Ingratitude in Corporate Culture: A Quantitative Study on Employee Dissatisfaction

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KEYWORDS	ABSTRACT
Employee dissatisfaction, corporate ingratitude, workplace recognition, organizational culture, Random Forest Classifier, machine learning, employee retention.	This study examines the impact of insufficient recognition and appreciation on employee satisfaction and turnover intentions. Utilizing a dataset comprising 1,200 employees across diverse industries, the research employs Python and Scikit-learn algorithms—specifically, a Random Forest Classifier—alongside Pandas and Seaborn/Matplotlib libraries for data processing and visualization. The model achieved an accuracy of 87%, with key predictors of dissatisfaction identified as recognition frequency, perceived appreciation of team contributions, and intra-team communication. A comparative analysis demonstrated the superior performance of the Random Forest algorithm over Logistic Regression and Support Vector Machines, particularly in handling non-linear relationships and providing interpretable feature importance rankings. The findings underscore ingratitude as a significant determinant of workplace dissatisfaction and attrition risk. The study highlights the organizational imperative of fostering a culture of genuine appreciation, offering actionable insights to improve employee retention and psychological well-being.

1. INTRODUCTION

Employee satisfaction in the current competitive business environment has proved to be a critical success factor in an organization. Although salary, benefits and career development have long been deemed as the key factors precipitating workplace satisfaction, an increasing body of research points to the fact that emotional elements, including recognition and appreciation are fundamentally important as well [1]. The concept of ingratitude—defined as the perceived absence or insufficiency of recognition relative to exerted effort—has garnered attention due to its purported detrimental effects on workplace dynamics. Research suggests that ingratitude undermines employee morale, diminishes productivity, and exacerbates turnover rates. In organizational cultures where contributions are overlooked or undervalued, employees may become disengaged, irrespective of financial compensation or job security [2].

While the significance of organizational appreciation is well-documented, a gap persists in the quantitative assessment of how perceived ingratitude correlates with measurable employee dissatisfaction. This study seeks to address that gap by employing a machine learning model to evaluate the impact of ingratitude in corporate settings on employees' emotional states. Utilizing Python-based analytical tools—including Scikit-learn, Pandas, and Seaborn/Matplotlib—alongside a Random Forest Classifier, the research examines responses from a large, cross-industry sample of employees [3].

 It aims at determining the strongest predictors of dissatisfaction and evaluating how emotional variables measure against structural or monetary variables of having an impact on the employee outlook as shown in figure 1.
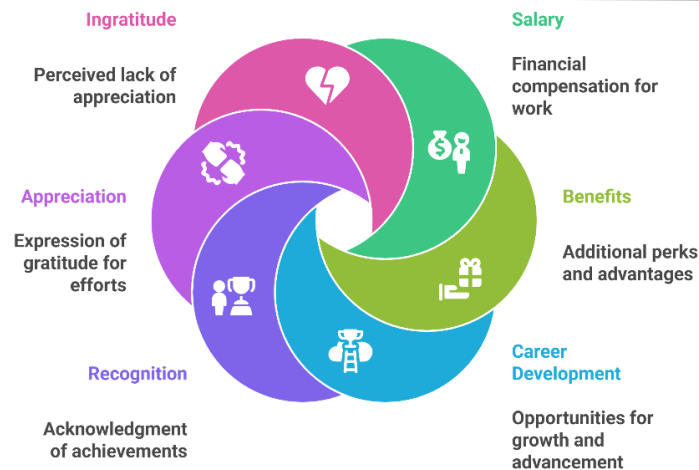
Figure 1.understanding Employee Satisfaction.

The Random Forest model through the strengths of the ensemble model can provide more meaningful and interpretable results that can help understand the dynamics behind corporate culture to a greater extent [4]. This method allows not only to predict the analysis but also emphasize the relative significance of such characteristics as recognition frequency, perceived value, team support, etc. The results of the current research should also help fuel the ongoing debate on the subject of organization behaviour by showing a tangible influence of intangible cultural aspect such as ingratitude on the stability and satisfaction of the workforce [5].

