Analysis of the Impact of Individual Differences on Technical Stress and Prediction by Machine Learning

Manhang Li[1,*]
2019160901024@std.uestc.edu.cn[1,*]

University of Electronic Science and Technology of China, No.4, Section 2, North Jianshe Road, Chengdu, Sichuan, P.R. China[1]

Abstract. With the gradual penetration of the Internet into people's lives, it has also caused many people to panic about Internet technology, resulting in technical pressure. In this study, a meta-analysis technique was used to clarify the relationship between demographic characteristics, personality characteristics and employee technical stress. The results showed that there was a significant positive correlation between employee's education level and technical stress in demography; There is a significant negative correlation between employee age and technical pressure, which breaks through people's previous understanding of technical pressure; At the same time, female employees are more likely to feel technical pressure than male employees. Among the five personalities, neuroticism is positively correlated with technical stress. Openness, sense of responsibility and extroversion are all negatively correlated with technical stress. However, there is no significant relationship between human and technological pressure. This study revealed the relationship among demographic variables, personality characteristics and technical stress, providing a more accurate estimate of individual differences for predicting technical stress. In addition, a multi-layer perceptron-based employee stress prediction technology is also proposed. The technology uses questionnaires to obtain the eigenvectors of each employee, and then uses the multi-layer perceptron training network to predict the state of subsequent employees.

Keywords: Data analysis; Modeling; Technical pressure; Demographic characteristics; Big five personality; Meta-analysis; Multi-layer perceptron.

1 Introduction

In recent years, the information and communication technology (ICT) products gradually integrated into people's lives have brought great convenience to people's lives, but also brought some hidden worries to people's lives - such as technological pressure.

Technical stress can be defined as the process of anxiety, fear, tension and anxiety that a person produces when directly or indirectly learning and using computer technology, which ultimately leads to psychological and emotional exclusion and prevents him from further learning or using computer technology.[1] Although the research of scholars like Hang Y is about the technical pressure of employees, it is too specific to specific fields: such as enterprises, hospitals and other large institutions, which are not widely representative.[2] Christoph Golz and other scholars conducted relevant research on how demographic variables affect employees' perception of technical stress, but they did not combine the Big Five personality traits.[3]

Based on the inadequacies of the current research, this paper finds that gender, education,

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neuroticism and technical pressure are significantly positively correlated, while age, openness, responsibility, extraversion and technical pressure are significantly negatively correlated, while the relationship between humanity and technical pressure is not significant.

2 Related works

Personality, also known as personality, is a measurable trait, both internal and external. In the field of personality research, the "Big Five" models proposed by the trait school have been widely recognized by researchers. The model believes that a person's personality essence can be roughly summarized as five characteristics, namely, openness, responsibility, extroversion, agreebleness and neuroticism. Mayer connected personality with the research in the field of information systems;[4] Anis investigated the influence of personality characteristics on job burnout and other psychological conditions.[5]

However, these studies lack of research on its direct impact. At present, some studies have found that there is a significant relationship between technology pressure and individuals and industries: for example, personal productivity and willingness to expand the use of information technology are both negatively affected by technology pressure. There are many studies on the influencing factors of technical pressure.

3 Research Assumptions and Research Methods

In real life, there are many factors that lead to the change of perceived technology pressure. In this study, for the purpose of simplifying analysis, based on the following assumptions, this paper will adopt meta-analysis to systematically analyze the impact of personality traits and demographic characteristics on perceived technical stress, in order to reach a unified conclusion.

3.1 Research assumptions

Gender is a major factor affecting perceived technology pressure and men show a more positive attitude towards computer use and lower anxiety level. Consequently, this study proposes the following assumptions:

- **H1:** Gender will affect the individual's perception of technical pressure. Women are more vulnerable to technical pressure than men.
- **H2:** Age is positively correlated with the perception of technical pressure. The older the age, the greater the perceived technical pressure.
- **H3:** The education level is positively related to the technical pressure. The higher the education level is, the higher the individual perceives the technical pressure.
- **H4:** The openness of experience negatively regulates the technical pressure.
- **H5:** Neuroticism is positively correlated with perceived technical stress.
- **H6:** The agreeableness is negatively correlated with perceived technical stress.
- **H7:** Sense of responsibility is negatively related to perceived technical stress.

