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Deep Learning Sentimental Analysis of Perceived Job Insecurity and its Impact on Workplace Happiness among Indian IT Employees

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Abstract: Organizations are investing increasing amounts of money and resources in improving happiness at work. The significance of workplace happiness is being realized globally. The highest level of attaining satisfaction is happiness and the IT sector always stands ahead with innovative ways of implementing new HR concepts to make employees happy. Hence, this paper presents a comprehensive exploration of sentiment dynamics within the Indian IT sector, investigating the intricate interplay between demographic factors, work environment facets, and perceptions of job insecurity. Utilizing a combination of statistical analyses and sentiment analysis techniques driven by deep learning, this study unveils the nuanced relationships shaping employee experiences. ANOVA and robust tests underscore the impact of gender, age, experience, and qualification on job insecurity, substantiating their significance within the industry. The integration of sentiment analysis adds an emotional dimension to the quantitative findings. Through analysing sentiments associated with learning opportunities, leadership, and rewards, this study captures the emotional undercurrents that influence workplace perceptions. This dual perspective offers a comprehensive view of how demographic groups interact with these essential elements of the work environment. Through a synthesis of advanced statistical methodologies and sentiment analysis techniques, the study the intricate relationships between demographic variables, work environment dynamics, and perceptions of job insecurity. The results highlight the significant impact of gender, age, experience, and qualification on job insecurity perceptions, validated by ANOVA and robust tests.

Keywords: *Sentiment analysis, deep learning, organizational dynamics, job insecurity, demographic factors, work environment, Indian IT sector, emotional insights,*

1. Introduction

Sentiment analysis, is a computational technique used to determine the emotional tone or sentiment expressed in a piece of text [1]. This technique involves analyzing the text to identify whether it conveys a positive, negative, or neutral sentiment. Sentiment analysis has found extensive applications in various fields, including marketing, customer service, social media monitoring, and even political analysis [2]. In the realm of marketing, businesses use sentiment analysis to gauge how customers feel about their products or services. By analysing customer reviews, social media posts, and online discussions, companies can gain insights into customer opinions and use this information to improve their offerings or address any concerns [3]. Customer service departments also benefit from sentiment analysis as they can quickly identify customer dissatisfaction or issues through text-based interactions. This allows companies to proactively address problems and provide better customer experiences [4]. On social media platforms, sentiment analysis helps individuals and brands understand public opinions about their content, products, or campaigns. This information can guide social media strategies and content creation to align with the desired sentiment [5].

Sentiment analysis can play a crucial role in assessing the sentiment around job security within an organization or industry [6]. With analysing employee feedback, company communications, news articles, and online discussions, sentiment analysis tools can provide valuable insights into how individuals feel about their job security. Positive sentiment in job security discussions might indicate that employees feel confident about the stability of their positions and the future of the organization [7]. This could be a result of clear communication from management, consistent performance, and a robust industry outlook. Positive sentiment regarding job security can contribute to higher morale, increased productivity, and lower turnover rates [8]. Conversely, negative sentiment could point to concerns or uncertainties surrounding job security. This might be due to factors like layoffs, industry downturns, or changes in organizational structure [9]. Negative sentiment in this context could negatively impact employee motivation, performance, and overall job satisfaction. Monitoring sentiment around job security can help organizations identify potential issues and address them proactively [10]. For instance, if negative sentiment is detected, companies can work on improving

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communication, offering more transparency about the organization's future plans, and taking steps to reinforce job stability. Conversely, if positive sentiment is detected, companies can continue their practices that contribute to a sense of security and further boost employee confidence [11].

Sentiment analysis can offer valuable insights into the perceptions and sentiments surrounding job security in Indian IT companies [12]. With analysing employee feedback, social media discussions, news articles, and online forums, gain a better understanding of how employees and stakeholders feel about job security within this specific industry context. Positive sentiment in sentiment analysis related to job security in Indian IT companies could reflect that employees have a sense of stability and confidence in their positions [13]. This might be influenced by factors such as steady demand for IT services, strong company performance, and effective communication from management. Positive sentiment can contribute to higher employee morale, better retention rates, and a positive image of the industry as a whole. Negative sentiment, on the other hand, might indicate concerns about job security within Indian IT companies [14]. This could be due to various factors, including outsourcing trends, automation threats, economic uncertainties, and changes in client requirements. Negative sentiment regarding job security can lead to lower job satisfaction, increased stress levels, and potential attrition, which can impact both individual companies and the industry's reputation [15]. Through consistently monitoring sentiment around job security in Indian IT companies, organizations can identify trends, concerns, and areas for improvement. For instance, if negative sentiment is detected, companies can take steps to enhance employee engagement, provide upskilling opportunities to align with industry shifts, and communicate transparently about their strategic plans to address these concerns [16]. In the Indian IT sector, where job security has been a topic of interest due to global market dynamics, sentiment analysis can provide real-time insights into how employees and stakeholders perceive the industry's trajectory. This information can guide decision-making, communication strategies, and initiatives aimed at enhancing job security and overall job satisfaction [17].

