TEM Journal. Volume 13, Issue 4, pages 3231-3240, ISSN 2217-8309, DOI: 10.18421/TEM134-57, November 2024.

An Analysis of Technostress Factors Among Teachers in Hunan, China Through Statistical Methods and K-means Clustering

Siyu Li [1], Chia Yean Lim [1], Sau Loong Ang [2]

[1] *Universiti Sains Malaysia, Minden, Penang, Malaysia*
[2] *Tunku Abdul Rahman University of Management and Technology, Penang Branch, Tanjung Bungah, Malaysia*

***Abstract* – The adoption of information technology for teaching and learning activities has caused technostress among teachers. The China teachers' technostress research in the past few years was limited to factors such as techno-overload, techno-complexity, techno-insecurity, techno-uncertainty, and techno-invasion, and neglected an emerging factor which is the new technology adoption. Moreover, all the technostress research did not identify the teachers' groups according to the technostress factors for further deliberations. This research covers the scope of technostress factors identification and teacher cluster generation among teachers in Hunan, China. A questionnaire was adopted to gather the teachers' agreement on five technostress factors, and the responses were measured with statistical methods. The findings showed that all investigated factors have positive and significant relationships with technostress among Hunan, China's teachers. The teachers were clustered into five distinct clusters with the K-means clustering method. This research discovered new technology adoption as a new technostress factor and successfully clustered the teachers into significant clusters to enable China's Education Department to provide targeted technological training to the teachers.**

Keywords – Clustering, new technology adoption, statistical analysis, teachers, technostress.

DOI: 10.18421/TEM134-57
https://doi.org/10.18421/TEM134-57

Corresponding author: Chia Yean Lim,
Universiti Sains Malaysia, Minden, Penang, Malaysia.
Email: cylim@usm.my

Received: 10 April 2024.
Revised: 11 August 2024.
Accepted: 02 September 2024.
Published: 27 November 2024.

1. Introduction

This section introduces the education system in China. Following this, the technostress research context is explored to determine the research theoretical framework. In addition, the clustering method used in this research is also reviewed and discussed.

1.1. Overview of the Education System in China

In the twenty-first-century education system, information and communication technology (ICT) is important for teaching and learning deliveries. During the COVID-19 pandemic in 2019, the World Health Organization (WHO) has advised the teaching and learning activities for school children to be conducted via online mode. This request took most of the teachers off guard as they were required to adapt to ICT immediately from offline classrooms to online teaching platforms. Bi [1] found that most teachers felt anxious about the shift in teaching delivery mode. Consequently, it has caused fatigue and mental stress among the teachers.

According to the research from Li [2], ICT is significantly important in China's education system nowadays. Teachers are required to use ICT in the teaching processes to stay ahead in the global digital age. Concerning statistics from the China Ministry of Education [3], primary and secondary school teachers are the largest category in the teacher's population with 56.7%, followed by preschool education teachers with 17.3%, senior high school teachers with 15.2%, college teachers with 10.5% and others 0.3%. There are more female teachers (61.36%) in comparison to male teachers (38.64%) in China. The age group distribution of China teachers in 2023 showed that most teachers are in the age range from 20 to 39 years old (32.7%), followed by teachers in the age of 40 to 40 years old (25.9%), below 29 years old (23%), and above 50 years old (18.4%).

Relevant research about teachers' technostress discovered that age, gender, salary, workload, access to ICT tools, and Internet access are among the factors that caused teachers' stress during the pandemic [4], [5], [6], [7].

Although China is considered a well-developed country, the rapid development of new and emerging technologies such as artificial intelligence (AI) and cloud computing which are widely and popularly used in the education industry, has urged the teachers to learn and adapt the technologies for better and more effective teaching deliveries. Moreover, there were around 44% of China teachers aged 40 and above in 2023 with the number of older teachers dominating the total population of China teachers. The new and emerging technologies were new to this generation of teachers. The study by Tan [6] and Liu [8] discovered that older teachers were more anxious about online teaching and the use of ICT tools than younger teachers.

1.2. Technostress Overview

Technostress can be defined as a negative psychological state related to the use of ICTs or the threat of its use in the future [5]. It refers to a psychological state whereby there is a mismatch between demand and associated resources that develops with the use of ICTs, resulting in high levels of unpleasant psychophysiological activation and negative attitudes towards ICTs. Besides, technostress can also refer to an adaptive disease that is caused by the lack of ability to deal with new computer technologies healthily from a medical perspective [4].

While research about teachers' technostress was lacking in China, it was also observed that the existing research did not consider the new adoption of technology as a technostress factor in their research. Furthermore, the studies only identified the technostress factors but did not further cluster the teachers into their related technostress factors for further deliberation such as technological training support. To fill the research gap, this research aimed to identify the technostress factors among primary and secondary school teachers in Hunan, China, and further apply the K-means clustering method to cluster the teachers with the identified technostress factors, so that the human education department can design the right technological training programs based on targeted groups of teachers' technostress needs.

The teachers' technostress research was conducted in many developed countries such as Australia and the United Kingdom [9], [10], [11] while it has not been widely considered by researchers in China.

Only 126 relevant papers from 1994 to 2021 were found when an online search was conducted on the China National Knowledge Infrastructure (CNKI) website with the search title "Anxiety/Stress (Chinese version)". The search was conducted under the restricted sources of CSSCI and Peking University core journals.

