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The Impact of Technology/IT Workplaces on Mental Health Treatment

Mingjie Yao[1,a,*]

[1]*School of Mathematical Sciences, Capital Normal University, Beijing, 100048, China*
a. 2230502185@cnu.edu.cn
**corresponding author*

Abstract: With the development of information technology, mental health issues among information technology (IT) industry employees have become increasingly prominent and have become a focus of societal concern. However, there is a gap in current research on the mental health challenges faced by IT employees. This study addresses the inadequacies of existing literature on mental health impacts in IT workplaces, which are not comprehensive and have unclear results. Based on the Mental Health in Tech Survey dataset provided by Kaggle, this study employs quantitative research methods to conduct an in-depth analysis of the factors influencing the mental health of IT employees. The research results indicate that various factors in the work environment have a significant impact on employees' mental health. Based on the research findings, targeted improvement strategies and suggestions are proposed, emphasizing gender-sensitive health interventions and public education, to provide a reference for enterprises and policymakers, promote employee mental health, and enhance work efficiency, and drive widespread societal attention to mental health issues.

Keywords: IT industry, mental health, work environment, influencing factors, improvement strategies

1. Introduction

With the rapid advancements in information technology, the global technology and IT industry has achieved significant development, making IT workplaces a preferred career choice for many young people. However, the competitive and stressful environment in this field has increasingly negative impacts on employees' mental health. Relevant surveys show that IT industry employees generally suffer from mental health issues such as anxiety, depression, and interpersonal tension, a phenomenon that urgently needs attention and resolution.

According to the research in "Supporting Mental Health in the Tech Workplace," mental health issues are particularly prevalent in the IT industry. The study indicates that approximately one-fifth of adults suffer from mental illness, and this proportion may be even higher in the technology industry. This suggests that the mental health issues of IT industry employees require special attention. Wang Yong et al. points out that IT technology workers experience higher stress levels than other white-collar employees, mainly stemming from the characteristics of the work itself and career development. Factors such as high workload, project deadlines, and rapid technological updates increase employees' psychological pressure [1]. Xiang Jing found that IT practitioners commonly suffer from physical health issues such as conjunctivitis, high blood uric acid, allergic rhinitis, external hemorrhoids, breast

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lobular hyperplasia, and neck and back pain. At the same time, mental health issues such as anxiety disorders, low well-being, and depression are also prevalent. Liao Han suggests starting with the commonly occurring diseases of depression and anxiety to investigate the mental health status of IT technology workers deeply. Technology enterprises should establish dedicated psychological counseling rooms, dynamically pay attention to employees' career planning, formulate humane work systems, and maximize the fulfillment of different psychological needs of employees [2].

Although existing research has initially revealed various impacts of technology/IT workplaces on employees' mental health and some of their causes, there is still a lack of systematic and in-depth discussion, especially in specific cultural and social contexts [3-5]. Therefore, this study aims to fill this research gap, increase enterprises' emphasis on mental health issues, promote employees' mental health, enhance work efficiency, and provide a reference for enterprises and policymakers. This study is based on the Mental Health in Tech Survey dataset provided by Kaggle to analyze the impact of different work environment factors on the mental health of IT employees [6-10].

This study aims to reveal the current situation and distribution of employees' mental health issues in technology/IT workplaces, identify the main work environment factors affecting IT employees' mental health, propose strategies and suggestions for improving IT employees' mental health, and provide a reference for enterprises and policymakers.

2. Methods

2.1. Dataset

The dataset originates from the "Mental Health in Tech Survey" dataset created by the Open Sourcing Mental Illness (OSMI) organization in 2014. This dataset aims to investigate the mental health status of employees in the technology industry. It includes survey results on respondents' mental health status, attitudes towards mental health issues, mental health support provided by the company, and personal mental health history.

Data cleaning: Handle missing values, outliers, and inconsistent data.

Gender, family history, treatment, tech company, benefits, and remote work are dichotomous data, represented by 0 and 1, where 1 may represent "yes" or "male," and 0 represents "no" or "female."

