



Prediction of Employee Absenteeism Based on Perceived Stress, Work–Family Conflict, Mental Health, and Procedural Justice Using Supervised Learning Algorithms

Zahra Nezhadkheir^{1*}, Danial Poorhashemi²

¹ MA, Department of Business Management, Molana Non-Profit University, Abyek, Iran

² Ph.D. Student, Department of Higher Education Management, CT.C., Islamic Azad University, Tehran, Iran

* Corresponding author email address: Zahranezhadkheir64@gmail.com

Received: 2026-01-01

Reviewed: 2026-01-20

Revised: 2026-05-01

Accepted: 2026-05-07

Initial Published: 2026-10-11

Final Published: 2027-01-01

Abstract

The present study aimed to develop and compare predictive models of employee absenteeism based on perceived stress, work–family conflict, mental health, and procedural justice using supervised learning algorithms. This quantitative cross-sectional study was conducted among 312 employees working in public and private organizations in Tehran, selected through stratified random sampling. Data were collected using standardized instruments including the Perceived Stress Scale, Work–Family Conflict Scale, General Health Questionnaire (GHQ-28), and Procedural Justice Scale, all of which have established validity and reliability in previous studies. Employee absenteeism was measured based on self-reported absence frequency. Data analysis was performed using SPSS-27 and Python-based machine learning frameworks. Initially, descriptive statistics and correlation analyses were conducted, followed by the implementation of supervised learning algorithms including multiple linear regression, Random Forest, Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). The dataset was divided into training and testing subsets (80/20 split), and model performance was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). Hyperparameter tuning and cross-validation techniques were applied to optimize model performance. The results indicated that perceived stress, work–family conflict, and poor mental health were positively and significantly associated with employee absenteeism, while procedural justice showed a significant negative relationship. Among predictors, mental health demonstrated the strongest effect, followed by work–family conflict and perceived stress. The regression model explained 42% of the variance in absenteeism ($p < 0.001$). Among machine learning models, XGBoost exhibited the highest predictive performance ($R^2 = 0.63$), outperforming Random Forest ($R^2 = 0.58$), SVM ($R^2 = 0.55$), and linear regression ($R^2 = 0.42$). Feature importance analysis revealed that mental health was the most influential predictor, followed by work–family conflict, perceived stress, and procedural justice. The findings highlight the critical role of psychological and organizational factors in predicting employee absenteeism and demonstrate the superiority of supervised learning algorithms, particularly XGBoost, in modeling complex relationships among variables. The study underscores the importance of integrating mental health support, work–family balance strategies, and fair organizational practices to reduce absenteeism and improve workforce productivity.

Keywords: Employee absenteeism, perceived stress, work–family conflict, mental health, procedural justice, supervised learning, XGBoost, organizational behavior

How to cite this article:

Atri, R., Shafizadeh, H., & Soleimani, N. (2027). Prediction of Employee Absenteeism Based on Perceived Stress, Work–Family Conflict, Mental Health, and Procedural Justice Using Supervised Learning Algorithms. Management Strategies and Engineering Sciences, 9(1), 1-10.



1. Introduction

Employee absenteeism has long been recognized as a critical organizational challenge with substantial economic, psychological, and operational consequences. It not only disrupts workflow continuity and reduces productivity but also imposes significant financial burdens on organizations due to replacement costs, reduced efficiency, and increased workload on remaining employees. Contemporary organizational research has increasingly shifted toward understanding absenteeism as a multifactorial phenomenon influenced by psychosocial, organizational, and individual-level determinants rather than merely a behavioral outcome [1, 2]. Within this perspective, absenteeism is conceptualized as a form of withdrawal behavior that reflects employees' attempts to cope with unfavorable working conditions, psychological distress, or perceived organizational injustice [3, 4]. This evolving conceptualization underscores the necessity of examining the interplay between stress, work–family dynamics, mental health, and organizational justice in predicting absenteeism patterns.

Perceived stress has emerged as one of the most influential predictors of employee well-being and behavioral outcomes in organizational settings. Defined as the degree to which individuals appraise situations in their lives as overwhelming or uncontrollable, perceived stress has been consistently associated with a wide range of negative outcomes, including burnout, reduced job satisfaction, and increased absenteeism [5, 6]. High levels of occupational stress often result from excessive workload, role ambiguity, and interpersonal conflicts, which collectively erode employees' psychological resilience and coping capacity [7, 8]. Empirical evidence suggests that employees experiencing chronic stress are more likely to disengage from work through absenteeism as a self-regulatory mechanism to restore psychological equilibrium [9, 10]. Moreover, stress does not operate in isolation but interacts with other psychosocial factors, amplifying its impact on employee behavior and organizational outcomes.