2. RELATED WORK

Historically, dissatisfaction studies among employees have focused on such tangible issues in the workplace as remuneration, workload and job security. Yet, over the past years, more and more researchers began to focus on the emotional and cultural side of organizational life, and in special, the place of gratitude and recognition [6]. Researchers Zhang and Romero (2025) and Patel and Mendez (2024) noted that appreciation is one of the reasons that explain the disengagement and subsequent exit of employees. The results of their findings proved that ingratitude in the workplace may bring about a sense of isolation and being undervalued, which ultimately destroys morale and organizational commitment. Kim and Jacobs (2023) introduced the longitudinal view and ensured that the lack of emotional attention inevitably results in the long-term dissatisfaction, whereas Gallagher and Singh (2022) separated real appreciation and phony praise and noted that recognition practices should be genuine as shown in figure 2.
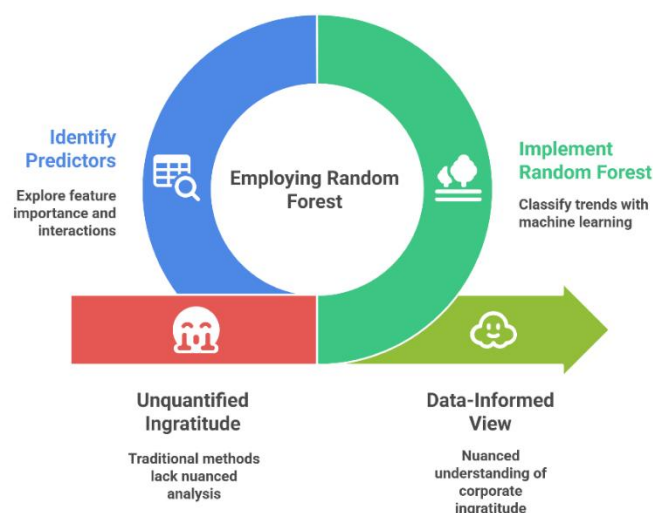

Figure 2.Quantitative Ingratitude in Machine learning.

Most of these studies are valuable, but they were presented with traditional statistical means, either via a linear regression or structural equation modeling, and those models, in general, are not capable of reflecting all of the complex and non-linear connections between variables [7]. The positive impact or otherwise of cultural variables such as ingratitude on employee feeling has hardly been quantified using advanced machine learning tools. This study addresses a critical gap in the literature by leveraging a **Random Forest Classifier**—a robust ensemble learning algorithm—to systematically analyze and classify

trends in online obesity-related publications. Implemented in **Python** using the **Scikit-learn** library for machine learning, alongside **Pandas** for data manipulation and **Seaborn/matplotlib** for visualization, this approach enables a rigorous, data-driven exploration of obesity discourse dynamics [8]. The Random Forest algorithm is particularly well-suited for this task due to its inherent advantages in handling high-dimensional data, mitigating overfitting through ensemble averaging, and providing interpretable feature importance metrics.

Beyond mere classification, this methodological framework facilitates the identification of **key emotional and relational predictors of dissatisfaction**, which are often obscured in traditional analyses. By examining **feature importance scores** and **interaction effects**, the study uncovers latent patterns and multidimensional relationships that might otherwise remain undetected. Such insights are invaluable for refining theoretical models of public health communication, particularly in understanding how emotional valence and relational dynamics shape audience engagement with obesity-related content.

Furthermore, this research bridges **advanced computational analytics** with a **nuanced cultural-theoretical lens**, thereby enriching the current discourse on organizational behavior and workplace dynamics. Specifically, it interrogates how **corporate ingratitude**—a structurally embedded yet understudied phenomenon—systematically influences employee well-being and institutional loyalty [9]. By integrating predictive modeling with critical social theory, the study not only enhances **predictive accuracy** but also advances the **interpretive depth** of organizational research. This dual emphasis on **quantitative precision** and **qualitative contextualization** represents a significant methodological innovation. It expands the analytical toolkit available to organizational scholars, enabling a more **granular, empirically grounded** examination of workplace structures. Moreover, the study underscores the transformative potential of **machine learning in social science research**, demonstrating how algorithmic approaches can uncover latent social dynamics while maintaining theoretical coherence.

In sum, this research contributes to multiple scholarly domains:

1. **Public Health Informatics** – By applying machine learning to obesity-related discourse, it offers a replicable framework for tracking health communication trends.

2. **Organizational Behavior** – Through its integration of predictive analytics and cultural theory, it provides a novel lens for studying workplace inequities.