- **H8:** Extraversion is negatively correlated with perceived technical stress.

3.2 Research methods

3.2.1 Methods and technologies

This study uses the meta-analysis method to systematically sort out the influencing factors of employees' perception of technical stress, carry out relevant empirical research, quantitatively test the relevance of the influencing factors [6]

As shown in Figure 1, the overall idea of this study is to first set a certain threshold value from the web of science platform for literature retrieval and download. After that, select part of articles for the next step of coding. The screening method is as shown in the figure. The coding content is shown in the figure, and "basic information of literature", "basic characteristics of samples", and "variable and relationship results" need to be recorded respectively. Finally, the coded literature is meta analyzed, and the meta-analysis results are interpreted, and the assumptions are reviewed to draw the conclusion.

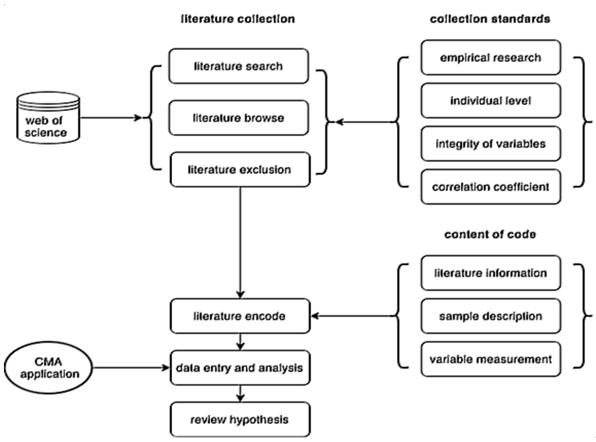

Fig 1. Flow chart of research ideas.

3.2.2 Document collection and screening

This study mainly uses the Web of Science database because many empirical research literatures do not use demographic characteristics as keywords, and some studies neglect to explain the relationship between demographic characteristics and technical pressure in the discussion of results, while demographic characteristics exist in most studies, this study does not specify demographic characteristics keywords. Instead, the articles will be screened one by one in the subsequent screening process. Therefore, the subject term of English search is determined as technostress. The literature search will be conducted until March 2022, and a total of 405 literatures will be obtained. The obtained literatures will be screened through the following criteria:

a) Research is an empirical study on technology pressure.

b) The research level is the individual level.

c) The research includes both technical pressure and individual characteristic variables, that is, the independent variable IV (age, gender, education, tension, capital status, ICT use experience, the Big Five personality traits: agreement, consistency, extraversion, openness, neuroma) and the dependent variable DV (techno stressor, techno overload, techno innovation, techno complexity, techno security, techno uncertainty);

d) The effect value between IV and DV is reported in the research, the correlation coefficient is reported in the non-experimental papers, and the convertible statistics are reported in the experimental papers, such as Fisher's F ratio, computed value of *t* test, mean value and SD (Standard development).

Out of 405 articles, there are 36 articles that finally meet the above standards, all of which are English journal articles. Finally obtained in this study. These 39 English literatures are representative and can be used in meta-analysis.

3.2.3 Document code

The documents included in the meta-analysis are coded as follows: literature information, sample size, sample collection time, average age, gender sample attributes, education level, ICT use experience, sample industry, marital status, sample source, Research status, independent variable, dependent variable, reliability level of each variable, correlation coefficient between independent variable and dependent variable. Each independent sample is coded once. If there are multiple independent samples in a document, they are coded separately; Repeated published studies are coded only once.