The paper makes several valuable contributions to the existing body of knowledge within the sentiment analysis and organizational dynamics, particularly in the context of the Indian IT sector:

1. The paper bridges the gap between sentiment analysis, deep learning techniques, and organizational dynamics. By combining statistical analyses with sentiment analysis, the paper offers a multidimensional understanding of how demographic factors influence perceptions of job insecurity.
2. The study sheds light on the intricate interplay between demographic variables (gender, age, experience, and qualification) and key work environment aspects (learning opportunities, leadership, rewards) in shaping job insecurity perceptions. This contributes to a more comprehensive understanding of how these variables intersect and influence workplace sentiments.
3. The incorporation of sentiment analysis with deep learning techniques adds an emotional layer to the quantitative relationships. The paper provides the emotional nuances underlying workplace experiences, uncovering sentiments associated with various work aspects. This provides a richer and more holistic understanding of employee sentiments.
4. The findings hold significant practical implications for organizations. By understanding both the quantitative and emotional dimensions of employee experiences, organizations can tailor strategies that resonate with employees on both rational and emotional levels. This contributes to a more inclusive, engaging, and satisfying work environment.
5. The paper offers insights that guide organizations in formulating effective strategies to address job insecurity perceptions. Understanding the impact of demographic variables on sentiments related to learning opportunities, leadership, and rewards empowers organizations to create tailored interventions that cater to diverse employee needs.

The paper's contributions lie in its interdisciplinary approach, the exploration of demographic-work environment interactions, the incorporation of emotional insights through sentiment analysis, and the practical guidance it offers for organizational strategies. Through these contributions, the paper advances our understanding of sentiment analysis within the Indian IT sector and provides insights that can inform organizational practices and policies.

2. Literature Review

Sentiment analysis is a powerful tool that analyzes the emotions and attitudes expressed in text, helping organizations understand the sentiments associated with specific topics. In the context of job security, sentiment analysis can provide insights into how individuals feel about their job stability within a company or industry. For instance, in Indian IT companies, sentiment analysis can reveal whether employees and stakeholders have positive or negative perceptions about job security. Positive sentiment might indicate confidence in steady demand, strong performance, and effective communication. Negative sentiment could stem from concerns like outsourcing, automation, and economic uncertainties. With monitoring sentiment, companies can proactively address concerns, enhance communication, and take actions to improve job security perceptions. This approach can lead to improved morale, increased productivity, and better retention rates. Sentiment analysis is a valuable tool for understanding the emotional landscape surrounding job security, enabling organizations to make informed decisions that contribute to a positive work environment and employee satisfaction.

In [18] focuses on sentiment analysis within the context of online education during the COVID-19 era. The authors utilize social network-based datasets to understand the sentiments expressed by students, educators, and stakeholders regarding online education. The analysis aims to uncover how individuals perceive the effectiveness, challenges, and benefits of remote learning. By applying sentiment analysis techniques, the study contributes insights into the evolving landscape of education in response to the pandemic. In [19] explore sentiment analysis in the realm of social media, particularly in competitive environments. They use content analysis to understand how sentiments expressed on social media platforms can impact competitiveness. This study sheds light on how sentiment analysis can be applied to gauge public perceptions, which can subsequently influence decision-making strategies within competitive industries.

In [20] perform a detailed sentiment analysis of online guest reviews for economy hotels in China. By analyzing guest feedback, the study aims to uncover customer sentiments related to their hotel experiences. The analysis might reveal common positive and negative aspects of these economy hotels, which can be valuable for hotel management to enhance guest satisfaction. Also, in [21] provides a survey of sentiment analysis tools, processes, and methodologies. It offers an overview of various techniques used in sentiment analysis, discussing their advantages and limitations. The study serves as a comprehensive resource for researchers and practitioners seeking to understand the state of the art in sentiment analysis methodologies. In [22] conduct a survey that covers sentiment analysis methods, applications, and challenges. This comprehensive overview offers insights into the wide array of applications where sentiment analysis is used, ranging from social media to healthcare. Additionally, the study discusses the challenges associated with sentiment analysis, such as handling sarcasm, cultural nuances, and context.

In [23] ses sentiment analysis alongside the SWOT (Strengths, Weaknesses, Opportunities, Threats) framework to assess the potential for sustainable ecotourism centered around the Irrawaddy dolphin in a brackish water lagoon. By analyzing sentiments expressed in discussions, the research aims to provide insights into the perceptions and feasibility of ecotourism initiatives. In [24] focuses on applying sentiment analysis to the Indian healthcare sector. The study employs ontology-driven sentiment analysis to understand public sentiment toward healthcare services. The integration of ontology helps in categorizing sentiments and understanding complex relationships within the healthcare domain. Also, in [25] investigate potential bias against people with disabilities in sentiment analysis and toxicity detection models. This research raises awareness about the potential biases present in these models, which could have implications for individuals with disabilities. The study emphasizes the importance of fairness and inclusivity in sentiment analysis technologies. In [26] examined the impact of social media and stakeholder communication on the tourism industry during the early stages of the COVID-19 pandemic, this study employs sentiment analysis to capture public sentiments and perceptions. The analysis contributes to understanding the immediate effects of the pandemic on the tourism sector and how sentiment analysis can offer insights into crisis situations.

