them to a broader population, as the study is limited to a single case analysis and a sample size of only 156 observations. As a potential future extension, the authors aim to undertake a more comprehensive investigation by conducting a larger-scale survey utilizing stratified random sampling. This approach intends to ensure the representation of diverse job roles within the IT field in Sri Lanka, thus enhancing the generalizability and robustness of the findings.

5. Conclusions

In conclusion, this pioneering research has employed Artificial Neural Networks (ANNs) to investigate the factors influencing job satisfaction among IT professionals in Sri Lanka. Through the analysis of data collected from a survey of 156 IT professionals, seven key factors that significantly impact job satisfaction were identified and utilized as inputs for the ANN model. The accuracy of the ANN model in predicting job satisfaction reached an impressive level of 94.64%.

The outcomes of this study demonstrate the potential of ANNs as a powerful tool for identifying critical factors contributing to job satisfaction among IT employees. Specifically, the research revealed that working conditions, family-friendly policies, and the level of autonomy at work play pivotal roles in determining job satisfaction. These findings provide valuable insights for employers to enhance employee satisfaction by implementing appropriate policies and interventions targeted towards these factors.

Moreover, the fitted ANN model serves as a valuable resource for identifying employees who may be at risk of leaving their positions. By utilizing the customized interventions derived from the ANN predictions, employers can proactively address potential issues and take appropriate measures to retain valuable employees.

While this research provides a pioneering exploration of using ANNs to examine job satisfaction in the IT sector, there is room for further investigation and refinement. Future studies could expand the sample size and consider additional factors influencing job satisfaction, such as career advancement opportunities, salary, and work-life balance. Additionally, the ANN model can be fine-tuned and validated with larger datasets to enhance its predictive capabilities and generalizability.

In summary, this research demonstrates the efficacy of employing ANNs to analyze factors affecting job satisfaction among IT professionals in Sri Lanka. The findings offer valuable insights for employers in the IT industry to improve employee satisfaction, enhance retention strategies, and create a more conducive work environment. With the potential for further development and refinement, ANNs provide a promising avenue for future research and practical applications in employee satisfaction and organizational success.

6. References

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