There were three teachers' technostress research conducted by Chinese scholars Du [12], Tian [7], and Tan [6]. Du [12] and Tan [6] adopted three technostress factors such as techno-overload, techno-invasion, and techno-complexity, and found that all three factors were significant factors of technostress among China teachers. Meanwhile, Tian [7] researched five technostress factors (techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty). It was found that techno-overload and techno-uncertainty were significant technostress factors whereas techno-invasion, techno-complexity, and techno-insecurity were not significant technostress factors among the China teachers. The three researches were conducted in various districts and cities in China.

Muslimin *et al*. [13] from Indonesia conducted technostress research for English lecturers in universities by using the same set of technostress factors as Tian [7] from China. However, the findings showed that the technostress factors among the teachers in Indonesia were different from China (refer to the comparison of technostress research findings in Table 1).

Table 1. Summary table of factors influencing teachers' technostress

Technostress exploration factors	Is a significant technostress factor	Researchers
Techno-overload	Yes	Tian [7]
	Yes	Tan [6]
	No	Muslimin *et al.* [13]
Techno-invasion	Yes	Tian [7]
	Yes	Tan [6]
	No	Muslimin *et al.* [13]
Techno-complexity	No	Tian [7]
	Yes	Tan [6]
	Yes	Muslimin *et al.* [13]
Techno-insecurity	No	Tan [6]
	Yes	Muslimin *et al.* [13]
Techno-uncertainty	Yes	Tian [7]
	Yes	Muslimin *et al.* [13]
Learning-teaching process	No	Mokh *et al.* [14]
Profession-oriented	No	Mokh *et al.* [14]
Technical issue-oriented	Yes	Mokh *et al.* [14]
Personal-oriented	No	Mokh *et al.* [14]
Social-oriented	No	Mokh *et al.* [14]

Meanwhile, Mokh *et al.* [14] from Palestine explored different technostress factors (learning-teaching process, profession-oriented process, technical issue-oriented, personal-oriented, and social-oriented) for the teachers. The findings showed that the teachers rated low to moderate levels (63% - 75.6%) for all five technostress factors. It showed that all the technostress factors only have low to moderate significance levels among Palestine's teachers.

From the above review, the original teachers' technostress framework proposed by Tian [7] is now more than five years old. Muslimin *et al.* [13] adopted the framework entirely without adding any new technostress factor for exploration. While modern information technologies such as AI and cloud computing have developed rapidly over the past few years, the adoption of new technology could be a new technostress factor among teachers, especially for the China teachers whereby the education department highly encouraged the use of new technology to facilitate teaching and learning in the classrooms and online teaching.

Song [15] pointed out six applications of AI technology in the field of education which included realizing personalised teaching, automating the coaching process and intelligent evaluation mode, gamifying teaching platform, early childhood education robots, and educational decision-making. Some research also encouraged AI technology in schools such as AI + primary school science [16], AI real-time translation technology [17], AI-assisted precise teaching [18], and AI virtual digital human technology [19].

On the other hand, cloud computing has played a role as an emerging platform and infrastructure for online and remote teaching, especially during and after the COVID-19 pandemic [20]. The teachers had to learn about how to use cloud computing to build a teaching resource base [21], implement a flipped classroom [22], and construct characteristic laboratory and innovative practice teaching [23]. While not every teacher is highly technology savvy and well-trained in technological tools' adoption, this new AI and cloud computing technology adoption might be the new technostress factor among teachers, especially in China's situation.

1.3. Clustering Methods for Identifying Teachers' Groups

The intention of using K-means clustering is to group the teachers based on the result of the technostress factor's exploration survey. K-means clustering is an unsupervised learning method to perform data clustering analysis.

The advantages of adopting K-means clustering include an effective grouping of non-hierarchical data [24], simplicity and ease, increment in computational efficiency, and scalable. Some significant K-means data clustering research includes clustering of corn planting feasible areas [24], customer segmentation [25], and identification of red zone infected areas during the COVID-19 pandemic period in Indonesia [26]. In this research, the results of the clustering method can easily divide teachers into different clusters based on distance proximity as the level of each technostress factor was rated on a nominal scale.

There are various distance calculation methods employed in the K-means algorithm such as Euclidean distance, Manhattan distance, and Chebyshev distance. This research only focused on using the Euclidean distance and Manhattan distance to generate teachers' clusters. Each distance calculation method has its strengths and weaknesses as summarised in Table 2.

Table 2. Comparisons of Euclidean distance and Manhattan distance

Dimension	Euclidean distance	Manhattan distance
Calculation speed	Requires calculating the sum of squares of the difference between each coordinate and taking the root of the square, which is relatively complex and can be slower in a large number of calculations.	Only needs to calculate the sum of the absolute values of the difference between each coordinate, which is faster and more suitable for scenarios that require a lot of calculation.
Coordinate range	Greatly affected by the value between coordinates, so there are strict requirements on the coordinate range.	Not affected by the value between the coordinates, but only considers the relative distance, so it is suitable for scenes with uncertain and irregular coordinate ranges.
Outlier sensitivity	Greatly affected by the change of a single coordinate value, and its fault tolerance is poor, so it is more sensitive to outliers.	Not affected by the change of a single coordinate value, and the fault tolerance is strong.