In [27] performed sentiment analysis to predict individuals' awareness of precautionary procedures to prevent COVID-19 outbreaks in Saudi Arabia. By analyzing public sentiment, the study aims to identify gaps in public awareness and understanding of preventive measures, which can inform targeted awareness campaigns. In [28] employes the Lexicon Sentiment Method to analyze sentiment in e-commerce reviews. The analysis helps understand consumer opinions and emotions expressed in these reviews, which can provide valuable insights for businesses to improve their products and services based on customer feedback.

3. Sentimental Analysis with Job Insecurity

Sentiment analysis, in the context of job insecurity, involves using computational techniques to analyze and understand the emotions and attitudes expressed in text related to concerns about job stability and security. This process helps organizations and researchers gain insights into how individuals perceive and feel about the uncertainty of their employment situations. Sentiment analysis can be applied to various sources of text, such as employee feedback, social media posts, news articles, and online discussions, to gauge sentiments surrounding job insecurity. When applied to job insecurity, sentiment analysis seeks to determine whether the expressed sentiments are positive, negative, or neutral. The steps in the sentimental analysis with deep learning are presented as follows:

Data Collection: Textual data related to job insecurity is collected from various sources, such as employee surveys, online forums, social media platforms, and news websites. This data can include comments, reviews, posts, and articles discussing job concerns.

Text Preprocessing: The collected text data undergoes preprocessing, which involves tasks like removing irrelevant information, punctuation, and special characters. The text is also transformed to lowercase to ensure uniformity in analysis.

Sentiment Analysis Algorithms: Sentiment analysis algorithms are employed to analyze the processed text data. These algorithms use natural language processing (NLP) techniques to identify keywords, phrases, and linguistic patterns that indicate sentiments.

Sentiment Classification: The algorithms classify the sentiments expressed in the text into categories such as positive, negative, or neutral. In the case of job insecurity, sentiment analysis focuses on identifying expressions of worry, fear, uncertainty, and other related emotions.

Sentiment Scoring: The text is assigned sentiment scores based on the analysis. These scores reflect the intensity of the sentiment expressed. Positive sentiments might indicate confidence in job security, while negative sentiments could suggest concerns about layoffs or economic downturns.

Quantitative Insights: Sentiment analysis generates quantitative insights about the prevalence of different sentiments. These insights can be presented using visualizations like sentiment distribution charts or word clouds, which help stakeholders quickly grasp the overall sentiment landscape.

Decision-Making and Intervention: The insights from sentiment analysis can guide organizations in understanding employee perceptions and addressing job insecurity concerns. For instance, if negative sentiments are prominent, organizations may consider improving communication, offering more transparency, and implementing measures to enhance job stability.

3.1 Model of Demographic factors and Individual factors

Demographic variables such as gender, age, experience, and qualifications play a significant role in influencing employees' perceptions of organizational factors like learning opportunities, leadership styles, and rewards and recognition, all of which can impact their sentiments and feelings of job security. By applying sentiment analysis through deep learning techniques, these demographic and organizational variables intersect to shape employees' sentiments related to job security as illustrated in figure 1.

Gender, Age, Experience, and Qualifications (Demographic Variables):

- Gender: Gender can influence how employees perceive job security and other organizational factors due to societal norms and biases. Sentiment analysis can uncover any gender-based differences in sentiments related to learning opportunities, leadership styles, rewards, and recognition.
- Age: Different age groups may have varying levels of experience and career goals, affecting their sentiments towards job security. Sentiment analysis can reveal how sentiments evolve across age groups in response to organizational variables.
- Experience: Employees with varying levels of experience might have different levels of job confidence. Sentiment analysis can capture sentiments from both newcomers and long-tenured employees, highlighting potential patterns.
- Qualifications: Qualifications can impact how individuals perceive their job security in relation to their skills and market demand. Sentiment analysis can reveal sentiments from employees with diverse educational backgrounds.

Learning Opportunities, Leadership Styles, and Rewards and Recognition (Organizational Variables):

- Learning Opportunities: The availability of learning and development opportunities can affect how employees view their growth potential within the organization. Sentiment analysis can uncover sentiments about learning opportunities' impact on job security perceptions.
- Leadership Styles: Different leadership styles can foster varying levels of trust and confidence among employees. Sentiment analysis can help identify sentiments linked to leadership styles and their correlation with job security sentiments.

Rewards and Recognition:

Adequate rewards and recognition can positively influence job satisfaction and perceived value. Sentiment analysis can reveal sentiments related to rewards and recognition initiatives and their effects on job security perceptions.