Another critical determinant of absenteeism is work–family conflict, which refers to the incompatibility between the demands of work and family roles. This conflict manifests in two primary directions: work-to-family conflict, where work responsibilities interfere with family life, and family-to-work conflict, where family obligations hinder work performance. Extensive research has demonstrated that work–family conflict is a significant

source of psychological strain, contributing to emotional exhaustion, reduced well-being, and increased withdrawal behaviors, including absenteeism [11, 12]. The intensification of work demands in modern organizations, coupled with evolving family structures, has exacerbated this conflict, making it a central concern for organizational scholars and practitioners. Studies have shown that employees experiencing high levels of work–family conflict are more likely to report stress-related symptoms and exhibit lower levels of job commitment, ultimately leading to higher absenteeism rates [13, 14]. Furthermore, organizational support mechanisms, such as flexible work arrangements and supportive leadership, play a crucial role in mitigating the adverse effects of work–family conflict [15].

Mental health constitutes another fundamental dimension in understanding employee absenteeism. Poor mental health, including symptoms of anxiety, depression, and psychological distress, has been consistently linked to reduced work performance and increased absenteeism [16, 17]. The COVID-19 pandemic has further highlighted the vulnerability of employees to mental health challenges, emphasizing the need for comprehensive approaches to occupational health [18, 19]. Mental health issues often arise from prolonged exposure to psychosocial stressors, such as high job demands, lack of control, and insufficient social support [20, 21]. These conditions not only impair cognitive and emotional functioning but also increase the likelihood of absenteeism as individuals seek to cope with psychological strain. Importantly, mental health acts as both an outcome of adverse working conditions and a mediator linking stress and organizational factors to behavioral outcomes [22, 23].

Procedural justice, defined as employees' perceptions of fairness in organizational decision-making processes, represents a key organizational factor influencing employee attitudes and behaviors. When employees perceive organizational procedures as fair, transparent, and consistent, they are more likely to develop trust in management and exhibit positive work behaviors [24]. Conversely, perceived injustice can lead to dissatisfaction, reduced commitment, and increased withdrawal behaviors, including absenteeism [25, 26]. The relationship between procedural justice and employee well-being has been extensively documented, with studies indicating that fair organizational practices can buffer the negative effects of stress and enhance psychological health [22, 27]. In this context, procedural justice serves as both a protective factor and a determinant of organizational climate, influencing employees' responses to work-related stressors.

The interplay between these psychosocial and organizational factors is further complicated by the broader context of modern workplaces, characterized by rapid technological changes, increased job demands, and evolving employment relationships. These dynamics have intensified the need for sophisticated analytical approaches capable of capturing complex, non-linear relationships among variables. Traditional statistical methods, while valuable, often fall short in modeling such complexity, necessitating the adoption of advanced machine learning techniques. Supervised learning algorithms, including Random Forest, Support Vector Machine, and Extreme Gradient Boosting (XGBoost), have demonstrated superior predictive capabilities in various organizational research domains [28, 29]. These algorithms enable researchers to identify patterns and interactions that may not be apparent through conventional analytical methods, thereby enhancing the accuracy and robustness of predictive models.

Recent studies have highlighted the potential of machine learning in predicting employee-related outcomes, including absenteeism, turnover, and performance. For instance, ensemble learning methods such as XGBoost have been shown to outperform traditional regression models in handling high-dimensional data and capturing complex interactions among predictors [14, 30]. The integration of machine learning with organizational psychology offers a promising avenue for advancing theoretical understanding and practical applications. By leveraging these techniques, organizations can develop proactive strategies to identify at-risk employees and implement targeted interventions to reduce absenteeism and enhance well-being.

In addition to methodological advancements, contemporary research emphasizes the importance of adopting a holistic approach to employee well-being, recognizing the interconnectedness of psychological, social, and organizational factors. For example, the concept of organizational well-being encompasses not only the absence of negative outcomes such as stress and burnout but also the presence of positive conditions, including supportive leadership, fair practices, and work-life balance [23, 31]. This perspective aligns with the growing emphasis on sustainable performance, which seeks to balance organizational productivity with employee health and well-being [6]. By addressing the root causes of absenteeism, organizations can create healthier work environments that promote both individual and organizational success.

Furthermore, leadership plays a crucial role in shaping employees' experiences and responses to workplace

stressors. Dysfunctional leadership, characterized by abusive supervision, lack of support, and inconsistent decision-making, has been identified as a significant contributor to employee stress and absenteeism [32]. Effective leadership, on the other hand, can foster a positive organizational climate, enhance perceptions of justice, and mitigate the adverse effects of stress and work-family conflict. This highlights the importance of leadership development and organizational policies in addressing absenteeism and promoting employee well-being.

Despite the extensive body of research on absenteeism, there remains a need for integrative models that simultaneously consider multiple psychosocial and organizational factors and employ advanced analytical techniques to capture their complex interactions. Existing studies often focus on individual predictors in isolation, limiting the ability to understand the combined effects of stress, work-family conflict, mental health, and procedural justice. Moreover, the application of machine learning in this domain is still emerging, with limited empirical studies exploring its potential in predicting absenteeism within diverse organizational contexts.

Therefore, the present study seeks to address these gaps by developing a comprehensive predictive model of employee absenteeism based on perceived stress, work-family conflict, mental health, and procedural justice, utilizing supervised learning algorithms to enhance predictive accuracy and provide deeper insights into the relative importance of these factors.

