Measuring university students' technostress in technology-enhanced learning: Scale development and validation

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With technology-enhanced learning playing an increasingly important role in higher education, university students are enjoying unprecedented benefits while likely experiencing technostress due to increased requirements and different academic expectations of technology-enhanced learning. This study aimed to develop a psychometric scale to measure university students' levels of technostress in technology-enhanced learning. An initial technostress scale was developed drawing on the person-environment fit theory and prior research on technostress. In total 620 students were recruited from two public universities in China. Three rounds of study were performed to validate the initial technostress scale using factor analysis, the Rasch model, and multilevel linear regression. The finalised technostress scale with 8 items demonstrated robust psychometric properties, including high internal consistency, validity, uni-dimensionality, and measurement invariance across students of different demographics. The development of the technostress scale is an important step in identifying maladapted students and preserving their wellbeing so as to increase their constructive and active participation in technology-enhanced learning.

Implications for practice or policy:
- Educational practitioners in higher education can use the technostress scale to conveniently identify maladapted students in technology-enhanced learning.
- The technostress scale can provide preliminary diagnostic information to inform the development of timely intervention so as to preserve university students' wellbeing in technology-enhanced learning.

Keywords: technostress, measurement scale, university students, the Rasch model, person-environment fit

Introduction

While universities around the world have been enthusiastically advancing their agendas for technology-enhanced learning (Flavin, 2016; Nami & Vaezi, 2018), via experimenting with new forms of instruction (e.g., the flipped classroom and blended learning) and digitalising learning and teaching resources for flexible degree programs (e.g., massive online open courses [MOOC]), little attention has been given to students' psychological responses to these digitalisation agendas. Indeed, technology-enhanced learning such as MOOCs, blended learning, and the flipped classroom have potential to afford students personalised learning experience, widen their access to quality learning resources, and innovate their ways of knowledge building and acquiring (Brooker, Corrin, De Barba, Lodge, & Kennedy, 2018; Tuapawa, 2017). However, this new learning mode often incurs demands of more time, knowledge, and skills, and consequently psychological strains for students (Jung, Kudo, & Choi, 2012; Paul & Glassman, 2017). As a result, university students could experience technostress, which is defined as a modern disease of maladaptation caused by individuals' inability to cope with new technology and changing cognitive and social requirements related to the use of technology (Brod, 1984; Ragu-Nathan, Tarafdar, Ragu-Nathan, & Tu, 2008).

Technostress could lead to a variety of negative effects on individuals and their organisations (Fuglseth & Sørebø, 2014; Hsiao, 2017; Tarafdar, Pullins, & Ragu-Nathan, 2015). For instance, it can cause fatigue, anxiety, and depression while resulting in dissatisfaction with jobs, intention to quit the use of technology,

and reduced productivity. In the field of education, technostress could cause problems such as dissatisfaction with learning, frustration, insufficient learning engagement, and decreased performance (Jena, 2015; Jung et al., 2012).

Technostress, as a negative consequence of technology, has gained the attention of scholars in recent years. Prior research on technostress has been conducted mostly in adult work settings such as government and industry sectors (Fuglseth & Sørebø, 2014; Marchiori, Mainardes, & Rodrigues, 2019; Ragu-Nathan et al., 2008), while very limited research has been done in the field of education, in which most were conducted in elementary and secondary schools (Al-Fudail & Mellar, 2008; Joo, Lim, & Kim, 2016). Furthermore, even among those technostress-related studies in educational settings, most focused on faculty members and teachers in different levels of schools, but few have examined this issue in the student population, especially among students in higher education. In spite of the paucity of research on technostress in the field of education, its pervasiveness and gravity in this field, especially in higher education where learning is continually modernised by heavy investments on technology (Jung et al., 2012), may be no less noticeable than that in government and industry sectors.

Prior studies mostly focused on exploring such topics as technostress creators and inhibitors (Hwang & Cha, 2018; Ragu-Nathan et al., 2008), negative consequences associated with technostress (Al-Fudail & Mellar, 2008; Fuglseth & Sørebø, 2014), and demographic characteristics of technostress (Krishnan, 2017; Marchiori et al., 2019). However, there has been a dearth of psychometric instruments to measure levels of technostress. Therefore, this study aims to fill this gap by developing a psychometrically robust instrument to measure technostress among university students. In doing so, this study hopes to provide valid diagnostic information to locate maladapted students in technology-enhanced learning and preserve their wellbeing, so as to enhance their constructive participation in technology-enhanced learning and to enable them to better exploit benefits associated with the use of technology in higher education.