Nonetheless, each distance calculation method had proven its efficacy in various researches [27], [28], [29] that used Euclidean distance, and [30], [31], [32] that used Manhattan distance.

As every set of data is unique, it is crucial to consider the unique characteristics of the data before deciding to use and adopt the right type of distance calculation method in the K-means clustering.

2. Methodology

This section describes the research procedures for conducting the exploratory research. The theoretical framework including the hypotheses is provided together with the questionnaire design.

2.1. Research Procedure

This research was conducted in two major phases. In the first phase, a questionnaire was designed to collect responses among the Hunan, China teachers' responses regarding technostress situations. Three test stages were used to conduct the quantitative analysis. In the pre-test stage, seven teachers with more than 16 years of teaching experience were engaged to review the questionnaire. The questionnaire was revised accordingly and used in the next pilot test stage whereby 50 teachers were approached to complete the questionnaire. The collected responses were analysed by using a reliability test. Again, the questionnaire was revised before it was released for data collection among 500 primary and secondary school teachers in Hunan, China in the full test stage. The responses were analysed with hypothesis testing and regression analysis tests to determine the significant technostress factors.

In the second phase, based on the identification of technostress factors among the Hunan, China's teachers, the K-means clustering method was used to cluster the teachers with both Euclidean and Manhattan distances methods. The K-means algorithm was run in four steps such as initialisation of centroids, allocation of data point to a cluster, update of the centroid, and finalisation when the centroid no longer changes significantly, or the upper number of iterations is reached. The clustering output was presented in graphical charts for better visual illustration. Based on the comparison of two distance methods, the research proposed the best K-means clustering distance method for identifying the Hunan, China teachers' technostress clusters.

2.2. Theoretical Framework

This research decided to adopt four existing technostress factors namely techno-overload, techno-complexity, techno-insecurity, techno-uncertainty, and proposed a new technostress factor which is the new technology adoption. The justification for adopting the four technostress factors is given in Table 3. This research excluded the techno-invasion factor because it is not of great help to the research goal of this study. This research did not adopt any technostress factor from Mokh *et al.* [14]'s research because some of the factors are focused on social and personal aspects (non-computing related), whereas the aspect of technical issue-oriented was already included in the techno-insecurity factor. The research theoretical framework and hypotheses are shown in Figure 1.

Table 3. Overview of justification for variables selection

Selected variable	Definition/description	Justification	Previously used in
techno-overload	ICT users are forced to work faster and longer hours [7]	It is a significant technostress factor in China	Tian [7], China Tan [6], China Muslimin *et al* [13], Indonesia
techno-complexity	Due to the complexity of the technology, ICT users feel that they do not have enough time and energy to learn and use the technology [7]	It is a significant technostress factor in China and Indonesia	Tian [7], China Tan [6], China Muslimin *et al* [13], Indonesia
techno-insecurity	ICT users feel threatened by technology, believing that they will lose their jobs or be replaced by new technology [7]	It is a significant technostress factor in Indonesia	Tian [7], China, Muslimin *et al* [13], Indonesia
techno-uncertainty	The speed of ICT users' self-development lags behind the speed of technological development, and cannot adapt well to work under new technological conditions [7]	It is a significant technostress factor in China and Indonesia	Tian [7], China, Muslimin *et al* [13], Indonesia

Hypothesis：

H1 Techno-overload is positive and significantly related to the technostress status of Hunan, China teachers.

H2 Techno-complexity is positive and significantly related to the technostress status of Hunan, China teachers.

H3 Techno-insecurity is positive and significantly related to the technostress status of Hunan, China teachers.

H4 Techno-uncertainty is positive and significantly related to the technostress status of Hunan, China teachers.

H5 New technology adoption is positive and significantly related to the technostress status of Hunan, China teachers.

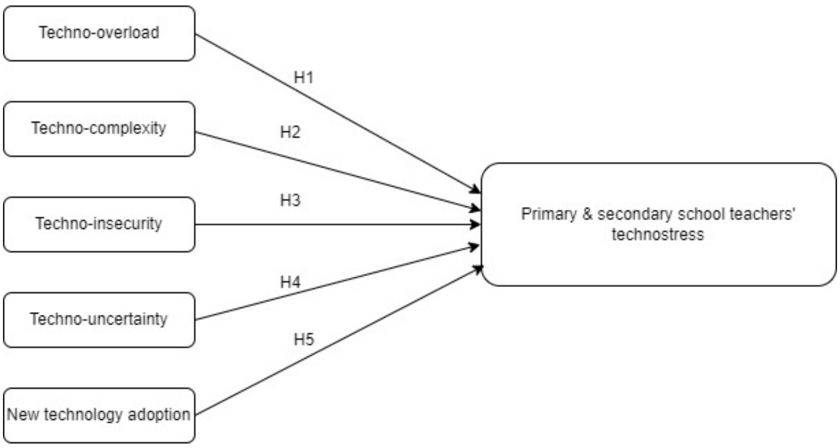

Figure 1. Research theoretical framework

2.3. Design of Questionnaire

The questionnaire is used as a research instrument. Part one of the questionnaire gathered the fundamental personal details of Hunan, China's teachers such as gender, educational background, teaching experience, current teaching field, level of teaching, and frequency of using the Internet. Part two focused on the answering of teachers' technostress status, by adopting the five technostress factors, with the questionnaire model adopted from Tan [6] and Muslimin *et al*. [13]. Each factor has four to eight questions. The answer choices are a five-point Likert scale of 1 as strongly disagree to 5 as strongly agree. The questionnaire was hosted in an online survey system named "*Wenjuanxing*".