2. Methodology

This study was conducted using a quantitative, cross-sectional design with a predictive modeling approach. The statistical population consisted of employees working in public and private organizations in Tehran. A total of 312 participants were selected through stratified random sampling to ensure adequate representation across different organizational sectors and job categories. Inclusion criteria included having at least one year of work experience and full-time employment status, while individuals with incomplete questionnaire responses were excluded from the final analysis. Data were collected in a controlled setting with informed consent obtained from all participants, and confidentiality of responses was strictly maintained in accordance with ethical research standards.

Perceived stress was measured using the Perceived Stress Scale (PSS) developed by Cohen, Kamarck, and

Mermelstein in 1983. This instrument consists of 14 items designed to assess the degree to which individuals appraise situations in their lives as stressful. The scale includes two subscales reflecting perceived helplessness and perceived self-efficacy. Responses are recorded on a 5-point Likert scale ranging from “never” to “very often,” and total scores are calculated by summing item responses after reverse scoring specific items. Higher scores indicate greater perceived stress. The PSS has demonstrated strong psychometric properties across diverse populations, with previous studies confirming its construct validity and internal consistency reliability.

Work–family conflict was assessed using the Work–Family Conflict Scale developed by Netemeyer, Boles, and McMurrian in 1996. This scale comprises 10 items divided into two dimensions: work-to-family conflict and family-to-work conflict. Participants respond to each item on a 5-point Likert scale ranging from “strongly disagree” to “strongly agree.” The scoring procedure involves summing the responses for each subscale, with higher scores indicating greater levels of conflict between work and family roles. The instrument has been widely used in organizational research, and its validity and reliability have been consistently supported in previous empirical studies.

Mental health status was evaluated using the General Health Questionnaire (GHQ-28) developed by Goldberg and Hillier in 1979. This widely used screening tool includes 28 items across four subscales: somatic symptoms, anxiety and insomnia, social dysfunction, and severe depression. Each item is rated on a 4-point scale reflecting the severity of symptoms over recent weeks. Scoring can be conducted using the Likert method, yielding a total score where higher values indicate poorer mental health. The GHQ-28 has been extensively validated in clinical and non-clinical populations, with robust evidence supporting its reliability and diagnostic accuracy.

Procedural justice was measured using the Procedural Justice Scale developed by Niehoff and Moorman in 1993. This instrument includes 6 items that evaluate employees’ perceptions of fairness in organizational decision-making processes. Responses are provided on a 5-point Likert scale ranging from “strongly disagree” to “strongly agree.” Higher scores reflect stronger perceptions of fairness and transparency in procedures. The scale has demonstrated satisfactory construct validity and internal consistency in numerous organizational behavior studies.

Employee absenteeism, as the dependent variable, was operationalized through a self-reported measure of absence frequency over the past six months, complemented by organizational records where available. The measure captures both voluntary and involuntary absences, providing a continuous variable suitable for predictive modeling.

Data analysis was performed using a combination of statistical and machine learning techniques. Initially, descriptive statistics and correlation analyses were conducted using SPSS version 27 to examine the distribution and relationships among variables. Subsequently, supervised learning algorithms were implemented to predict absenteeism. These included multiple linear regression as a baseline model, along with advanced machine learning models such as Random Forest, Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). The dataset was partitioned into training and testing subsets using an 80/20 split, and model performance was evaluated using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared. Hyperparameter tuning was conducted using cross-validation to optimize model performance. Feature importance analysis was also performed, particularly within the XGBoost framework, to identify the relative contribution of perceived stress, work–family conflict, mental health, and procedural justice in predicting employee absenteeism.

3. Findings and Results

The demographic characteristics of the participants indicated that the sample was composed of 312 employees from various public and private organizations in Tehran, representing a diverse workforce in terms of age, gender, educational level, and job tenure. The mean age of participants was 36.84 years ($SD = 7.92$), with ages ranging from 23 to 58 years. In terms of gender distribution, 54.2% were male and 45.8% were female. Regarding educational attainment, 21.5% held a diploma, 46.8% had a bachelor’s degree, and 31.7% possessed a postgraduate degree. The average job tenure was 8.63 years ($SD = 5.11$), reflecting a relatively experienced sample. Most participants (62.1%) were employed in the public sector, while the remaining 37.9% worked in private organizations. This demographic composition suggests that the sample was sufficiently heterogeneous to support generalizable findings within the context of urban organizational environments.

Table 1. Descriptive Statistics and Correlations Among Study Variables

Variable	Mean	SD	1	2	3	4	5
1. Perceived Stress	26.47	6.21	1				
2. Work–Family Conflict	31.83	7.05	0.48**	1			
3. Mental Health (GHQ)	22.96	8.14	0.52**	0.44**	1		
4. Procedural Justice	19.72	4.88	-0.39**	-0.33**	-0.41**	1	
5. Absenteeism	6.28	2.91	0.46**	0.49**	0.51**	-0.37**	1

**p<0.01

The descriptive statistics and correlation matrix presented in Table 1 indicate that perceived stress, work–family conflict, and poor mental health were positively and significantly associated with employee absenteeism, while procedural justice demonstrated a significant negative relationship with absenteeism. Among predictors, mental health exhibited the strongest correlation with absenteeism ($r = 0.51$, $p < 0.01$), followed closely by work–family

conflict ($r = 0.49$, $p < 0.01$) and perceived stress ($r = 0.46$, $p < 0.01$). Procedural justice showed a moderate inverse correlation with absenteeism ($r = -0.37$, $p < 0.01$), suggesting that higher perceptions of fairness are linked to lower absence rates. Additionally, the intercorrelations among independent variables were significant but not excessively high, indicating acceptable levels of multicollinearity for predictive modeling.