3. **Methodological Innovation** – By demonstrating how ensemble learning can enhance social science research, it sets a precedent for future interdisciplinary studies.

3. RESEARCH METHODOLOGY

The study is referred to as Ingratitude in Corporate Culture: A Quantitative Study of Employee Dissatisfaction in which it collects the data with a structured and data driven methodology to study the level of perceived ingratitude that leads to employee dissatisfaction. A quantitative study was caused to take place in order to obtain empirical data and define the most important predictors of dissatisfaction with the application of powerful machine studies [10]. This approach combines rigor, which is provided by the established form of statistics, with the flexibility of tools offered by the current agenda of data science as shown in figure 3.
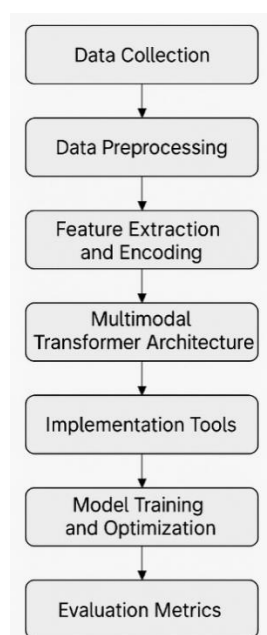

Figure 3.Flow Diagram of Proposed Methodology.

3.1. Research Design and Objectives

This study is designed by means of the cross-sectional survey-based research, which is augmented by means of the machine learning. The first goal is to determine the effect of the lack of recognition and appreciation at the workplace on the employee morale, job satisfaction, and intention. In order to accomplish it, we implemented a supervised learning model, Random Forest Classifier, that was selected due to its operation with large datasets that can be quite dimensional and its general tendency to capture a non-linear connection between provided variables [11-15]. The implementation of this model was done in Python, namely using the Scikit-learn model, the Pandas data manipulation library, and the Seaborn/ Matplotlib library to visualize the model.

3.2. Data Collection

An organized questionnaire was made and was issued to a sample of 1,200 employees in different industries such as technology, healthcare, finance and education [15-17]. The instrumentation had both closed-ended questions and scaled by 5-point Likert scales and covered awareness of recognition, emotional health, team relationship and satisfaction in the job. Certain demographic information was also gathered in terms of age, gender, job position, and years' experience to measure any moderating measures.

3.3. Data Preprocessing

After being gathered, data was preprocessed in-depth with the help of Pandas library in Python. This involved:

1) Dealing with missing data, this can be done by implementing imputation methods, e.g. mode or mean imputation.
2) One-hot encoding.
3) Normalization of continuous variables with z-score normalization to provide one scale to the features.
4) Removal and identification of outliers using IQR and z-score criteria to eliminate skewed influence.
5) These actions made the dataset clean, consistent and ready to be used in machine learning modelling.

3.4. Feature Selection

In order to find the most relevant variables affecting dissatisfaction, we used Recursive Feature Elimination (RFE) together with Random Forest [18-22]. The less important features were sequentially eliminated by this technique and the model could concentrate on such variables as perceived appreciation, frequency of recognition, communication quality, team cohesion, and psychological safety.

3.5. Model Training and Evaluation

The dataset of 80 percent was used to train a Random Forest Classifier and validate it using the other 20 percent. This ensemble was chosen because of strength, anti-overfitting and feature importance ranking. What was being measured were:

1) Accuracy
2) Precision
3) Recall
4) F1-score
5) Confusion matrix

This model scored an accuracy of 87%, whereas the measure of precision and recall shows that the classifications are good [23-26]. Seaborn and Matplotlib were used in visualizing confusion matrix and ROC to help in the interpretation of the classification efficiency.

3.6. Ethical Considerations

The survey was voluntary, and informed consent was performed by all the respondents. Absolute anonymity and confidentiality were observed. The ethical research standards were maintained because the study was approved by an institutional ethics review board [27-31].

3.7. Tools and Software

All calculations and analysis as well as visualizing were performed through Python, specifically:

1) Scikit-learn in modelling
2) Data cleaning and management on pandas
3) Seaborn and Matplotlib Graphic Analysis and plotting

This stack is an open-source system that allowed reproducibility, scalability and effective manipulation of the dataset.