3. Results

This section describes the steps and output of statistical analysis to answer the hypotheses. Meanwhile, the clustering analysis with its visualisation output is also deliberated.

3.1. Quantitative Analysis with Questionnaire

The pretest stage collected feedback from seven experienced secondary school students. The teachers reviewed the questionnaire and provided feedback regarding the suitability and quality of the questionnaire construction. All teachers commented that the questionnaire design was comprehensive, and the surveyed factors adequately covered the technostress topic among China's teachers. There was one teacher who commented that the questionnaire was slightly lengthy. This aspect would be reviewed again during the next pilot test phase, whereby low reliable questions to be removed. Another teacher suggested that a question about the age that teachers do not require to learn new skills could be added.

As this research did not use age as a research moderation variable, the suggestion is kept in view for the time being.

50 teachers from Changsha Foreign Language School were invited to answer the questionnaire at the pilot study stage. The responses were analysed by using a reliability test, in SPSS version 28. Several rounds of reliability tests were conducted to improve the reliability level of the overall questionnaire. Upon removal of two questions from the techno-overload factor and one question from the techno-uncertainty factor, the questionnaire achieved an acceptable to excellent level of reliability with the Cronbach alpha values 0.908 (techno-overload), 0.807 (techno-complexity), 0.811 (techno-insecurity), 0.738 (techno-uncertainty), 0.883 (new technology adoption), and 0.838 (technostress status).

A total of 507 Hunan, China primary and secondary school teachers participated in the questionnaire survey for the full test stage. The demographic analysis of the questionnaire respondents showed that 52.5% of respondents were female and 47.5% were male. Approximately 40% of respondents had teaching experience of around 5 to 10 years, followed by 32% with 11-15 years of experience, and another 20% and 8% of teachers with either less than 5 years or more than 16 years of teaching experience. A balanced mix of teachers from primary and secondary schools with 53% and 47% participated in the survey. Overall, the well-distributed and balanced demographic background among the participating teachers would contribute to the significant findings of the research.

The summary of the frequency count of each question's responses is shown in Figure 2. Most teachers answered with a rating of 4 (agree) and 5 (strongly agree), with moderate selection for a rating of 3 (neither agree or disagree), and less selection for a rating of 1 (strongly disagree) and 2 (disagree). The summary of statistical test results is shown in Table 4. The dataset is stored in an open dataset of a university [33].

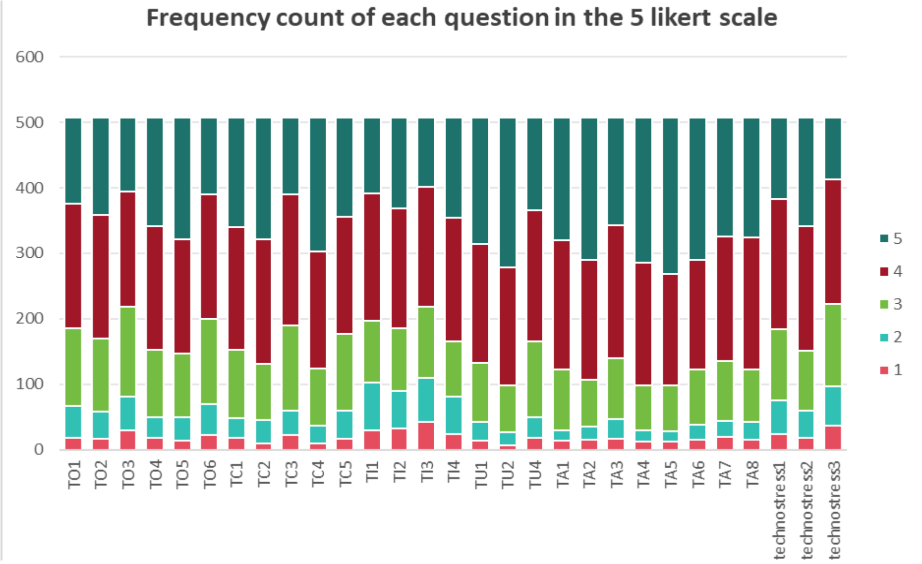

Figure 2. Summary of the frequency count of each question's responses in the 5 Likert scale