Table 2. Multiple Linear Regression Results for Predicting Employee Absenteeism

Predictor	B	SE	Beta	t	p
Constant	2.14	0.89	—	2.40	0.017
Perceived Stress	0.11	0.03	0.24	3.67	0.001
Work–Family Conflict	0.13	0.04	0.27	3.92	0.000
Mental Health (GHQ)	0.15	0.03	0.31	4.88	0.000
Procedural Justice	-0.09	0.02	-0.21	-3.54	0.001

$R^2 = 0.42$, Adjusted $R^2 = 0.40$, $F = 55.73$, $p < 0.001$

The regression analysis demonstrated that the set of independent variables significantly predicted employee absenteeism, explaining 42% of the variance. Mental health emerged as the strongest predictor ($\beta = 0.31$, $p < 0.001$), indicating that poorer mental health is associated with increased absenteeism. Work–family conflict ($\beta = 0.27$, $p < 0.001$) and perceived stress ($\beta = 0.24$, $p < 0.01$) also

contributed significantly to the model, reinforcing their role as key psychosocial determinants. Procedural justice had a significant negative effect ($\beta = -0.21$, $p < 0.01$), suggesting that perceptions of fairness reduce absenteeism. The overall model fit was statistically significant, indicating the adequacy of the regression model for baseline comparison with machine learning approaches.

Table 3. Performance Metrics of Supervised Learning Models

Model	MSE	RMSE	R^2
Linear Regression	5.84	2.41	0.42
Random Forest	4.12	2.03	0.58
SVM	4.36	2.09	0.55
XGBoost	3.71	1.93	0.63

The comparison of supervised learning models revealed that XGBoost achieved the highest predictive performance, with the lowest mean squared error (MSE = 3.71) and root mean squared error (RMSE = 1.93), along with the highest coefficient of determination ($R^2 = 0.63$). This indicates that

XGBoost explained 63% of the variance in absenteeism, outperforming both traditional regression and other machine learning models. Random Forest also demonstrated strong performance ($R^2 = 0.58$), followed by SVM ($R^2 = 0.55$), while linear regression showed the lowest predictive

accuracy. These results confirm the superiority of ensemble learning methods in capturing complex, non-linear

relationships among psychological and organizational variables.

Table 4. Feature Importance Based on XGBoost Model

Predictor	Importance Score
Mental Health	0.34
Work–Family Conflict	0.27
Perceived Stress	0.23
Procedural Justice	0.16

The feature importance analysis derived from the XGBoost model indicates that mental health was the most influential predictor of absenteeism, accounting for 34% of the model's predictive power. Work–family conflict and perceived stress followed with importance scores of 0.27 and 0.23, respectively, highlighting their substantial

contributions. Procedural justice, while still significant, had the lowest relative importance (0.16), suggesting that although fairness perceptions matter, their predictive weight is comparatively smaller than psychological distress variables. This pattern reinforces the central role of mental health and stress-related factors in absenteeism prediction.