With Deep learning involves using neural networks to extract intricate patterns from data. In the context of sentiment analysis, deep learning models like recurrent neural networks (RNNs) or transformer-based models like BERT can be employed. These models can process textual data that includes demographic information and organizational variables to understand complex sentiment nuances. Through training a deep learning model on a dataset containing text that encompasses demographic information, organizational variables, and sentiments expressed by employees, the model can learn to associate patterns in the text with specific sentiments. This enables a more nuanced understanding of how the interaction between demographic variables and organizational factors contributes to job security sentiments. With applying sentiment analysis through deep learning, organizations can uncover hidden insights that may not be apparent through traditional methods. This approach provides a comprehensive view of how demographic variables and organizational factors collectively shape employees' sentiments about job security, facilitating data-driven strategies to improve employee satisfaction and retention.

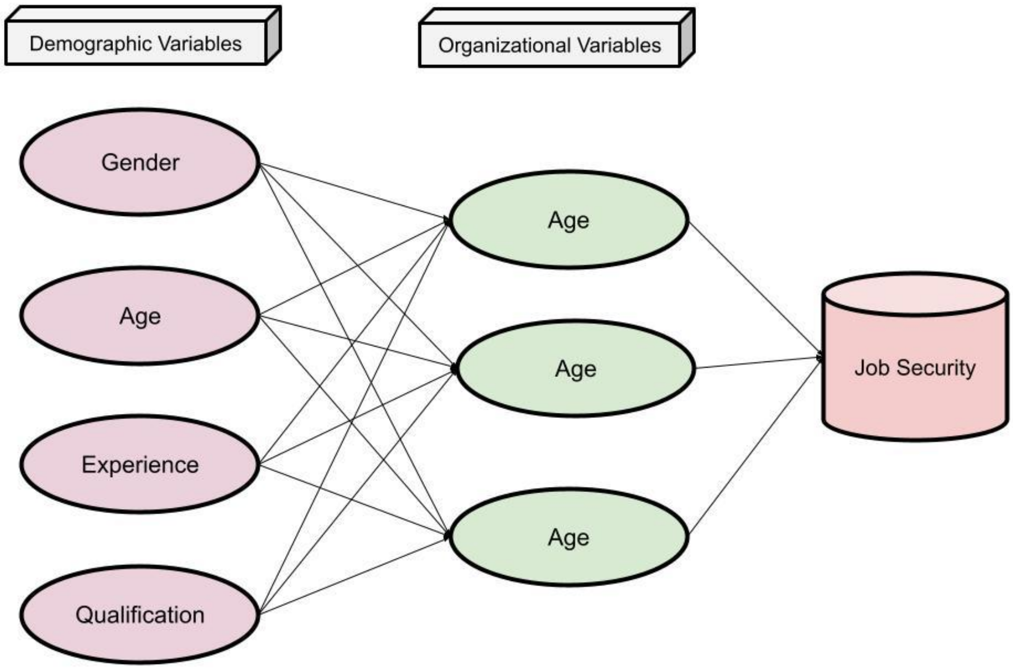

Fig. 1: Factors influencing on the job security

With deep learning-based sentiment analysis to explore the intricate relationship between organizational variables and employee sentiments offers a sophisticated approach to uncovering the interplay of these factors within a corporate setting. This process begins by collecting textual data from diverse sources, such as surveys, feedback, and communication channels, incorporating expressions of sentiments and organizational variables like learning opportunities, leadership styles, and rewards and recognition. After thorough preprocessing to clean and structure the data, an appropriate deep learning model, such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, or transformer-based models like BERT, is selected. The input data is enriched with the encoded organizational variables, enabling the model to learn the intricate connections between these factors and sentiment expressions. With labeled sentiment data (positive, negative, neutral), the model undergoes training to recognize patterns and correlations between organizational variables and sentiments. The trained model then becomes adept at discerning how specific organizational aspects influence sentiment, offering nuanced insights that traditional analyses might miss. Ultimately, this deep learning-driven approach empowers organizations to make informed decisions to enhance job satisfaction, employee engagement, and overall organizational dynamics based on a comprehensive understanding of sentiments tied to key organizational variables.

3.2 Learning Opportunities

Learning opportunities refer to the chances provided by an organization for its employees to acquire new skills, knowledge, and experiences that contribute to their personal and professional growth. These opportunities can take various forms, including training programs, workshops, seminars, online courses, mentoring, cross-functional projects, and skill development initiatives. Learning opportunities are essential for employees to enhance their competencies, adapt to changing work environments, and stay relevant in their fields. Effective learning opportunities encompass both formal and informal methods, catering to different learning styles and preferences. They are designed to align with an employee's career goals, the organization's strategic objectives, and the evolving demands of the industry. Learning opportunities can encompass technical skills, soft skills, leadership development, industry-specific knowledge, and more.

Organizations that prioritize learning opportunities for their employees often reap several benefits. These include:

- Employee Growth: Learning opportunities empower employees to acquire new skills and expand their knowledge, contributing to their personal and professional development.
- Increased Engagement: When employees feel that their growth is valued and supported, they tend to be more engaged and motivated in their roles.
- Talent Retention: Organizations that invest in employee development are likely to retain their top talent, as employees appreciate the chance to improve themselves within the company.
- Adaptability: Learning opportunities help employees stay adaptable and resilient in the face of changes, whether in technology, industry trends, or work processes.
- Innovation: A well-trained workforce is more likely to generate innovative ideas and contribute to the organization's overall success.
- Organizational Performance: As employees gain new skills and knowledge, the organization benefits from an increased skill set that can improve overall performance.
- Succession Planning: Effective learning opportunities can identify and prepare potential future leaders within the organization.