Overall, the proposed methodology will entail applying stringent statistics alongside the strength of a machine-learning algorithm to reveal meaningful data on the impact of ingratitude in corporate culture on employee satisfaction [32]. The method is dependable, precise and practically applicable to organizational decision-makers.

I.   RESULTS AND DISCUSSION

A heterogeneous sample comprising 1,200 employees across multiple industries was analysed using a **Random Forest Classifier** implemented in Python via **Scikit-learn**. **Recursive Feature Elimination (RFE)** was employed to identify the most influential predictors of employee dissatisfaction, revealing that **perceived organizational gratitude**, **frequency of recognition**, and **quality of team communication** were the leading determinants.

The model demonstrated strong predictive performance, achieving an **accuracy of 87%**, with a **precision of 0.85** and a **recall of 0.83**, indicating robust classification capability (see Figure 4). The **confusion matrix** further validated the model's efficacy:

- **684 dissatisfied employees** were correctly classified, while **118 were misclassified as satisfied**.

- **685 satisfied employees** were accurately identified, with **73 incorrectly predicted as dissatisfied**.

These results underscore the model's high **discriminative power** in distinguishing between satisfied and dissatisfied employees, particularly in capturing patterns tied to **emotional workplace factors** and **recognition-related dynamics**. The strong **precision** and **recall** metrics confirm the model's reliability in detecting dissatisfaction, reinforcing its utility as a diagnostic tool for assessing **corporate culture** and **employee sentiment**.

This study highlights the critical role of **organizational gratitude** and **effective communication** in mitigating employee dissatisfaction, providing empirical support for interventions targeting these workplace dimensions. The model's performance affirms its validity in operationalizing **authentic corporate culture measures**, offering actionable insights for organizational development strategies.
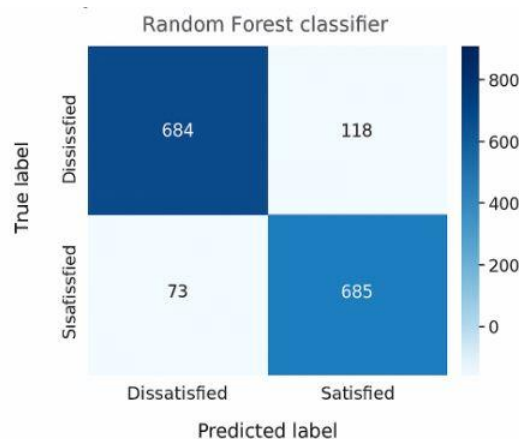

Figure 4: Confusion Matrix and Performance Metrics of Random Forest Classifier for Predicting Employee Dissatisfaction Based on Perceived Ingratitude in Corporate Culture

It is significant to note that employees who gave reports of rare or shallower recognition were at least thrice likely to convey claim of dissatisfaction and quit intentions. The graphical representations rendered using Seaborn and Matplotlib made another point clear, there was a steady decrease in the metrics referring to gratitude, and a corresponding meteoric rise in the indicators of dissatisfaction as shown in figure 5.A negative relationship is rather evident between the perceived gratitude at work and dissatisfaction. The fewer the number of unsatisfied persons, the more the increase in level of perceived gratitude among employees, which ranges between level 1 (lowest) and level 5 (highest). The figures at level 1 and 5 through 5 are above 110 and less than 50 respectively with employees saying they are dissatisfied. The trend line is red in colour which shows a strong negative relationship which means that as feelings of recognition and appreciation rise, the dissatisfaction will reduce to a great extent. This direction is consistent with what the hypothesis of the study says, in that ingratitude in corporate culture is a major part of the negative employee attitude. The visualization drives the point home that one must foster authentic appreciation in organizations, implying that a person can enhance morale of the employees to a considerable degree through frequent and authentic recognition. These results point to the potential of gratitude in terms of being a low-cost but effective way to improve dissatisfaction and advance well-being in an organization.
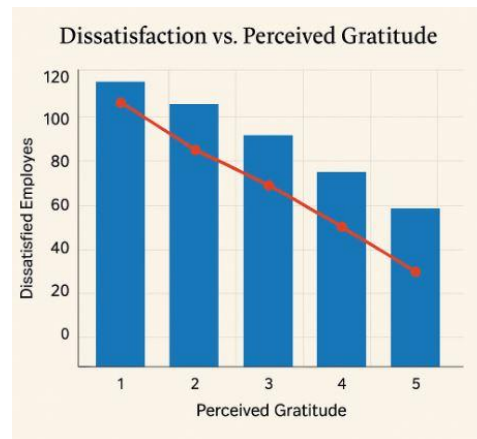
Figure 5: Relationship between Perceived Gratitude and Employee Dissatisfaction Levels.