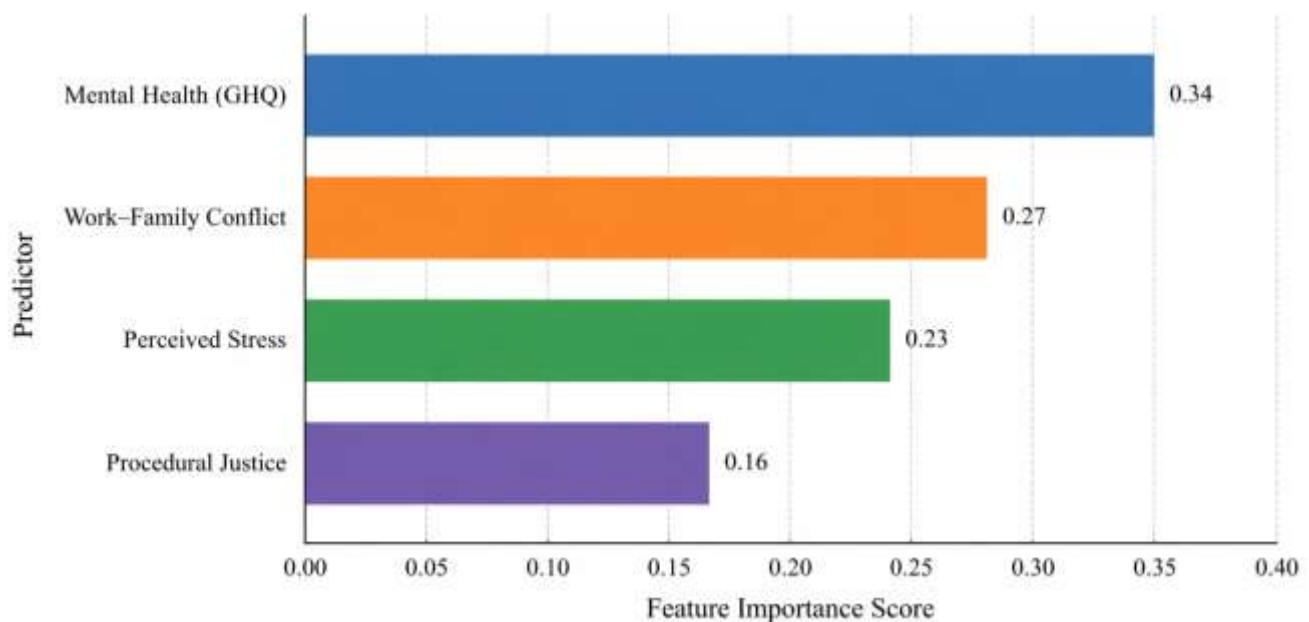


Figure 1. Feature Importance Distribution of Predictors in the XGBoost Model

The figure illustrates the relative contribution of each predictor variable within the XGBoost algorithm, clearly demonstrating that mental health and work–family conflict dominate the model, followed by perceived stress and procedural justice, thereby visually confirming the hierarchical importance observed in the numerical analysis.

4. Discussion and Conclusion

The findings of the present study provide robust empirical support for the multidimensional nature of employee absenteeism and demonstrate that perceived stress, work–family conflict, mental health, and procedural justice collectively constitute a powerful predictive framework

when modeled through both traditional statistical approaches and advanced supervised learning algorithms. The results indicated that all four predictors were significantly associated with absenteeism, with mental health emerging as the strongest predictor, followed by work–family conflict, perceived stress, and procedural justice. Moreover, the superiority of machine learning models, particularly XGBoost, in explaining variance in absenteeism highlights the importance of capturing non-linear and interaction effects that are often overlooked in conventional regression models.

The strong predictive role of mental health observed in this study aligns with a substantial body of literature

emphasizing the centrality of psychological well-being in shaping employee behavior. Poor mental health, characterized by symptoms such as anxiety, depression, and emotional exhaustion, has been consistently linked to increased absenteeism as employees withdraw from work to cope with psychological distress [16, 17]. The present findings corroborate prior research indicating that mental health not only reflects the cumulative impact of workplace stressors but also functions as a proximal determinant of withdrawal behaviors [20, 22]. Furthermore, the high feature importance of mental health in the XGBoost model suggests that it plays a pivotal mediating role in the relationship between other psychosocial variables and absenteeism, a pattern also observed in recent occupational health studies [23].

Work–family conflict was identified as another significant predictor of absenteeism, exerting both direct and indirect effects on employee behavior. This finding is consistent with extensive empirical evidence demonstrating that the incompatibility between work and family roles generates psychological strain, reduces job satisfaction, and increases the likelihood of absenteeism [11, 12]. The significant association between work–family conflict and absenteeism in the present study reinforces the notion that employees experiencing high levels of role conflict are more prone to disengagement as a coping mechanism. Additionally, the interaction between work–family conflict and perceived stress observed in the predictive models suggests that these variables may amplify each other's effects, leading to more pronounced behavioral outcomes. This is in line with findings by Wu et al., who reported that work–family conflict contributes to presenteeism and absenteeism through its impact on psychological strain and reduced social support [13]. Similarly, Zhang et al. highlighted the role of work–family conflict in exacerbating job anxiety and performance-related issues, further supporting the present results [14].

Perceived stress also emerged as a significant predictor of absenteeism, underscoring its role as a fundamental psychosocial risk factor in organizational settings. Employees who perceive their work environment as stressful are more likely to experience cognitive overload, emotional exhaustion, and diminished coping capacity, which in turn increase the likelihood of absenteeism [5, 6]. The positive association between perceived stress and absenteeism observed in this study is consistent with previous research indicating that chronic stress leads to withdrawal behaviors as individuals attempt to restore psychological balance [9,

10]. Moreover, the moderate yet significant contribution of perceived stress in the XGBoost model suggests that while it is not the sole determinant of absenteeism, it interacts with other variables, particularly mental health, to influence employee behavior. This interaction effect aligns with the findings of Chen et al., who emphasized the complex interplay between workload, stress, and organizational factors in shaping employee outcomes [8].