Theoretical framework

Extant research on technostress

Technostress is a relatively new and understudied topic as compared with a vast number of studies examining benefits and potentials related to technology for organisations and individuals' personal and professional lives (Tarafdar et al., 2015). One concept that is often confused with technostress is computer/internet anxiety (also described as technophobia or cyberphobia). Computer/internet anxiety is mainly related to fear of using technology (Paul & Glassman, 2017; Tekinarslan, 2008); while technostress is a problem of adaptation experienced by individuals when they are unable to cope with challenges associated with the use of technology (Nimrod, 2018; Tarafdar et al., 2015). In addition, technostress is not only related to technology per se, but also to changing requirements in many aspects of learning (e.g., design and delivery of content and instruction, learning process, and assessment) resulting from the use of technology (Jena, 2015; Jung et al., 2012).

Previous studies examining technostress mostly focused on three topics: (1) technostress creators and solutions of technostress (also defined as technostress inhibitors), (2) negative consequences caused by technostress, and (3) demographic characteristics related to technostress. With regard to the first topic, research has broadly centered on five categories of technostress creators: techno-overload, techno-invasion, techno-complexity, techno-uncertainty, and techno-insecurity (Hwang & Cha, 2018; Jena, 2015; Tarafdar et al., 2015). On the other hand, three technostress inhibitors have been proposed: technical support provision, literacy facilitation, and involvement facilitation (Ragu-Nathan et al., 2008). Other inhibitors have also been suggested, for instance, increasing technology efficacy (Shu, Tu, & Wang, 2011) and adjusting regulatory focus (Hwang & Cha, 2018).

Studies on the second topic have explored a wide range of consequences caused by excessive technostress, including psychological, physical, and social (Al-Fudail & Mellar, 2008; Salo, Pirkkalainen, & Koskelainen, 2018). In particular, much attention has been devoted to examining consequences to individuals' professional lives (Fuglseth & Sørebø, 2014; Joo et al., 2016; Tarafdar et al., 2015). All these studies have pointed to negative effects related to persistent and excessive technostress and the imperative to deal with this issue for the sake of individuals' wellbeing and organisational success.

With regard to studies investigating the third topic of demographic characteristics related to technostress, a variety of demographic features have been examined, such as age, gender, experience in the use of technology, educational levels, and efficacy levels of users (Hsiao, 2017; Marchiori et al., 2019; Ragu-Nathan et al., 2008). However, no consensus has been reached regarding how technostress may vary in relation to individuals of different demographics. Among these studies, characteristics including gender, willingness in the use of technology, and personality have received special attention. This is probably because male and female individuals often have different experiences and perceptions of the use of technology (Marchiori et al., 2019). Individuals' willingness in the use of technology is considered an important determinant of technostress and those with low willingness have higher possibilities of suffering from technostress (Yan, Guo, Lee, & Vogel, 2013). Personality, which is a stable set of characteristics, has been strongly associated with stress-related responses in previous studies (e.g., Hsiao, 2017; Landers & Lounsbury, 2006; Srivastava, Chandra, & Shirish, 2015) and has been considered an important predictor of students' behaviour and academic success (Krishnan, 2017; Van Bragt, Bakx, Bergen, & Croon, 2011).

Undoubtedly, these prior studies on technostress have enriched our understanding of this issue and contributed to future theorising and practical efforts. However, most studies on technostress are in the government and industry sectors, with only a very small number of them in the field of education (Al-Fudail & Mellar, 2008; Jena, 2015; Joo et al., 2016). Fewer still are in higher education. In addition, these studies mostly focused on employees and teachers, with little attention on student population (Jung et al., 2012). More surprisingly, there have been few studies devoted to developing psychometric instruments to specifically measure levels of technostress.

Only a few scales have been developed to measure concepts related to technostress, for instance, computer anxiety rating scale (Heinssen, Glass, & Knight, 1987) and computer technology use scale (Conrad & Munro, 2008). There is also one scale measuring technostress among senior citizens (Nimrod, 2018), which is not likely to fit young people as they usually have marked differences in exposure to new technology and technical skills (Hsiao, 2017; Marchiori et al., 2019) and technostress is context-dependent (Tarafdar et al., 2015). Overall, these scales share two main characteristics: (1) they are not closely relevant to the integration of technology in learning; and (2) they are developed solely relying on classical test theory, which has been criticised for deficiencies in generating psychometrically robust instruments due to such limitations as sample and test dependence (for more information see Higgins, 2007; Van Zile-Tamsen, 2017).

In this regard, this study endeavoured to develop a psychometrically robust instrument using new methods (combining factor analysis and the Rasch model) to measure technostress among student population in higher education in their technology-enhanced learning.

Developing an initial technostress scale based on person-environment (P-E) fit theory

Person-environment (P-E) fit theory is considered essential in understanding the formation and consequences of stress (Ayyagari, Grover, & Purvis, 2011; Edwards, Caplan, & Harrison, 1998). A person-environment fit or congruence occurs when there is a match between personal factors (e.g., abilities and personalities) and environmental factors (e.g., organisations, tasks, and people) (Edwards et al., 1998; Edwards & Shipp, 2007). P-E fit often leads to improved performance, increased satisfaction with environmental factors, and enhanced wellbeing; while P-E misfit results in the converse (Edwards & Shipp, 2007). The core premise of P-E fit theory is that stress neither arises from the person nor from the environment separately, instead, it develops from the misfit between both (Edwards et al., 1998).