Table 4. Summary of quantitative analysis in full test

Factors/questions	Cronbach alpha value	Pearson Correlation value	MRA Unstandardised Coefficients
Techno-overload (TO) TO1: Technology forced me to work at a faster pace. TO2: Using new technology has increased my workload. TO3: Technology forced me to schedule more tight hours. TO4: Technology forced a change in the way I work. TO5: I was forced to change my work habits to adapt to the new technology. TO6: I spend a lot of time reading the email every day.	0.867	0.424*	0.211
Techno-complexity (TC) TC1: The new technology is too complex for me to understand and use. TC2: I know too little about new technologies to handle my work satisfactorily. TC3: It takes me a long time to understand and use new technologies. TC4: I need more time to learn and improve my skills. TC5: I need to master new skills to catch up with my school colleagues.	0.850	0.420*	0.227
Techno-insecurity (TI) TI1: I fear because digital tools are more common in teaching & learning. TI2: I am worried about the safety & restiveness of my data in a virtual environment. TI3: I feel professional jealousy will arise because of technological competency among colleagues. TI4: I feel pressured by my colleagues to work with new technology.	0.879	0.442*	0.211
Techno-uncertainty (TU) TU1: I think ICT development is too rapid, & some people in other countries have used something different. TU2: I am afraid that the technology I am learning will not be relevant tomorrow. TU4: I am not sure technology should always be in class after the COVID-19 pandemic.	0.763	0.390*	0.195
New Technology Adoption (TA) TA1: I feel that it is difficult to use AI technology to achieve personalised learning. TA2: I feel that it is difficult to use AI to customise class assignments and final exams. TA3: I feel that it is difficult to use AI to achieve virtual learning environments. TA4: I feel that it is difficult to use AI technology to quickly realise the design of teaching classrooms. TA5: I feel that it is difficult to build a network learning environment. TA6: Using the cloud platform to realise the sharing and storage of resources (uploading courseware, videos and other resources) makes me feel anxious. TA7: It is difficult for me to use the cloud platform for online teaching and distance learning. TA8: I feel anxious about using the cloud platform to manage students' electronic files.	0.898	0.426*	0.255

** the p value is < 0.05 indicate significant condition.*

The statistical analysis was conducted by using SPSS software version 28. In the reliability test, all the variables including the five factors and technostress status had acceptable to good reliability levels ranging from 0.763 to 0.898. No question is required to be removed as the reliability level is good. Following on, Pearson correlation analysis was conducted to test the hypotheses. All the hypotheses were accepted, and it showed that the five technostress factors are positive and significantly related to the technostress status of Hunan, China teachers. However, the correlation value only showed a low positive correlation from the lowest 0.39 (techno-uncertainty) to the highest 0.442 (techno-insecurity).

In the multiple regression analysis, the result of R square indicated that 41.8% of the variation in technostress could be explained by techno-overload, techno-complexity, techno-insecurity, techno-uncertainty, and new technology adoption. The analysis also showed that all the five technostress factors are significant and can be included in the regression model. All technostress factors were determined by the most significant to less significant by standard coefficients successively with new technology adoption (0.255), techno-complexity (0.227), techno-overload (0.211), techno-insecurity (0.211), and techno-uncertainty (0.195).

3.2. Clustering Analysis

To better understand the needs of the teachers, this study employed the K-means clustering method to elucidate the five identified technostress factors among the teachers, with two distance calculation methods namely Euclidean and Manhattan. The K-means algorithm was run with Weka open software.

The number of clusters was set to five because there are five significant technostress factors according to the survey result.

The output from Euclidean and Manhattan distance methods are illustrated as radar charts in Figures 3 and 4 were compared and the more appropriate one will be proposed as the finding of this research.

Figure 3 illustrates the distinctive technostress factors across five teacher clusters. In Cluster 1, the largest group of teachers (total of 195 over 507) exhibited high mean scores of 4.28 across all technostress factors, particularly notable in techno-overload (TO), techno-complexity (TC), and new technology adoption (TA). It indicated that teachers in this cluster need comprehensive training related to all five technostress factors. Cluster 2, while maintaining an overall positive technostress profile, places a greater emphasis on techno-complexity (TC) and techno-insecurity (TI). Teachers in Cluster 2 showed low technostress in techno-overload (TO). Cluster 3 stood out for its relatively lower mean score of 2.61, indicating a lower level of agreement on all technostress factors, with techno-overload (TO) being notably low. Cluster 3 teachers did not need to be trained in these five factors. Cluster 4 demonstrated a mixed technostress profile, with moderate mean scores across all factors, except for techno-insecurity (TI) being notably low. The scales of teachers in Cluster 4 on the four factors of techno-overload, techno-complexity, techno-insecurity, and techno-uncertainty are all lower than 4, which meant that teachers in Cluster 4 have low technostress in techno-overload, techno-complexity, techno-insecurity and techno-uncertainty and only need to train for new technology. Cluster 5 with the least number of teachers in the cluster displayed a distinctive pattern characterised by lower mean scores in new technology adoption, indicating these teachers do not require new technology adoption training.