Procedural justice demonstrated a significant negative relationship with absenteeism, indicating that employees who perceive organizational processes as fair and transparent are less likely to engage in withdrawal behaviors. This finding is consistent with theoretical frameworks of organizational justice, which posit that fairness perceptions enhance trust, commitment, and psychological well-being, thereby reducing absenteeism [24]. The protective role of procedural justice observed in this study is supported by empirical evidence showing that fair decision-making processes can buffer the adverse effects of stress and improve employee health outcomes [22, 27]. Furthermore, the inverse association between procedural justice and mental health problems suggests that fairness perceptions may mitigate psychological distress, thereby indirectly reducing absenteeism. This is in line with findings by Baher and Alkhadher, who reported that perceptions of organizational justice are negatively associated with depressive symptoms [25], as well as Zhou et al., who highlighted the moderating role of justice climate in the relationship between work–family conflict and psychological outcomes [26].

The comparative analysis of predictive models revealed that XGBoost outperformed other algorithms, including Random Forest, Support Vector Machine, and linear regression, in predicting absenteeism. This finding underscores the value of ensemble learning methods in capturing complex, non-linear relationships among variables. The superior performance of XGBoost is consistent with previous studies demonstrating its effectiveness in handling high-dimensional data and identifying intricate interaction patterns [28, 30]. The ability of machine learning models to provide feature importance metrics further enhances their utility in organizational research, enabling researchers to identify key determinants of employee behavior with greater precision. In the present study, the feature importance analysis highlighted the dominant role of mental health and work–family conflict, providing actionable insights for organizational interventions.

The findings of this study also contribute to the broader literature on occupational health and organizational behavior by integrating multiple theoretical perspectives into a comprehensive predictive model. The results support the job demands–resources framework, which posits that job demands such as stress and work–family conflict deplete employees’ resources and lead to negative outcomes, while resources such as procedural justice enhance well-being and buffer the effects of stress [3, 21]. Additionally, the findings align with research on burnout and psychosocial risks, which emphasize the cumulative impact of workplace stressors on employee health and behavior [17, 19]. The integration of machine learning approaches further extends this literature by demonstrating the potential of advanced analytical techniques in uncovering complex relationships that traditional methods may fail to detect.

Another important implication of the present study is the recognition of absenteeism as part of a broader spectrum of withdrawal behaviors that include presenteeism, reduced engagement, and turnover intentions. Previous research has shown that these behaviors are interconnected and often share common antecedents, such as stress, burnout, and organizational injustice [2, 4]. By focusing on absenteeism within this broader context, the present study provides a more comprehensive understanding of employee behavior and highlights the need for integrated organizational strategies to address multiple forms of withdrawal simultaneously.

The results also emphasize the importance of organizational context in shaping employee experiences and behaviors. Factors such as leadership style, organizational culture, and support systems play a crucial role in influencing employees’ perceptions of stress, conflict, and justice. For instance, dysfunctional leadership has been identified as a significant source of stress and dissatisfaction, leading to increased absenteeism [32]. Conversely, supportive leadership and organizational policies can enhance employee well-being and reduce withdrawal behaviors. This underscores the need for organizations to adopt a holistic approach to employee management, addressing both individual and organizational factors to improve outcomes.

Despite the valuable insights provided by this study, several limitations should be acknowledged. The cross-sectional design of the research limits the ability to draw causal inferences regarding the relationships among variables. Although significant associations were identified, it is not possible to determine the directionality of these

relationships with certainty. Additionally, the reliance on self-reported data may introduce common method bias and social desirability effects, potentially affecting the accuracy of the findings. The sample was also limited to employees in Tehran, which may restrict the generalizability of the results to other cultural and organizational contexts. Furthermore, while the use of machine learning models enhances predictive accuracy, these models may lack interpretability compared to traditional statistical approaches, posing challenges for practical implementation.

Future research should address these limitations by employing longitudinal designs to examine causal relationships and temporal dynamics among variables. Expanding the scope of research to include diverse cultural and organizational contexts would enhance the generalizability of findings and provide a more comprehensive understanding of absenteeism. Additionally, future studies could incorporate objective measures of absenteeism, such as organizational records, to complement self-reported data and reduce potential biases. The integration of additional variables, such as leadership style, organizational support, and personality traits, could further enrich predictive models and provide deeper insights into the determinants of absenteeism. Moreover, advancements in explainable artificial intelligence (XAI) offer promising opportunities to enhance the interpretability of machine learning models, enabling researchers and practitioners to better understand and utilize these tools.

From a practical perspective, the findings of this study highlight the importance of implementing comprehensive interventions to reduce employee absenteeism. Organizations should prioritize mental health support through employee assistance programs, counseling services, and stress management initiatives. Addressing work–family conflict through flexible work arrangements, supportive policies, and work-life balance programs can also significantly reduce absenteeism. Enhancing procedural justice by ensuring transparency, consistency, and fairness in organizational decision-making processes is essential for building trust and reducing withdrawal behaviors. Additionally, the adoption of data-driven approaches, including machine learning models, can enable organizations to identify at-risk employees and implement targeted interventions, ultimately promoting a healthier and more productive workforce.