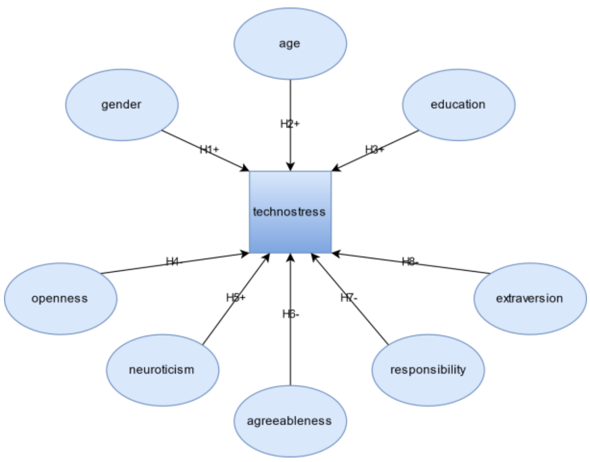

Fig. 2. Theoretical Framework.

3.2.4 Statistical Analysis

The meta-analysis software used in this study is CMA 3.0 to analyze and test the data. The meta-analysis method of Hunter and Schmidt was used for analysis. Where, gender: 1 = male, 2 = female; The larger the age, the older the age. Heterogeneity test and main effect test were conducted in turn, and k, N, ρ, Q, I^2 is effect value of independent sample, total number of samples, correlation coefficient, heterogeneity test statistics

Table 1. Variable Table

Variables	Description
k	Effect value of independent sample
N	Total number of samples
ρ	Correlation coefficient
Q	Heterogeneity test statistics
I^2	Heterogeneity test statistics

Note: The meaning of variables involved in this meta-analysis can be seen from Table 1, which is convenient for interpretation of subsequent results.

4 Results and Analysis

4.1 Main effect test results

The main effect test results of demographic characteristics and technical pressure are shown in Table 2:

Table 2. Main Effect Test Results

Variables	k	N	ρ	95% confidence interval		Two tailed tests		Q	I^2
				Low	High	Z Value	p Value		
Gender	21	9191	0.025	0.004	0.045	2.363	0.018	226.857***	91.184
Age	29	14339	-0.040	-0.056	-0.023	-4.752	0.000	180.491***	84.487
Education	13	5266	0.053	0.026	0.079	3.877	0.000	30.841**	61.091
Openness	7	1401	-0.067	-0.119	-0.015	-2.531	0.011	32.010***	81.256
Nervous	10	2017	0.221	0.181	0.261	10.545	0.000	25.996**	65.379
Agreeableness	6	1241	-0.037	-0.089	0.014	-1.412	0.158	54.978***	90.905
Responsibility	4	810	-0.089	-0.157	-0.020	-2.516	0.012	20.331***	85.245
Extraversion	8	1525	-0.053	-0.100	-0.006	-2.197	0.028	19.272**	63.678

Note: k represents the number of independent samples of the effect value; N represents cumulative sample; ρ Represents the weighted average effect value of the sample. Q value and significance represent the degree of heterogeneity of each effect value, and I2 represents the proportion of heterogeneity in the total variation * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2 shows that all demographic characteristics and Q values of public service motivation have reached a statistically significant level ($p < 0.01$), of which gender, age, openness, agreeableness, sense of responsibility even reached a significant level of $P < 0.001$.

It can be clearly seen from Figure 3 that the I^2 of this meta-analysis is between 61.091% and 91.184%, higher than 50%. Since meta-analysis determines the use of relevant models according to I^2, and 50% serves as the boundary between the random effect model and the fixed effect model, the random effect model is required for this study.

Fig 3. I^2 Line Chart.

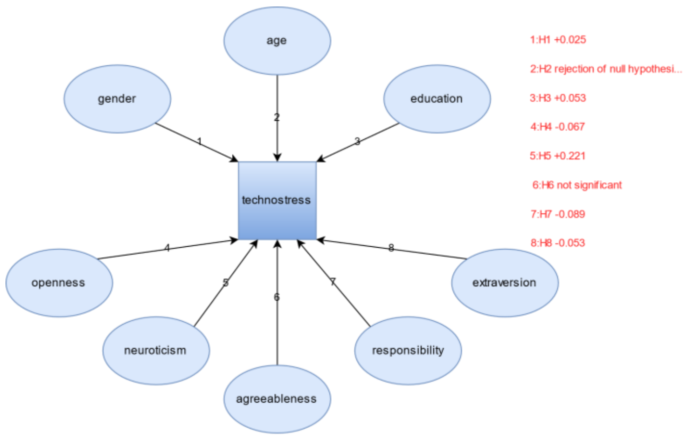

Fig. 4. Model Results.