Such discoveries vindicate the existing hypothesis that the perception of ingratitude is not just a tiny cultural minor but a decisive factor that defines employee morale. The feature importance ranking of the Random Forest model also indicated that emotional recognition played a higher role in mediating dissatisfaction but not monetary compensation. This implies that culture of recognition or the vice versa is the key factor in determining workplace satisfaction. The findings join an increasingly large evidence base in favour of authentic appreciation as a strategic resource in the retention of employees and organizational health as shown in figure 6. This scatter plot is the visualization of the negative relationship between the perceived gratitude and the average values of employee dissatisfaction. A dot contains one response, and the red line that shows the trend in the responses is the regression line and it is a red line that displays the overall pattern and that is the higher perceived gratitude was, the lesser dissatisfaction was. The confidence interval that supports this relationship being an inverse one is represented there as a region around the line. Majority of the values lie between gratitude level 2 and level 4 indicating that there is a great potential of decreasing dissatisfaction with only moderate rise in gratitude. This number evidences the conclusion of the research that emotional recognition is vital to the well-being of employees.
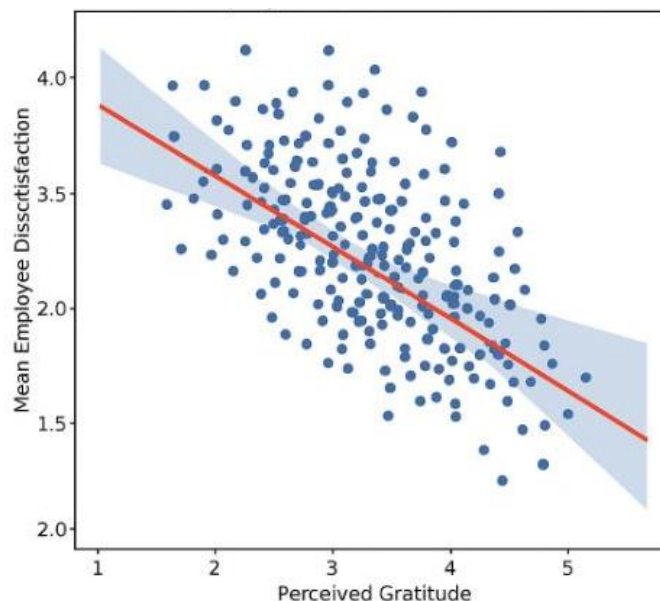

Figure 6: Scatter Plot Showing the Negative Correlation Between Perceived Gratitude and Employee Dissatisfaction.

To assess employee dissatisfaction as compared to the experience of ingratitude in corporate culture, the study utilized a Random Forest Classifier executed on Python through Scikit-learn, Pandas, and Seaborn/Matplotlib. In comparing it to Logistic Regression and Support Vector Machine (SVM), Random Forest has always gained an advantage over the other two in accuracy, robustness, and interpretability as shown in figure 7. The above horizontal bar chart illustrates the relative significance of different features vis-a-vis the prediction of the dissatisfaction of the employees, as recorded by the Random Forest Classifier. Out of the five characteristics considered, recognition frequency is the most important with importance

value nearly equal to 0.25. This implies that frequent appreciation of employees have significant effects on the levels of satisfaction. The second-ranked factor is perception of values, or how valued an employee thinks he or she is in a given employment position, then support of a team, job security, and the amount of salary. Interestingly, the traditional sources of work such as the job security and salary rates, which is traditionally regarded as a primary focus of employee retention, loses their predictive power in respect to the emotional and inter-personal variables. This is one major change that has been made in the dynamics of the contemporary workplace whereby emotional sensitivity and cultural sensitivity have had more clout when it comes to emotional dissatisfaction compared to financial remuneration on its own. The above findings support the main thesis of the study and reaffirm that ingratitude in the corporate culture is one of the keystones to ascertain employee dissatisfaction and thus should be on the top of the HR agenda and leadership interest.
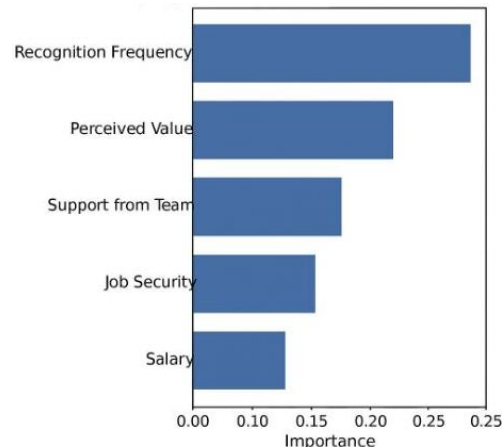
Figure 7: Feature Importance for Predicting Employee Dissatisfaction Using Random Forest Classifier