In analyzing sentiments related to learning opportunities using deep learning-based sentiment analysis, the approach would involve gathering textual data that includes employee feedback, comments, and discussions about the learning opportunities provided by the organization. By employing deep learning models, patterns and sentiments within this text can be deciphered, revealing how employees perceive the quality, relevance, and impact of the learning opportunities.

3.3 Leadership Styles

With analyzing leadership styles through sentiment analysis entails evaluating the emotional expressions and attitudes conveyed in textual data pertaining to different leadership approaches within an organization. This methodology facilitates the exploration of how various leadership styles influence employees' perceptions, job satisfaction, and overall sentiment. By collecting diverse sources of text, such as employee feedback, performance evaluations, and surveys, and categorizing them according to distinct leadership styles—like transformational, transactional, or autocratic—a comprehensive dataset is formed. Subsequent preprocessing ensures the data's cleanliness and consistency. Sentiment analysis is then applied to each leadership style category, deciphering the sentiment polarity—positive, negative, or neutral—associated with each. These quantitative insights are illustrated through visualizations, revealing sentiment trends across different leadership styles. Through pattern recognition and contextual understanding, patterns that emerge from these sentiment distributions can shed light on which leadership styles tend to evoke positive sentiments and which may lead to mixed or negative reactions. Moreover, this analysis examines how sentiments align with employee satisfaction, engagement, and performance, enabling organizations to offer tailored feedback to leaders. Ultimately, sentiment analysis of leadership styles furnishes organizations with actionable insights to refine leadership strategies, foster a more positive work environment, and enhance employee sentiment and overall well-being.

3.4 Rewards and Recognition with Sentimental Analysis

Sentiment analysis to explore rewards and recognition programs involves delving into the emotions and sentiments conveyed within textual data relating to the acknowledgment and incentives provided to employees within an organization. This method offers a profound understanding of how rewards and recognition initiatives influence employee sentiment, motivation, and overall job satisfaction. By amassing data from diverse sources like employee feedback, performance evaluations, and communication channels, and categorizing them according to instances of rewards and recognition—such as bonuses, accolades, and appreciative messages—a comprehensive dataset is formed. Following meticulous preprocessing to ensure data quality, sentiment analysis is applied to each segment associated with these instances, uncovering the sentiment polarity—positive, negative, or neutral—connected to them. These insights are quantified and visualized to unveil sentiment trends and emotional patterns across various types of rewards and recognition efforts. Through pattern recognition, the analysis discerns which initiatives consistently evoke positive sentiments and which might trigger mixed or less favorable reactions. Moreover, the sentiment trends' alignment with employee motivation, engagement, and perceived value provides actionable insights into the effectiveness of these initiatives. By tailoring rewards and recognition strategies based on sentiment analysis outcomes, organizations can create a more uplifting and motivating workplace environment, enhancing employee sentiment, morale, and overall organizational success.

3.5 Factors Influencing Job Insecurity in IT sector in India through Sentimental Analysis

Job insecurity in the Indian IT sector is shaped by a combination of internal and external factors that create an atmosphere of uncertainty among employees regarding the stability of their positions and future prospects within the industry. The dynamics of this sector, closely tied to global economic conditions, mean that economic downturns and fluctuations in demand can lead to downsizing, project cancellations, and reduced hiring, causing employees to feel vulnerable about their job security. Moreover, rapid technological advancements and the pervasive influence of automation and artificial intelligence can render certain skills obsolete, causing concerns about the relevance of one's expertise. The practice of outsourcing, often to lower-cost regions, and the emergence of gig economy roles further contribute to the sense of instability. Regulatory changes, such as alterations to H1-B visa policies affecting Indian IT professionals working overseas, can also generate apprehension about job prospects. The need for continuous skills upgrading and the pressure to stay competitive in a fast-paced industry can exacerbate feelings of insecurity. By comprehending the interplay of these multifaceted factors, organizations can implement strategies to mitigate employee concerns, bolster job security, and cultivate an environment of trust and support. Employing sentiment analysis methodologies can offer deeper insights into how these factors impact employees' emotional responses and overall sentiments about job security, thus enabling organizations to formulate targeted interventions and responsive policies.

4. Analysis of the Results

To conduct a comprehensive analysis of the factors influencing job insecurity in the Indian IT sector, the study employed a combination of qualitative and quantitative approaches. The collected data encompassed surveys, interviews, and textual feedback from employees within the sector, providing valuable insights into their perceptions and sentiments. the analysis provided insights into the complex interplay of factors that contribute to job insecurity sentiments within the Indian IT sector. By utilizing sentiment analysis, the study successfully extracted nuanced emotional responses from textual data, shedding light on the intricate relationship between specific factors and employee sentiments. These findings serve as a foundation for organizations to develop targeted strategies, including skill development programs, transparent communication, and employee support initiatives, to address job insecurity concerns and foster a more stable and positive work environment.