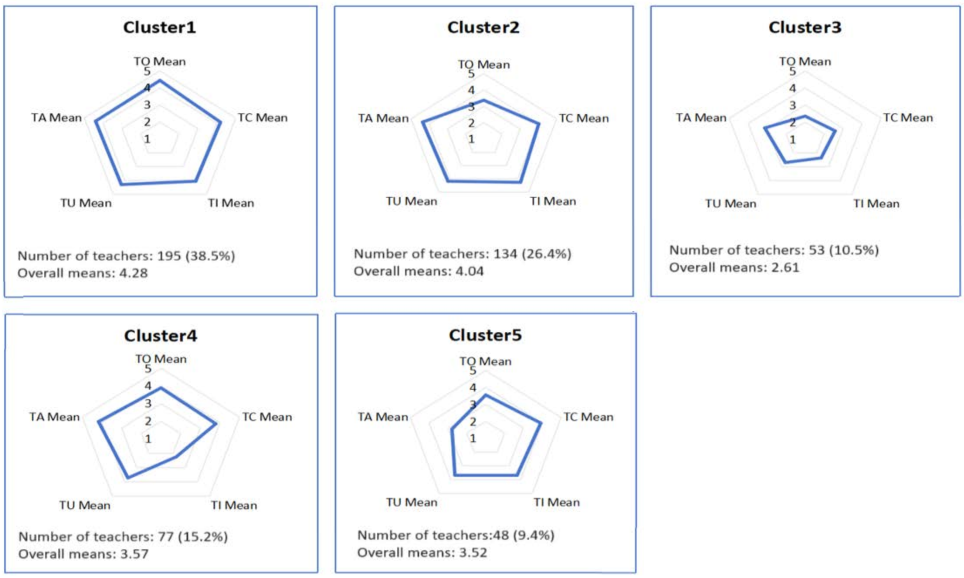

Figure 3. Clustering analysis output by using the K-means Euclidean distance method

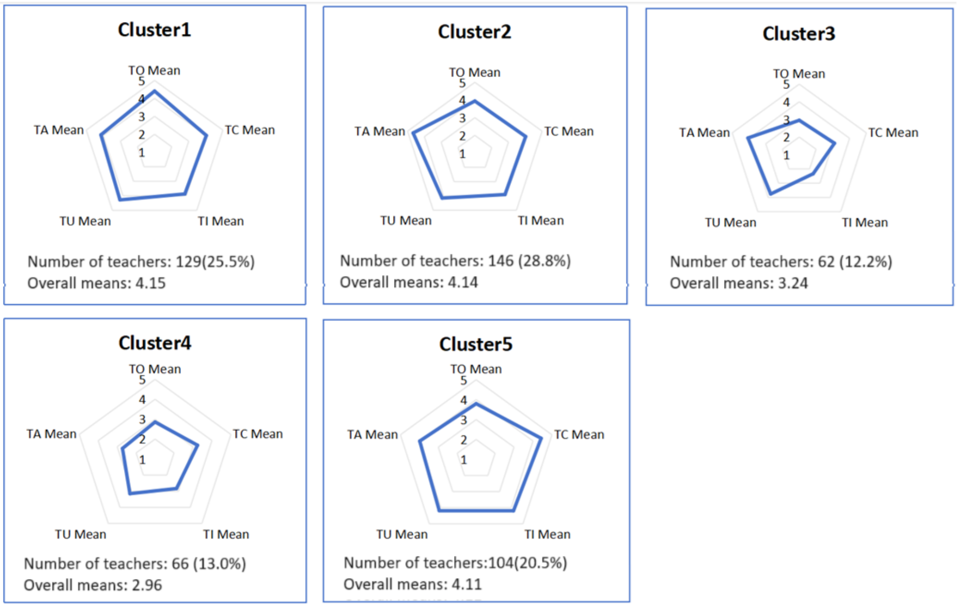

Figure 4. Clustering analysis output by using the K-means Manhattan distance method

With reference to Figure 4, Cluster 2 encompassed the largest number of teachers (146 over 507) and demonstrated a relatively balanced and moderate stance across various technostress factors. Cluster 3 stood out with lower values in techno-complexity (TC) and techno-insecurity (TI), suggesting that the 62 teachers did not face difficulties in handling digital tools and felt secure in using them. Cluster 4, with 13% of teachers provided a low rating of average 2.96 in all five technostress factors. This cluster of teachers might not need any technological training. Meanwhile, the teachers from Cluster 1 and 5 who gave high ratings (more than 4) in all five factors should undergo the necessary technological training to release the technostress.

4. Discussion

In stage one which involved quantitative analysis with a questionnaire, three test stages namely pretest, pilot test, and full test were conducted to obtain reliable and significant findings. The findings of this study on technostress factors (techno-complexity, techno-insecurity, techno-uncertainty) in teachers were consistent with research [7], [13]. The questionnaire construct was claimed to be high quality as only a slight removal of questions was required to improve the overall reliability of the questionnaire construct. In addition, the newly proposed technostress factor which was new technology adoption gained the highest Cronbach alpha value. It showed that the new factor was highly reliable. The findings from the hypothesis testing and multiple regression analysis also showed that the technostress factor of new technology adoption had the second highest positive correlation value among the five factors and achieved the highest MRA Unstandardised Coefficients value too. Thus, it could be claimed that the newly proposed technostress factor is significant in studying the technostress condition among teachers.

In stage two, the result from the K-means clustering analysis provided insights into the efficiency and effectiveness of the clustering algorithm, in different distance calculation methods. Firstly, the Euclidean calculation method required five iterations to converge and resulted in a within-cluster sum of squared errors of 602.16, whereas the Manhattan calculation method only required four iterations to converge, with a sun of within-cluster distances amounting to 2037.0. There is equal computational efficiency among the two distance calculation methods whereby only 0.01 seconds were required to complete the clustering process.