As shown in Table 3, the classification and arrangement of the results of various indicators are listed as follows.

Table 3. Correlation Arrangement Table.

positive correlation	negative correlation	non-significant correlation
gender (ρ = 0.025, 95% CI: 0.004 ~ 0.045)	age (ρ = -0.040, 95% CI: -0.056 ~ -0.023)	agreeableness (ρ = -0.037, 95% CI: -0.089 ~ 0.014)
Education (ρ= 0.053, 95% CI :0.026 ~ 0.079)	openness (ρ = -0.067, 95% CI: -0.119 ~ -0.015)	
neuroticism (ρ = 0.221, 95% CI: 0.181 ~ 0.261)	conscientiousness (ρ = -0.089, 95% CI: -0.157 ~ -0.020)	
	extraversion (ρ = -0.053, 95% CI: -0.100 ~ -0.006)	

It can be seen from Figure 4 that the results of this study basically respond to the previous assumptions, and only the results of age and agreeableness are inconsistent with the assumptions. Among them, the result of age refutes the hypothesis, and the result of humanity cannot verify the hypothesis because it is not significant.

4.2 Result analysis and interpretation

Figure 5 is the correlation coefficients ρ. In Figure 5, if the value of ρ is above the x-axis, indicating that its corresponding attribute is positively related to the perceived technical pressure. If the value of ρ is below the x-axis, indicating that its corresponding attribute is negatively correlated with perceived technical pressure.

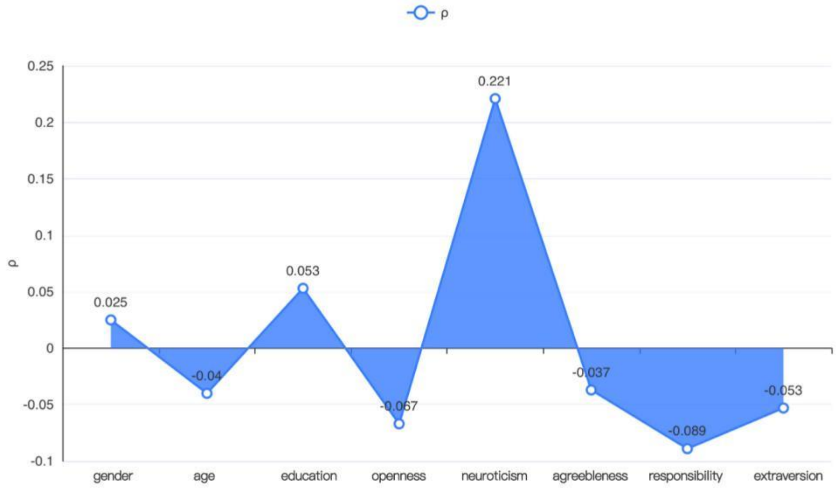

Fig. 5. ρ Thermodynamic diagram.

In addition, the numerical point corresponding to neuroticism attribute is the farthest from the x-axis, indicating that neuroticism has the strongest correlation with perceived technical pressure, while the numerical point corresponding to humanity attribute is the closest to the x-axis, indicating that the correlation between agreeableness and perceived technical pressure is the weakest.