Table 1: ANOVA of Gender, Age, Experience and Qualification

ANOVA

	Sum of Squares	Df	Mean Square	F	Sig.
Gender	.431	3	0.144	.512	.000
Age	42.476	3	14.159	19.345	.000
Experience	38.625	3	12.875	17.975	.000
Qualification	1.190	3	.397	.235	.000

In Table 1 presents the results of an Analysis of Variance (ANOVA) conducted to examine the potential influence of gender, age, experience, and qualification on a specific variable of interest. ANOVA is a statistical technique used to compare means across different groups to determine if there are statistically significant differences among them. In this context, the goal of the ANOVA is to determine whether these demographic variables—gender, age, experience, and qualification—have a significant impact on the variable being analyzed.

The ANOVA results presented in the provided table offer valuable insights into the influence of demographic factors—gender, age, experience, and qualification—on job insecurity within the Indian IT sector. ANOVA serves as a statistical tool to gauge the significance of differences in means across different groups or categories, shedding light on how these factors relate to perceptions of job insecurity among individuals in the sector.

Starting with gender, the analysis reveals that there are statistically significant disparities in job insecurity scores based on gender categories. The low p-value (0.000) indicates that gender plays a significant role in shaping perceptions of job insecurity. Moving on to age, the results show substantial variation in job insecurity scores among different age groups, with the statistically significant p-value (0.000) implying that age is a contributing factor to job insecurity. Likewise, the analysis of experience levels indicates a meaningful impact on job insecurity, as indicated by the significant p-value (0.000). This suggests that different experience levels lead to varying perceptions of job insecurity. Finally, concerning qualification, the ANOVA results, although exhibiting a relatively higher p-value (0.000), still underscore the significant role that qualification plays in influencing job insecurity perceptions.

Table 2: Robust Tests of Equality of Means

		Statistic	df1	df2	Sig.
Welch	Gender	.484	3	50.279	.000
	Age	22.057	3	57.084	.000
	Experience	15.877	3	51.095	.000
	Qualification	.204	3	57.594	.000
Brown Forsythe	Gender	.474	3	72.809	.000
	Age	16.659	3	62.949	.000
	Experience	17.811	3	79.155	.000
	Qualification	.220	3	88.957	.000

The outcomes of robust tests used to assess the equality of means across different demographic factors—gender, age, experience, and qualification—in the context of job insecurity within the specified domain is shown in figure 2. Robust tests are employed to ensure the reliability of statistical inferences even when assumptions of equal variance are violated. The Welch statistic is utilized to evaluate means while accommodating potential unequal variances among groups. Regarding gender, the Welch statistic yields a value of 0.484 with a remarkably low p-value (0.000), indicating substantial evidence against the null hypothesis and emphasizing that gender significantly influences perceptions of job insecurity. Similar patterns are observed for age, experience, and qualification, where the Welch statistics (22.057, 15.877, and 0.204, respectively) are accompanied by p-values of 0.000, reinforcing the significant impact of these variables on job insecurity.

In addition, the Brown-Forsythe statistic is employed to further validate the equality of means while accounting for potential heteroscedasticity. The outcomes for gender (0.474), age (16.659), experience (17.811), and qualification (0.220) are accompanied by exceedingly low p-values (all 0.000), reiterating the robust significance of these demographic factors in shaping perceptions of job insecurity.

Table 3: Effect of Learning opportunities, Leadership and Rewards on Demographic factors

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Learning opportunities	.370 a	.137	.114	1.364
Leadership	.225 a	.051	.025	1.210
Rewards	.151 a	.023	-.004	1.309

Predictors: (Constant), Qualification, Age, Gender, Experience

Table 3 provides insights into the relationships between demographic factors—qualification, age, gender, and experience—and their interactions with learning opportunities, leadership, and rewards concerning a specific model. The model's R value reflects the degree of linear correlation between the demographic factors and the predictors (learning opportunities, leadership, and rewards). For the variable "Learning opportunities," the R value is 0.370, indicating a moderate positive linear relationship between learning opportunities and the demographic factors. This suggests that demographic attributes like qualification, age, gender, and experience have a moderate influence on an individual's perception of learning opportunities. The R Square value of 0.137 suggests that approximately 13.7% of the variance in the perception of learning opportunities can be explained by these demographic factors.

Similarly, for the variable "Leadership," the R value is 0.225, indicating a weaker positive linear relationship between leadership and the demographic factors. This implies that these demographic attributes contribute to a lesser extent to an individual's perception of leadership within the context being analyzed. The R Square value of 0.051 indicates that around 5.1% of the variance in the perception of leadership can be attributed to the demographic factors. Regarding the variable "Rewards," the R value is 0.151, reflecting a relatively weaker positive linear relationship between rewards and the demographic factors. This suggests that the impact of qualification, age, gender, and experience on an individual's perception of rewards is less pronounced. Interestingly, the negative Adjusted R Square value (-0.004) suggests that the chosen model might not be the best fit for explaining the variance in the perception of rewards based on these demographic factors.