Since the efficiency of both distance calculation methods was similar, the decision of choosing which distance calculation method for generating the teachers' technostress clusters was to be determined by the specific characteristics of the dataset, as well as the goals of the clustering analysis. Concerning radar charts from Figures 3 and 4, it could be observed that the characteristics of each group of teachers are more obviously shown through Euclidean clustering. The Euclidean clustering method significantly clustered teachers with distinct technostress factors and their level of agreement. For example, Cluster 1 comprised teachers with technostress in all five-factor areas, and teachers from Cluster 2, 4, and 5 had one unique lower technostress area namely the techno-overload, techno-insecurity stress, and new technology adoption. Meanwhile, 3 out of 5 (Cluster 1, 2, and 5) clusters generated by the K-means Manhattan distancing method had similar characteristics.

It caused difficulties in identifying resources for teaching training support. Overall, the results show that Euclidean distance is more suitable than Manhattan to cluster teachers for identifying their technostress characteristics.

5. Conclusion

This research successfully identified five technostress factors among the 507 primary and secondary school teachers from Hunan, China. The quantitative analyses with questionnaire survey were conducted by using SPSS software version 28. The Pearson correlation analysis and multiple regression analysis showed that there are positive and significant relationships among the five technostress factors (techno-overload, techno-complexity, techno-insecurity, techno-uncertainty, new technology adoption) and the state of technostress among the teachers. In particular, this research proposed a new technostress factor called new technology adoption and this factor had the second highest correlation with teachers' technostress in Pearson correlation analysis and obtained the highest MRA unstandardised coefficients among the five technostress factors. The subsequent research about teachers' technostress should include the new factor of new technology adoption.

This research also successfully applied and determined the more significant clustering with the K-means Euclidean distance method to cluster the Hunan, China's teachers, based on the identified five technostress factors. By evaluating the efficiency of the distance calculation method and the unique characteristics of the dataset, the Euclidean distance calculation method outperformed the Manhattan distance calculation method in this research. The output of the Euclidean clustering method could be used as a reference for the human education department to plan the right resources and target the right group of teachers to participate in various technological training programs.

It is recommended that the survey instrument be adopted by the Hunan Education Department as a mandatory survey among primary and secondary school teachers annually, with all teachers providing their identity in the survey response. Based on the collected responses, K-means clustering can be conducted to identify the teachers' technostress clusters. Based on the clustering output, the Hunan Education Department can further design different sets of technological training and request the relevant teachers to attend the upskilling training.

By converting raw survey data into useful clustering information with known teachers' identities, it is believed that the technological training could help the teachers to obtain relevant skills and new knowledge to resolve their technostress significantly.

In the future, the research could be expanded to the wider distinct province of China, using the five technostress factors agreed by the Hunan, China's teachers. Further research could also investigate other demographic aspects as moderator factors such as marital status, gender, and the number of roles and responsibilities in the school by the teachers. The researchers could also explore other suitable types of clustering methods to group the teachers.

References:

[1]. Bi, S. (2022). Booster or burden: the technostress on English teachers in China. *2022 7th International Conference on Social Sciences and Economic Development (ICSSED 2022)*, 1418-1424, Atlantis Press. Doi:10.2991/aebmr.k.220405.236

[2]. Li. C. (2023). Exploration and reflection on the construction of regional smart education in the digital era. *Modern information technology*, 24, 193-198. [in Chinese].

[3]. MOE. (2020). *National statistical bulletin on the development of education.* MOE. Retrieved from: http://www.moe.gov.cn/jyb_sjzl/sjzl_fztjgb/202108/t20210827_555004.html?eqid=cb1943ea0000090100000006647c3957 [accessed: 05 March 2024].

[4]. Wang, P., Lin, P., Cao, H., Jiao, T., Xu, Y., Gao, F., & Mashumba, L. P. (2009). The sources of work stress for chinese high school teachers. *Social behavior and personality: An International Journal, 37* (4), 459-465. Doi:10.2224/sbp.2009.37.4.459

[5]. Urbano, O. F. A., Chanchi, G. G. E., & Campo, M. W. Y. (2021). Technostress analysis in educational institutions during the COVID-19 confinement. *Tem Journal-Technology Education Management Informatics*, 1655-1661. Doi:10.18421/tem104-22

[6]. Tan, J. (2020). *A study on the technical pressure of middle school teachers and its countermeasures - a case study of Tianjin Middle School*, [Master's Theses, Tianjin Normal University]. [in Chinese].

[7]. Tian, Y. (2018). *Research on the technostress level and it's influencing factors of middle school teachers*, [Master's Theses, Central China Normal University]. [in Chinese].

[8]. Liu, S., & Onwuegbuzie, A. J. (2012). Chinese teachers' work stress and their turnover intention. *International journal of educational research*, *53*, 160-170. Doi:10.1016/j.ijer.2012.03.006

[9]. Lee, Y. H. (2019). Emotional labor, teacher burnout, and turnover intention in high-school physical education teaching. *European Physical Education Review*, *25* (1), 236-253. Doi:10.1177/1356336X17719559

[10]. Perryman, J., & Calvert, G. (2020). What motivates people to teach, and why do they leave? accountability, performativity and teacher retention. *British Journal of Educational Studies*, *68*(1), 3-23. Doi:10.1080/00071005.2019.1589417

[11]. Travers, C. J., & Cooper, C. L. (1995). *Teachers under pressure: stress in the teaching profession.* London: Routledge.

[12]. Du, H. (2013). Design of Teachers' Techno-Stress Scale. *China Educational Technology & Equipment* (3), 52-54.