Table 1: Basic Information of Various Statistics

Statistic	Age	Gender	Family history	Treatment	Tech company	Benefits	Remote work
Count	1259	1259	1259	1259	1259	1259	1259
Mean	32.008737	0.789515	0.390786	0.505957	0.818904	0.378872	0.298650
Std	7.363215	0.407815	0.488121	0.500163	0.385251	0.485299	0.457848
Min	5	0	0	0	0	0	0
25%	27	1	0	0	1	0	0
50%	31	1	0	1	1	0	0
75%	36	1	1	1	1	1	1
Max	1	1	1	1	1	1	1

Note: count represents the total number of data, mean represents the average, and std represents the standard deviation.

As shown in Table 1, this survey collected 1259 data entries, with 79% of respondents being male and about 21% being female. About 61% of respondents do not have a family history of mental illness, while 31% do. Approximately 50.6% of respondents have sought treatment for mental health issues, while 49.4% have not. About 29.9% of respondents work remotely for at least 50% of their time, while 70.1% do not. Approximately 81.9% of respondents work in technology companies, and 18.1%

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do not. About 37.9% of respondents have employers who provide mental health benefits, while 62.1% do not.

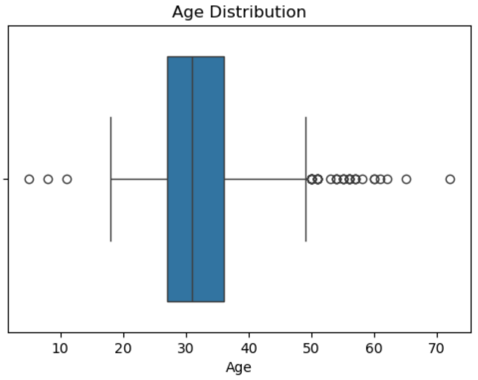

Figure 1: Age Distribution (Photo/Picture credit: Original).

As shown in Figure 1, the ages of respondents are concentrated around 30 years old, with an average age of 32.

2.2. Correlation analysis

Use correlation coefficients to preliminarily identify variables that may be related to the occurrence of mental health disorders.

To analyze the relationship between treatment and all other variables (gender, family history, remote work, working in a tech company, benefits), the following methods can be used:

For the relationship between treatment and other categorical variables (gender, family history, remote work, working in a tech company, benefits), Point-Biserial correlation can be used because these variables are dichotomous (0 or 1).

For the relationship between treatment and age (a continuous variable), Point-Biserial correlation can also be used.

Table 2: Correlation coefficients and p-values of various statistics

	Correlation Coefficient	p-value
Gender	-0.20	0.0000
Family	0.38	0.0000
Remote work	0.03	0.3396
Tech company	-0.03	0.2637
Benefit	0.21	0.0000
Age	0.07	0.0083

As shown in Table 2, there is a significant negative correlation between gender and seeking treatment. Although the correlation coefficient is low, indicating a weak relationship, the p-value suggests that this relationship is statistically significant. This means that women may be less likely to seek treatment than men, or men may seek treatment more frequently than women.

There is a significant positive correlation between family history and seeking treatment, with a relatively high correlation coefficient indicating a strong relationship. Individuals with a family history are more likely to seek treatment.

The p-values for remote work and working in a tech company are too high, indicating that these relationships are not statistically significant. Therefore, we cannot conclude that there is a significant relationship between remote work or working in a tech company and seeking treatment.

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There is a significant positive correlation between receiving benefits and seeking treatment. Individuals who receive benefits are more likely to seek treatment.

There is a weak but significant positive correlation between age and seeking treatment. This means that the likelihood of seeking treatment increases slightly with age.

Model Building: For the categorical outcome (whether there is a mental health disorder), a Logistic regression model was used.

Selection of Independent Variables: Based on the results of EDA and correlation analysis, potential predictor variables (such as age, gender, family history, work interference, etc.) were selected.

Model Fitting: Logistic regression analysis was used to determine which variables are significant predictors of mental health disorders.