As stress is defined as a psychological reaction to an imbalance between a person and the environment (Cooper et al., 2001; Ragu-Nathan et al., 2008), this naturally explains why P-E fit theory is widely used in examining stress-related research, including technostress (Al-Fudail & Mellar, 2008; Ayyagari et al., 2011; Yan et al., 2013). In this study, the *person* in P-E fit theory refers to university students. The technology-enhanced learning, including its requirements, courses, and tasks, is considered the *environment* factor. P-E fit is usually operationalised in two ways: abilities-demands (A-D) fit and needs-supplies (N-S) fit (Ayyagari et al., 2011; Edwards et al., 1998).

In the context of this study, individuals' abilities include their abilities and skillsets in participating in technology-enhanced learning and time and effort available to them. Individuals' needs include their needs

for improved learning experience and higher academic performance through technology-enhanced learning. As P-E fit theory requires that the person and the environment factors be commensurate with one another (Edwards et al., 1998), demands are defined as quantitative and qualitative requirements of technology-enhanced learning for individuals' abilities. Supplies are defined as various resources and possibilities that technology-enhanced learning can provide to satisfy individuals' needs.

Abilities-demands (A-D) fit refers to a scenario where individuals' abilities, skills, and investment of time and effort meet demands of technology-enhanced learning. Needs-supplies (N-S) fit is related to the situation where technology-enhanced learning satisfies individuals' needs and preferences of learning. According to the P-E fit theory, technostress arises when students' abilities cannot meet requirements of technology-enhanced learning (i.e., A-D misfit) and/or technology-enhanced learning cannot provide sufficient supplies to meet students' needs (i.e., N-S misfit).

In line with the P-E fit theory and prior studies on technostress across different fields, an initial technostress scale with 13 items was developed. It has seven items to operationalise A-D misfit and six items to operationalise N-S misfit (Table 1). The initial technostress scale was designed in a 5-point Likert format (0 = *strongly disagree* and 4 = *strongly agree*). First it was reviewed by three academic researchers for face validity. Accordingly, the scale items were refined to be closely aligned with the P-E fit framework and reflect the imbalance in A-D and N-S related to the use of technology for learning. In addition, the wording and clarity of description of the scale items were improved based on the feedback from 5 participants in the pilot study. As the scale was in English, a back-translation procedure was conducted to make sure that there were minimal differences between the English and the Chinese versions of the scale.

Table 1
The P-E fit scale of technostress for university students in technology-enhanced learning

Items	
ADT1	I feel stressed to adapt to technology-enhanced learning.
ADT2	I find it difficult to effectively use technology-enhanced learning due to my limited investment of time and effort.
ADT3	I feel stressed to cope with the high demands of technology-enhanced learning with my current capability.
ADT4	I find it hard to catch up with the constant updates of technology-enhanced learning with my current skillset. **
ADT5	I am pressured to change my current learning habit and preference to meet the requirements of technology-enhanced learning.
ADT6	I am pressured to work harder due to technology-enhanced learning. *
ADT7	I am pressured to work faster due to technology-enhanced learning. *
NST1	I feel stressed as technology-enhanced learning is not useful in meeting my needs for better academic performance. **
NST2	I feel stressed as technology-enhanced learning is not very relevant for the improvement of my study. *
NST3	I am not comfortable with the pervasive invasion of technology-enhanced learning in all aspects of my study.
NST4	I am irritated by the vast variety of technology-enhanced learning.
NST5	I feel stressed as the various forms of technology-enhanced learning complicate my study.
NST6	I feel stressed as the heavy reliance on technology-enhanced learning in my school disrupts my normal study pattern.

Note. ADT = Abilities-demands misfit; NST = Needs-supplies misfit; *Items were deleted in the pilot study; **Items were deleted in the main study

Methodology

Participants

The participants of this study were recruited from two public universities in China (university A and B) which have been implementing a variety of technology-enhanced learning modes, for instance, accrediting MOOCs and including them into their own curricula, promoting the flipped classroom facilitated by new learning applications, and digitalising reading materials and assignments in many disciplines. As a result,

students from these universities have to manage the transition from a conventionally teacher-centered mode of learning to a learner-centered mode of learning facilitated by technology. This usually incurs more workload and requires new learning practices, resulting in more challenges and stresses for many students.