[13]. Muslimin, A. I., Mukminatien, N., & Ivone, F. M. (2023). TPACK-SAMR Digital Literacy Competence, Technostress, and Teaching Performance: Correlational Study among EFL Lecturers. *Contemporary Educational Technology, 15*(2). Doi:10.30935/cedtech/12921

[14]. Mokh, A. J. A., Shayeb, S. J., Badah, A., Ismail, I. A., Ahmed, Y., Dawoud, L. K., & Ayoub, H. E. (2021). Levels of technostress resulting from online learning among language teachers in Palestine during Covid-19 pandemic. *American Journal of Educational Research*, *9*(5), 243-254. Doi:10.12691/education-9-5-1

[15]. Song, S. (2020). The application of AI technology in the field of education under the background of big data. *Network Security Technology & Application* (12),115-116. [in Chinese].

[16]. Liang, Y., Pu J., & Yuan, S. (2023). Interdisciplinary Teaching of "AI + Primary School Science" under the control of big concept-taking "Exploring the mystery of the change of four seasons" as an example. *Modern Educational Technology,* 11, 57-68. [in Chinese].

[17]. Hao, X., Tang, Y., Zhang, Q., Yan, B., Wu, B., & Zhou, D. (2023). Application of integrated classroom based on AI real-time translation technology in clinical teaching practice of epilepsy. *Journal of Epilepsy* (06), 517-520. [in Chinese].

[18]. Chen, X., & Wang, H. (2023). Research on high school precision teaching strategies based on "AI technology". *Primary and Middle School Educational Technology* (11), 7-9. [in Chinese].

[19]. Pan, M. H., Lv, X., Chen, S., Wang, F., & Huan, R. T. (2023). Innovation and practice of online teaching based on AI virtual digital human technology. *Modern Vocational Education,* 31, 1-4. [in Chinese].

[20]. Fu, L. (2020). Research on cloud application status and university education cloud architecture model (07), 170-171. [in Chinese].

[21]. Guan, Y., & Chen, Z. (2023). Practice Research on the Construction of Cloud Computing Teaching Resource Library. *Industry and Information Technology Education,* (10), 90-94. [in Chinese].

[22]. Zou, J. (2023). Research and discussion on the teaching mode of flipped classroom based on cloud computing. *Office Informatization,* (13), 28-34. [in Chinese].

[23]. Ruan, C., Liu, B., & Lin, X. (2023). Construction and innovative practice teaching based on cloud computing characteristic laboratory. *Laboratory Science*, (3), 141-149.

[24]. Aldino, A. A., Darwis, D., Prastowo, A. T., & Sujana, C. (2021). Implementation of K-means algorithm for clustering corn planting feasibility area in south Lampung regency. *Journal of Physics: Conference Series*, 1751 (1), 012038. IOP Publishing. Doi:10.1088/1742-6596/1751/1/012038

[25]. Kansal, T., Bahuguna, S., Singh, V., & Choudhury, T. (2018). Customer segmentation using K-means clustering. *In 2018 International Conference on Computational Techniques, Electronics and Mechanical Systems (CTEMS)*, 135-139. IEEE. Doi:10.1109/CTEMS.2018.8769171

[26]. Abdullah, D., Susilo, S., Ahmar, A. S., Rusli, R., & Hidayat, R. (2022). The application of K-means clustering for province clustering in Indonesia of the risk of the COVID-19 pandemic based on COVID-19 data. *Quality & Quantity*, *56*(3), 1283-1291. Doi:10.1007/s11135-021-01176-w

[27]. Tarafdar, M., Pullins, E. B., & Ragu-Nathan, T. S. (2015). Technostress: Negative effect on performance and possible mitigations. *Information Systems Journal*, *25*(2), 103-132. Doi:10.1111/isj.12042

[28]. Patel, S. P., & Upadhyay, S. H. (2020). Euclidean distance based feature ranking and subset selection for bearing fault diagnosis. *Expert Systems with Applications*, *154*, 113400. https://doi.org/10.1016/j.eswa.2020.113400

[29]. Wang, B., Liu, X., Yu, B., Jia, R., & Gan, X. (2019). An improved WiFi positioning method based on fingerprint clustering and signal weighted Euclidean distance. *Sensors*, *19*(10), 2300. Doi:10.3390/s19102300

[30]. Jiang, X., Hu, X., & He, T. (2016). Identification of the clustering structure in microbiome data by density clustering on the Manhattan distance. *Science China Information Sciences*, *59*, 1-7. Doi:10.1007/s11432-016-5587-8

[31]. Kapil, S., & Chawla, M. (2016). Performance evaluation of K-means clustering algorithm with various distance metrics. *In 2016 IEEE 1st international conference on power electronics, intelligent control and energy systems (ICPEICES)*, 1-4. Doi:10.1109/ICPEICES.2016.7853264

[32]. Strauss, T., & von Maltitz, M. J. (2017). Generalising Ward's method for use with Manhattan distances. *PloS one*, *12*(1), e0168288. Doi:10.1371/journal.pone.0168288

[33]. Li, S & Lim, C.Y (2024). *An Analysis of Technostress Factors Among Teachers in Hunan, China through Statistical Methods and K-means Clustering.* Open Data Set. Retrieved from: https://opendata.usm.my/handle/123456789/74703 [accessed: 09 April 2024]