Specifically, take female as 1, gender (ρ = 0.025, 95% CI 0.004~0.045), indicating that women are higher than men in sensing technical stress. It is difficult to balance the competitiveness and complexity of technology, which makes women feel more technical pressure than men [7]. There is a significant positive correlation between education and perceived technology stress. Specifically, education (ρ = 0.053, 95% CI is 0.026~0.079). One of the reasons may be that people with high education can get more opportunities in the job market, but they will have to bear more responsibility and pressure. [8] There is a significant negative correlation between age and perceived technical stress. Different from the assumed expectation, the results show that with the growth of age, there will be less and less technical pressure. Specifically, age (ρ = -0.040, 95% CI is -0.056 ~ -0.023). This is also different from people's cognition in life.

In the results obtained, there is a significant positive correlation between neuroticism and technical stress, and this positive correlation is the most obvious. Specifically, neuroticism (ρ = 0.221, 95% CI 0.181~0.261). There is a significant negative correlation between openness and technical pressure. The more open employees are, the less they perceive technical pressure. Specifically, openness (ρ = -0.067, 95% CI is -0.119 ~ -0.015). Employees with open personality can also think of more effective solutions when facing the technical pressure. [9] There is a significant negative correlation between responsibility and technical pressure. This shows that the more responsible employees are, the more likely they are to feel less technical pressure. Specifically, the sense of responsibility (ρ = - 0.089, 95% CI is -0.157~- 0.020). Because of their firm and positive attitude towards the goal, they feel less technical pressure. There is a significant negative correlation between extraversion and technical stress. Specifically, extraversion (ρ = - 0.053, 95% CI is -0.100~-0.006). Employees with strong openness are more willing to cooperate to solve technical problems, and because of their confident and optimistic nature, employees with stronger extraversion tend to feel less technical pressure. However, there is no significant correlation between humanity and perceived technology pressure.

5 Theoretical applications

After completing the analysis of technical stress from different angles, this paper proposes an evaluation method of technical stress based on machine learning. Based on the traditional machine learning algorithm, this method uses questionnaires to collect different responses of employees, and then sends them to the algorithm for analysis. During analysis, the answers are coded first. Because the questionnaire is set as multiple choices, these answers can be coded and standardized by scores. After standardization, each employee can be abstracted as a vector of the standardized problem, and trained with a multi-layer perceptron (MLP). This is a supervised training, and the training data can be expressed as: ***(vector, technical stress possibility).*** Finally, the trained model can be used to reason about other employees of the enterprise and predict their technical stress indicators, through this feedback method, it can help managers better understand the technical stress of employees, and timely intervention can be taken for employees with high technical pressure.

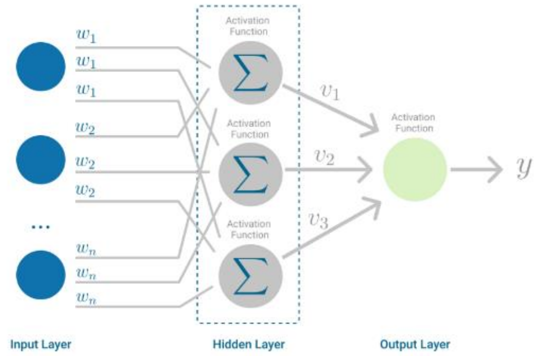

Fig. 6. Schematic diagram of the structure of the multilayer perceptron [10].

Among them, the input layer is the normalized coding vector, which is activated and calculated by the hidden layer, and finally outputs the corresponding technical pressure score through the activation function.

6 Summary and discussion

In this study, 36 effective empirical literatures were selected from 405 literatures by using the method of meta-analysis through the Web of Science database, and the relationship between demographic variables, personality characteristics and technical stress was explored. This study enriches the exploration of personal characteristics and technical pressure to a certain extent, and observes the relationship with employees' perception of technical pressure in combination with demographic characteristics and Big Five personality characteristics, which makes up for the gap in existing research and provides relevant enlightenment for enterprise managers. At the same time, a prediction technology of employee technical stress based on questionnaire and machine learning method is proposed. This technology uses questionnaires to collect employee problem information, then codes the collected problems into a feature matrix, and sends it to a multi-layer perceptron network for training. The trained model can be used to predict the level of technical stress of subsequent employees, which helps managers quickly understand the situation of employees and intervene in a timely manner.

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