Model Diagnosis: Check whether the model assumptions are met, such as using residual analysis.

Table 3: Model diagnosis results

	Coef	Std err	Z	P>|z|	[0.025	0.975]
Const	-0.8143	0.339	-2.402	0.016	-1.479	-0.150
Age	0.0193	0.009	2.197	0.028	0.002	0.036
Gender	-0.8201	0.162	-5.050	0.000	-1.138	-0.502
Family history	1.5403	0.131	11.729	0.000	1.283	1.798
Remote work	0.1436	0.140	1.025	0.306	-0.131	0.418
Tech company	0.0130	0.167	0.078	0.938	-0.315	0.341
Benefits	0.6529	0.133	4.916	0.000	0.393	0.913

3. Model summary

3.1. Coefficient estimates

Table 3 presents the coefficient estimates, standard errors, z-values, P>z-values, and 95% confidence intervals for each predictor variable:

Const (Intercept): -0.8143, representing the log-odds of the baseline probability when all predictor variables are zero. **Age**: 0.0193, indicating that for each additional year of age, the odds of seeking treatment increase by approximately 0.0193 (on the log-odds scale). The p-value of 0.028 suggests that age is a significant predictor. **Gender**: -0.8201, indicating that gender (coded as 1 for males and 0 for females) is a significant predictor, with males having lower odds of seeking treatment. **Family_history**: 1.5403, showing that individuals with a family history have significantly increased odds of seeking treatment. **Remote_work**: 0.1436, with a p-value of 0.306, suggesting that the association between remote work and seeking treatment is not statistically significant. **Tech_company**: 0.0130, with a p-value of 0.938, indicating that working in a tech company is not significantly associated with seeking treatment. **Benefits**: 0.6529, demonstrating that individuals whose employers provide benefits have significantly increased odds of seeking treatment.

3.2. Interpretation

Age is a significant predictor of seeking treatment, with the odds of seeking treatment increasing as age increases. Gender is also a significant predictor, with males having lower odds of seeking treatment compared to females. Individuals with a family history have significantly increased odds of seeking treatment. The variables remote work and working in a tech company are not significantly associated with seeking treatment. Individuals whose employers provide benefits have significantly increased odds of seeking treatment.

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3.3. Model diagnostics

The residual histogram is close to a normal distribution, indicating that the assumption of normality of residuals is met. There is no apparent pattern between residuals and fitted values, suggesting that the assumption of independence of residuals is satisfied. Ideally, residuals should be randomly distributed around the horizontal line (y=0). The Breusch-Pagan test p-value is greater than 0.05, failing to reject the null hypothesis of homoscedasticity, indicating that the variance of residuals is constant. The Durbin-Watson statistic, close to 2, suggests no autocorrelation among residuals. Overall, our model is reasonable.

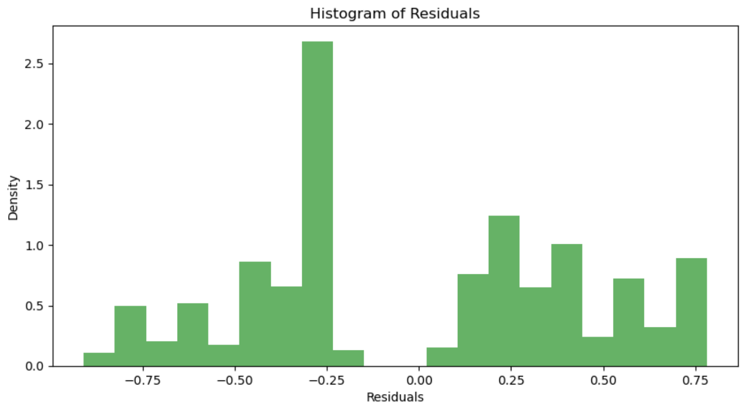

Figure 2: Histogram of residuals (Photo/Picture credit: Original).