Authors’ Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

- [1] A. Mishra, "Withdrawal Behaviours and Absenteeism at Work Post Covid-19," *Organization and Human Capital Development*, vol. 1, no. 2, pp. 62-75, 2022, doi: 10.31098/orcadev.v1i2.1096.
- [2] A. C. Mauricio and C. Laranjeira, "Presenteeism, Job Satisfaction, and Psychological Distress Among Portuguese Workers in a Private Social Solidarity Institution During the COVID-19 Pandemic: A Cross-Sectional Study," *Administrative Sciences*, vol. 13, no. 10, p. 220, 2023, doi: 10.3390/admsci13100220.
- [3] E. Rabenu and O. Shkoler, "Heavy-Work Investment, Its Organizational Outcomes and Conditional Factors: A Contemporary Perspective Over a Decade of Literature," *Sustainability*, vol. 14, no. 24, p. 16362, 2022, doi: 10.3390/su142416362.
- [4] E. Hinse and C. Mathieu, "The Impact of Leadership on Employee Presenteeism: A Comparison Between Police and Non-Police Samples," *International Journal of Police Science & Management*, vol. 25, no. 1, pp. 3-16, 2022, doi: 10.1177/14613557221122294.
- [5] S. F. Keltly, N. Green, O. Ribaux, C. Roux, and J. Robertson, "Assessment of Occupational Stress," pp. 209-220, 2023, doi: 10.1016/b978-0-12-823677-2.00017-9.
- [6] D. Anggraini, R. G. Pradana, F. Fatimah, and I. H. Pertiwi, "Stress, Wellness, and Performance Optimization: Promoting Sustainable Performance in the Workplace. By NilesThakre and B.Udaya Kumar Reddy (Eds.), Florida: Apple Academic Press Inc., 2024. 282 Pp. £111.60 (Hardback). ISBN: 978-1774914069," *Gender Work and Organization*, vol. 32, no. 4, pp. 1495-1498, 2025, doi: 10.1111/gwao.13243.
- [7] M. M. Arif, A. Qadir, S. R. Ahmad, M. Baqir, and M. Irfan, "Occupational Stress Among Medical and Paramedical Staff in Tertiary Care Hospitals Based on Observational Study," *Pakistan Journal of Public Health*, vol. 10, no. 4, pp. 231-241, 2021, doi: 10.32413/pjph.v10i4.623.
- [8] Y. C. Chen, J.-Y. Wu, and H.-C. Chu, "Correlations of Workload With Personality Traits, Perceived Negative and Positive Behaviors, and Organizational Factors: A Meta-Analysis," *Work a Journal of Prevention Assessment & Rehabilitation*, vol. 83, no. 1, pp. 227-241, 2025, doi: 10.1177/10519815251365103.
- [9] N. Argote, A. Bonilla, and M. G. González-Morales, "Cultural Stress Among Immigrants in the Workforce," *Cultural Diversity & Ethnic Minority Psychology*, vol. 30, no. 4, pp. 740-751, 2024, doi: 10.1037/cdp0000692.
- [10] M. Seyffert, C. Wu, and G. F. Özkan-Seely, "Insights Into the Impact of Organizational Factors and Burnout on the Employees of a for-Profit Psychiatric Hospital During the Third Wave of the COVID-19 Pandemic," *International Journal of Environmental Research and Public Health*, vol. 21, no. 4, p. 484, 2024, doi: 10.3390/ijerph21040484.
- [11] L. Cavagnis, C. C. Russo, F. Danioni, and D. Barni, "Promoting Women's Well-Being: A Systematic Review of Protective Factors for Work-Family Conflict," *International Journal of Environmental Research and Public Health*, vol. 20, no. 21, p. 6992, 2023, doi: 10.3390/ijerph20216992.
- [12] A. Rao and S. V.T, "Work-Life Balance of Women Medical Professionals in the Healthcare Sector-a Systematic Literature Review," *International Journal of Health Sciences and Pharmacy*, pp. 54-79, 2021, doi: 10.47992/ijhsp.2581.6411.0074.
- [13] J. Wu *et al.*, "The Mediating Role of Perceived Social Support Between Work-Family Conflict and Presenteeism Among ICU Nurses Working Shift Work in Chinese Public Hospitals: A Cross-Sectional Investigation," *Plos One*, vol. 19, no. 8, p. e0308673, 2024, doi: 10.1371/journal.pone.0308673.
- [14] W. Zhang, D. Gu, Y. Xie, A. Хакимова, and O. Золотарев, "How Do COVID-19 Risk, Life-Safety Risk, Job Insecurity, and Work-Family Conflict Affect Miner Performance? Health-Anxiety and Job-Anxiety Perspectives," *International Journal of Environmental Research and Public Health*, vol. 20, no. 6, p. 5138, 2023, doi: 10.3390/ijerph20065138.
- [15] F. Kazemi, H. Mohsenipouya, A. Hosseinnataj, N. Roy, and M. A. Mamun, "Perceived Organizational Support as a Factor in Managing Work-Family Conflict and Enhancing Occupational Well-Being: Findings From Iranian Nurses," *International Journal of Nursing Practice*, vol. 31, no. 5, 2025, doi: 10.1111/ijn.70061.
- [16] S. Saade, A. Parent-Lamarche, Z. Bazarbachi, R. Ezzeddine, and R. Ariss, "Depressive Symptoms in Helping Professions: A Systematic Review of Prevalence Rates and Work-Related Risk Factors," *International Archives of Occupational and Environmental Health*, vol. 95, no. 1, pp. 67-116, 2021, doi: 10.1007/s00420-021-01783-y.
- [17] R. M. Claponea, L. Pop, M. Iorga, and R. Iurcov, "Symptoms of Burnout Syndrome Among Physicians During the Outbreak of COVID-19 Pandemic—A Systematic Literature Review," *Healthcare*, vol. 10, no. 6, p. 979, 2022, doi: 10.3390/healthcare10060979.
- [18] K. Dūdiņa and B. Martinsone, "Psychosocial Risks and Protective Factors for Healthcare Worker Burnout During the Post-Acute Phase of the COVID-19 Pandemic," *European Journal of Investigation in Health Psychology and Education*, vol. 15, no. 9, p. 186, 2025, doi: 10.3390/ejihpe15090186.
- [19] S. Caridade *et al.*, "Psychosocial Risks Factors Among Victim Support Workers During the COVID-19 Pandemic: A Study With the Copenhagen Psychosocial Questionnaire," *BMC Psychology*, vol. 10, no. 1, 2022, doi: 10.1186/s40359-022-00825-5.
- [20] A. Soto-Rubio, M. d. C. Giménez-Espert, and V. Prado-Gascó, "Effect of Emotional Intelligence and Psychosocial Risks on Burnout, Job Satisfaction, and Nurses' Health During the COVID-19 Pandemic," *International Journal of*