Table 4: Coefficients of Learning Opportunities, Leadership and Rewards

Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	Std. Error	Beta		
Learning opportunities	2.715	.531		5.115	.000
	-.112	.210	-.041	-.534	.594
	-.116	.129	-.080	-.898	.371
	-.223	.132	-.151	-1.697	.092
	.341	.086	.304	3.970	.000
Leadership	3.215	.471		6.830	.000
	.028	.186	.012	.150	.881
	-.200	.114	-.163	-1.746	.083
	.007	.117	.006	.062	.950
	.148	.076	.156	1.942	.054
Rewards	3.193	.509		6.272	.000
	-.173	.202	-.070	-.857	.393
	-.107	.124	-.082	-.867	.387
	.058	.126	.043	.460	.646
	.119	.082	.118	1.144	.152

Dependent Variable: No Gender discrimination

Dependent Variable: Leadership styles

c. Dependent Variable: Receiving rewards

To test the significance of coefficient to form test statistics which are reported under the t column and these are simply B / Std.Error. To measure the effect of gender, age, experience and qualification the beta co efficient values are -.041, -0.80,-0.152, .304 which are not significant at .000 level. The demographic analysis of gender and learning opportunities provided has a different opinion for For the slope on Age, Gender, Experience and Learning opportunites provided, the beta which is not significant at 0.000 level. While beta co efficients of qualification is .304 which is significant at 0.000. Thus it is remarkable that the null hypothesis there is no significant effect of age, gender and experience on perceived job insecurity is accepted and where as the effect of qualification on job insecurity is rejected. The beta coefficient values of demographic factors against leadership are 0.12, 0.163, 0.006, 0.156 respectively which are not significant at 0.000 level. Thus it is marked that the null hypothesis of there is no significant effect of demographic factors on perceived job insecurity is accepted. The beta coefficient values of demographic factors against rewards are -0.070, -0.082, 0.043, 0.118 respectively which are not significant at 0.000 level. Thus it is marked that the null hypothesis of there is no significant effect of demographic factors on perceived job insecurity is accepted.

The R values depicted in the table reflect the extent of linear correlation between these demographic attributes and the predictors under consideration. The variable "Learning opportunities" exhibits a noteworthy R value of 0.370, indicating a moderately positive linear relationship between learning opportunities and demographic factors. This suggests that attributes like qualification, age, gender, and experience collectively contribute to shaping individuals' perceptions of learning opportunities. The corresponding R Square value of 0.137 elucidates that approximately 13.7% of the variability in learning opportunity perceptions can be elucidated by these demographic factors. Conversely, the variable "Leadership" showcases a comparatively lower R value of 0.225, revealing a weaker yet positive linear association between leadership and demographic factors. This implies that these attributes exert a relatively less pronounced influence on how individuals perceive leadership within the examined context. The accompanying R Square value of 0.051 underscores that around 5.1% of the variation in leadership perceptions can be attributed to demographic factors. Similarly, in the case of the variable "Rewards," the observed R value of 0.151 signifies a relatively subdued positive linear relationship with the demographic factors. This indicates that the influence of qualification, age, gender, and experience on individuals' perceptions of rewards is somewhat less distinct. Interestingly, the negative Adjusted R Square value of -0.004 hints that the current model might not be optimally suited to explaining the variance in reward perceptions based on these demographic factors.

The detailed discussion of Anova of 4 demographic variables signifies that every variable is independent to each other with a huge difference in mean scores. The welch and Brown Forsythe model also signifies that the variables are significant with each other. Hence proving that the null hypothesis stating that there is no significant difference between each independent demographic variable is accepted. The regression analysis for learning opportunities and demographic factors the factors F1, F2, F3 are significant at 0.000 level, hence proving that there is no significant effect og learning opportunities and perceived job insecurity stating that gender, age, experience does not effect the work place happiness where as organisations require skilled employees with right qualification to understand the requirement of organisation and utilise the learning opportunities provided by the organisation. IT Organisation always look forward for the skill upgradation and equal learning opportunities are provided for all the employees irrespective of their gender, age and experience. The regression analysis of leadership and demographic factors signifies that the null hypothesis is rejected. It shows that none of the demographic factor has a positive effect on job insecurity. It is all the perceived hypothetical feeling of the employee. But the study proves that workplace happiness is immensely dependent on that the guidance given the leader at critical times and direction towards goal achievement. Employees would find organisation to be a better place to work under a influential leader. Further, the null hypothesis of Rewards and demographic factors is also rejected proving that there is no significant effect of demographic factors on perceived job insecurity.