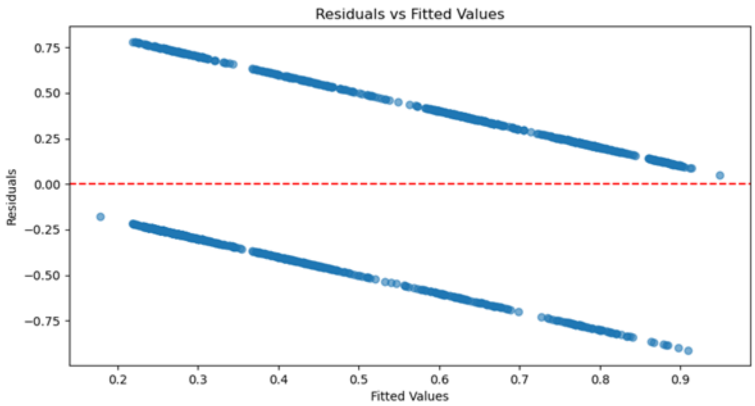

Figure 3: Residuals vs fitted values (Breusch-Pagan test statistic: 10.6966; p-value: 0.0982; Durbin-Watson statistic: 1.9384) (Photo/Picture credit: Original).

As shown in Figure 2 and Figure 3, the residual histogram is close to the normal distribution, and the hidden normal assumption is satisfied. There is no obvious pattern between the residual and the fitting value, and the residual independence hypothesis is satisfied. Ideally, the residues should be randomly distributed around the horizontal line (y = 0). Breusch-Pagan test: The P value is greater than 0.05, and the original fake of the same variance cannot be rejected, indicating that the difference between the residual squares is constant. Durbin-Watson test: DW statistics close to 2 indicate that there is no autocorrelation between residues. In summary, our model is reasonable.

4. Suggestions

Gender-sensitive health intervention: Given the impact of gender on psychological health disorders, it is recommended to formulate and implement gender-sensitive health intervention measures to improve the awareness of the psychological health of male groups and encourage them to seek help. According to the research on PUBMED, Gender-sensitive mental health care emphasizes the importance of considering gender differences in mental health care [11].

Pay attention to family medical history: Early identification and intervention measures should be provided for individuals with family medical histories to reduce the risk of psychological health obstacles.

Optimize welfare policies: Enterprises and management agencies should consider optimizing welfare policies, especially psychological health-related benefits to encourage employees to seek treatment when they have psychological health problems.

Further research: Although the impact of long-range work and the treatment of technology companies on the treatment of mental health disorders is not significant in this study, this does not mean that they have nothing to do with mental health. It is recommended to conduct more in -depth research to explore the potential connections of these factors and psychological health disorders.

Public education: Public education should be strengthened, awareness of psychological health obstacles should be improved, the stigma related to it should be reduced, and people should be encouraged to seek professional help in times when there is a psychological health problem. In the future, work can continue to expand the channels for psychological health education, use the advantages of network information and big data platforms to improve the efficiency of psychological crisis recognition, realize the personalized guidance of psychological rehabilitation skills, improve the top -level design, form a government coordinated management, the clear social division of labor, and multiple parties participating in multiple parties as soon as possible. Professional, multi -type, multi-level, sustainable practical system [12].

5. Conclusions

This article uses correlation analysis and Logistics model fitting and other methods to obtain the following results for factors affecting IT company employees receiving psychotherapy:

Gender has a significant impact on the treatment of mental health disorders: women are more likely to seek psychological health obstacles than men. Family medical history is an important predictive factor: individuals with family medical history are more likely to seek treatment of mental health disorders.

Impact of welfare policy: Individuals that provide welfare policies are more likely to seek treatment of mental health disorders.

The impact of remote work and the work of science and technology companies is not significant: whether it is remotely or in the treatment of working in technology companies with the treatment of psychological health obstacles.

In addition, this study does not distinguish the specific types of mental health disorders, which may cover up the differences in treatment of different obstacles in the treatment of behavior. At the same time, research fails to fully consider the severity of individual mental health disorders, which may be one of the important factors affecting the treatment of treatment. Therefore, when explaining and applying the results of this study, these potential restrictions must be taken into account.

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