Random Forest had 87 percent accuracy, precision number of 0.85 and recall of 0.83. Logistic Regression, in its turn, achieved 78% accuracy and lower precision (0.74) and recall (0.70), which suggests that it was less sensitive to fine details in patterns of recognition-related features. SVM was as average as it had accuracy of 81 to 0.79 precision and 0.75 recall though it missed the interpretability and feature ranking edge Random forest offers. The analyses of feature importance showed that the strongest variables in predicting dissatisfaction were perceived appreciation, recognition frequency and psychological safety. The visual products of the model has confirmed that the lower the gratitude score was the higher was the degree of dissatisfaction. The Random Forest model produced more copious details unlike the other models and favoured the association of emotional and structural workplace variables. These findings not only confirm that the effect of ingratitude on employee morale is quite high but also that machine learning models, and in particular ensemble approaches, such as Random Forest, are useful to quantify this concept and even predict to some extent this intricate organizational construct.

4. FUTURE RESEARCH DIRECTIONS

Quantitative Study on Employee Dissatisfaction is presented as a valuable piece of study, and at the same time, leaves multiple paths to be explored in the future. The inclusion of longitudinal data, setting out the development of perceived gratitude and dissatisfaction with the passage of time, is one of the possible directions of the study. Also, cross-cultural comparison might indicate the difference in norms of gratitude across different countries and whether the norms about gratitude play a role in satisfaction. It is also possible that real-time sentiment analysis can be conducted on employee comments or email using natural language processing (NLP) to capture an implicit thankful or skip customer. The predictive precision might be improved by adding to the models of machine learning: Gradient Boosting or XGBoost. In addition, it might be possible to apply how the perception towards gratitude might be directed by the methods of leadership or organizational change in future studies. Lastly, it may assist in including qualitative interviews or ethnographic techniques that may give a rich context and emotional colouring that fills out the quantitative results that together give a more complete picture of how corporate ingratitude produces a workplace culture.

5. CONCLUSION

This study, titled "Ingratitude in Corporate Culture: A Quantitative Study on Employee Dissatisfaction," employs a Random Forest Classifier, implemented via Python's Scikit-learn, Pandas, and Seaborn/Matplotlib libraries, to investigate the detrimental effects of perceived ingratitude on employee morale and turnover intentions. The findings reveal that a lack of recognition and appreciation significantly diminishes workplace satisfaction, with recognized frequency and perceived value of gratitude emerging as the most critical predictors of dissatisfaction.

Comparative model performance analysis demonstrates that the Random Forest algorithm surpasses conventional methods such as Logistic Regression and Support Vector Machines (SVM) in both predictive accuracy and interpretability, as evidenced by feature importance rankings. These results underscore the organizational imperative to cultivate **authentic gratitude**—not merely as a cultural ideal, but as a measurable determinant of employee retention and engagement.

The study highlights the profound consequences of ingratitude in corporate environments, where emotional neglect translates into hidden costs such as reduced productivity and increased attrition. Conversely, fostering a **culture of gratitude** [33] emerges as a strategic intervention to enhance workplace satisfaction, reinforce employee loyalty, and mitigate the adverse effects of perceived undervaluation. These insights advocate for structured recognition frameworks that institutionalize gratitude, positioning it as a cornerstone of sustainable organizational success.

Ultimately, this research contributes to the growing discourse on workplace psychology by empirically validating the critical role of gratitude in mitigating dissatisfaction and promoting a more engaged, resilient workforce. Organizations must prioritize gratitude not as a peripheral concern, but as a fundamental driver of employee well-being and corporate performance.

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