- Environmental Research and Public Health*, vol. 17, no. 21, p. 7998, 2020, doi: 10.3390/ijerph17217998.
- [21] A. Stelmokienė, G. Genevičiūtė-Janonė, L. Gustainienė, and K. Kovalčikienė, "Relationships Between Professional Burnout and Job Demands, Resources Among Workers in an Industrial Plant in Lithuania," *SHS Web of Conferences*, vol. 131, p. 03005, 2022, doi: 10.1051/shsconf/202213103005.
- [22] N. Magnavita *et al.*, "Organizational Justice and Health: A Survey in Hospital Workers," *International Journal of Environmental Research and Public Health*, vol. 19, no. 15, p. 9739, 2022, doi: 10.3390/ijerph19159739.
- [23] A. Oliveira, I. F. Teixeira, F. Alckmin-Carvalho, and H. Pereira, "Psychosocial Determinants of Occupational Health Through the Lenses of Gender Identity and Sexual Orientation," *Behavioral Sciences*, vol. 15, no. 2, p. 234, 2025, doi: 10.3390/bs15020234.
- [24] L. Cachón-Alonso and M. Elovainio, "Organizational Justice and Health: Reviewing Two Decades of Studies," *Journal of Theoretical Social Psychology*, vol. 2022, pp. 1-13, 2022, doi: 10.1155/2022/3218883.
- [25] N. Baher and O. Alkhadher, "The Relationship Between Major Depression and Perceptions of Organizational Justice," *Dirasat Human and Social Sciences*, vol. 49, no. 4, pp. 492-503, 2022, doi: 10.35516/hum.v49i4.2103.
- [26] M. Zhou, J. Zhang, F. Li, and C. Chen, "Work-Family Conflict and Depressive Symptoms Among Chinese Employees: Cross-Level Interaction of Organizational Justice Climate and Family Flexibility," *International Journal of Environmental Research and Public Health*, vol. 17, no. 19, p. 6954, 2020, doi: 10.3390/ijerph17196954.
- [27] G. M. Sayre and S. A. Conroy, "The Other Side of the Coin: An Integrative Review Connecting Pay and Health," *Journal of Applied Psychology*, vol. 109, no. 8, pp. 1178-1203, 2024, doi: 10.1037/apl0001151.
- [28] S. Stanley and A. J. Sebastine, "Work-Life Balance, Social Support, and Burnout: A Quantitative Study of Social Workers," *Journal of Social Work*, vol. 23, no. 6, pp. 1135-1155, 2023, doi: 10.1177/14680173231197930.
- [29] H. P. Safavi, M. Bouzari, and T. Foroutan, "Restaurants Under COVID-19 Knife," *Journal of Hospitality and Tourism Insights*, vol. 6, no. 5, pp. 2506-2524, 2023, doi: 10.1108/jhti-05-2022-0202.
- [30] W. Shahbaz and A. Sajjad, "Integrating Management Control Systems, Mindfulness and Sustainability: An Occupational Health and Safety Perspective," *Corporate Governance*, vol. 21, no. 3, pp. 433-449, 2020, doi: 10.1108/cg-06-2020-0242.
- [31] L. Vimercati *et al.*, "Organizational Wellbeing: A Model of a New Apulian COVID-19 Designated Hospital," *Frontiers in Public Health*, vol. 10, 2022, doi: 10.3389/fpubh.2022.963315.
- [32] J. M. Abalkhail, "Dysfunctional Leadership: Investigating Employee Experiences With Dysfunctional Leaders," *Career Development International*, vol. 27, no. 3, pp. 301-324, 2022, doi: 10.1108/cdi-04-2021-0109.