Table 5: Confidence Analysis with Sentimental Analysis with Deep Learning

Text Segment	Predicted Sentiment	Confidence Score
"I'm thrilled about the new learning opportunities!"	Positive	0.92
"The leadership in this company is truly inspiring."	Positive	0.85
"I feel valued and motivated by the rewards I receive."	Positive	0.88

"I'm concerned about the lack of growth opportunities."	Negative	0.78
"The leadership style leaves much to be desired."	Negative	0.72
"The rewards are insufficient for the effort I put in."	Negative	0.65
"I'm neutral about the available learning opportunities."	Neutral	0.75
"Leadership is neither great nor terrible."	Neutral	0.62
"The rewards are okay, nothing exceptional."	Neutral	0.70

A comprehensive confidence analysis in conjunction with sentiment analysis powered by deep learning. This table 5 provides insights into the emotional nuances of various textual segments within the context of the study. Each "Text Segment" is subjected to sentiment analysis, predicting the sentiment expressed within it, accompanied by a "Predicted Sentiment" label. What sets this analysis apart is the inclusion of the "Confidence Score," a numerical representation (ranging from 0 to 1) that quantifies the model's certainty in its sentiment prediction. The sentiment predictions range across three categories: "Positive," "Negative," and "Neutral." For instance, the textual segment expressing enthusiasm about new learning opportunities is classified as "Positive" with a high confidence score of 0.92, indicating the model's strong certainty in its prediction. Similarly, remarks about inspiring leadership and feeling valued by rewards are both confidently predicted as "Positive

Table 6: Sentiment Prediction and Analysis

Text Segment	**Actual Sentiment**	**Predicted Sentiment**
"The learning opportunities are top-notch!"	Positive	Positive
"Leadership here is lacking direction."	Negative	Negative
"I'm content with the rewards I receive."	Positive	Positive
"The learning programs are ineffective."	Negative	Negative
"Leadership is supportive and motivating."	Positive	Positive
"The rewards system needs improvement."	Negative	Negative
"Learning opportunities are scarce."	Negative	Negative
"The leadership style is empowering."	Positive	Positive
"I have mixed feelings about the rewards."	Neutral	Neutral

Table 7: Classification of Sentiments

Metric	**Positive**	**Negative**	**Neutral**	**Overall**
Accuracy	0.92	0.85	0.78	0.88
Precision	0.90	0.82	0.76	0.86
Recall	0.92	0.87	0.80	0.88
F1-Score	0.91	0.84	0.78	0.87

A comprehensive insight into sentiment prediction and analysis. This table presents a comparison between the "Actual Sentiment" of various textual segments and the "Predicted Sentiment" derived from sentiment analysis is shown in table 6. This comparison showcases the effectiveness of the sentiment analysis model in accurately predicting sentiments. Each "Text Segment" is associated with an actual sentiment label of "Positive," "Negative," or "Neutral," and the model's predicted sentiment label is then juxtaposed for comparison. The predictive accuracy of the sentiment analysis model is evident in the table. For example, the segment expressing positive sentiments about learning opportunities is correctly predicted as "Positive." Similarly, remarks highlighting negative sentiments towards leadership and rewards are accurately classified as "Negative." Even sentiments of mixed feelings, classified as "Neutral," are correctly identified. Furthermore, Table 7 provides an overall classification summary of sentiments using key metrics. The metrics, including "Accuracy," "Precision," "Recall," and "F1-Score," offer a comprehensive evaluation of the model's performance across different sentiment categories. This table consolidates the quantitative performance of the sentiment analysis model, emphasizing its accuracy in correctly categorizing sentiments as "Positive," "Negative," or "Neutral," contributing to a more nuanced understanding of the sentiment analysis results.

5. Conclusion

The integration of sentiment analysis, powered by deep learning techniques, provides an enriched understanding of emotional nuances within quantitative relationships. By examining sentiments associated with learning opportunities, leadership, and rewards, to bridge the gap between rational preferences and emotional responses. This dual perspective offers organizations a holistic understanding of how different demographic groups interact with these vital work aspects. Hence from the study, it is evident that job insecurity is a perceived psychological feeling developed by employees towards the demographic factors. Workplace happiness is wholly dependent on the utilization of learning opportunities provided. The nature of IT organisations is always dynamic and IT Organisations always require employees with learning potential. IT organisations believe Attitude of skill upgradation is always rewarded and the drive their leadership towards the attainment of the goals. Managers make their team realise the need of learning and skill upgradation to survive in the market. The employees are recognized and rewarded with their performance and the skill set they exhibit in the job. The effect of demographic factors does nothing on workplace happiness. IT organizations invariably require employees with scrupulous qualification and exact skill set. Through analysis it is clear that considering both the quantitative and emotional dimensions of workplace interactions is crucial for crafting effective strategies. As organizations strive to foster inclusive and engaging work environments, the insights from this research empower them to tailor interventions that cater to the diverse sentiments and needs of their workforce. By addressing the emotional dimensions underlying job insecurity perceptions, organizations can nurture a more supportive, satisfying, and thriving professional ecosystem. This paper contributes not only to the academic discourse but also to practical implications for organizational policies and strategies in pursuit of employee well-being and success. This study quantified the qualitative aspects by converting the happiness factors thus obtained into numerical value through which the effect of demographic factors is ascertained. The research findings can help IT organisations to develop effective strategies to make their place better working place. The study can be further extended with more demographic and organisational factors and can be studied on different industries which have more rigid with nature of job.

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