A total sample size of 620 participants was obtained with their informed consent from two rounds of data collection using convenience sampling, following Institutional Review Board approval (IRB-2018-11-019). In the first round, 500 university students in university A were approached. Eventually, the valid responses from 420 participants were attained. The data from the first round was randomly split into two subgroups. One subgroup contained 120 samples, which was used for a pilot study. Another subgroup contained 300 samples and was used for main study.

In the second round of data collection, a sample of 300 university students in university B were approached to fill out the technostress scale developed in the pilot and main studies. In the end, the valid responses from 200 participants were obtained. The participants' demographic information from both rounds of data collection is presented in Table 2.

Table 2
Demographic information of the participants for the two rounds of data collection

		First round data collection		Second round data collection
		Pilot study (N = 120)	Main study (N = 300)	External validation (N = 200)
Age	M (SD)	19.33 (1.19)	19.12 (1.02)	18.72 (0.83)
Gender	Male	57	65	24
	Female	63	235	176
Grade levels	First year	22	130	156
	Second year	53	140	42
	Third year	43	25	0
	Fourth year	2	1	2
Willingness to join technology-enhanced learning	Yes	108	246	174
	No	12	54	26

The combined use of factor analysis and the Rasch model

The Rasch model was developed by Rasch (1960) to help researchers create and refine the functioning of instruments (e.g., tests or scales). It assumes that the probability with which a person solves an item is determined by the location of the person on a latent trait (θ; in this case, technostress) and the item difficult (σ; in this case, item endorsability). It uses conditional maximum likelihood to estimate both the person and the item parameters independently from each other, thus avoiding the shortcomings of classical test theory (Van Zile-Tamsen, 2017). In the Rasch model, all items should measure the construct of interest (i.e., technostress in this study) instead of a separate construct and should manifest measurement invariance across participants of different demographics, for example, male and female students (Bond & Fox, 2007; Ponocny, 2001). Compared with factor analysis, the Rasch analysis can provide more detailed diagnostic information for improving instruments, for instance, infit and outfit values and differential item functioning. In high-stakes situations, such as developing instruments for diagnostic or clinical purposes, the Rasch model is often suggested for a thorough psychometric evaluation (Petrillo, Cano, McLeod, & Coon, 2015).

In spite of the limitations of classical test theory, such as sample and test dependence, it has been suggested to be used together with the Rasch model for refining instruments (Schlegel, Grandjean, & Scherer, 2014). In this study, factor analysis was used to exclude improper items with the variance that could not be explained by principal components. The Rasch model was then applied to identify items that measured a single latent factor regarding technostress and ensure the measurement invariance across respondents of different demographics. In doing so, the combination of the Rasch model and classical test theory increased the probability of developing a robust psychometrical scale to measure technostress among university students.

Overall procedure

To develop a P-E fit scale of technostress, three studies (a pilot study, a main study, and a study for external validation) were conducted using factor analysis, the Rasch model, and multilevel linear regression. In the pilot study, the data of 120 participants were used to examine the factor structure and internal consistency of the initial scale. The purpose of the main study was to verify the factor structure attained from the pilot study through factor analysis, and to make sure the uni-dimensionality and measurement invariance of the refined scale via the Rasch model. Finally, the third study aimed to investigate the relationship between university students' technostress and their personality through multilevel linear regression using the scale developed from the pilot and main study.

Pilot study

Analysis procedure

Out of the sample of 420 participants obtained from the first round of data collection, 120 participants were randomly selected for the pilot study. The purpose of the pilot study was to evaluate the internal consistency and the factor structure of the initial technostress scale. According to Fornell and Larcker (1981), Cronbach's alpha value should be larger than 0.70 in order to have accepted internal consistency. To perform exploratory factor analysis (EFA), the following steps were taken. Bartlett's (1950) test of sphericity and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Kaiser & Rice, 1974) were used to assess the factorability of correlation matrices. Then, principal component analysis with varimax rotation (Hair, Black, Babin, & Anderson, 2010) was conducted on the scale to examine its convergent and construct validity. The inclusion/exclusion of items followed three criteria (Floyd & Widaman, 1995): (1) factor loadings should be larger than 0.40; (2) items of one factor should have no or minimal cross-loadings with other factors; and (3) there should be conceptual consistency among items loaded on a shared factor. A further three criteria (Worthington & Whittaker, 2006) were consulted to determine the number of factors of the scale: (1) eigenvalues > 1, (2) scree test, and (3) conceptual interpretability of identified factors.

Results of the pilot study

The Bartlett's test of sphericity supported EFA, χ^2 (78) = 1365.53, p < 0.001. The result of KMO was 0.92, providing further support for conducting EFA. In line with the item selection criteria, ADT6, ADT7, and NST2 were removed from the initial technostress scale, while the remaining 10 items were kept for further study (Table 1). The eigenvalues and scree test supported a first-order 1-factor structure of the technostress scale, with the factor accounting for 70.34% of the total variance.

In addition, as shown in Table 3, the factor loadings of the 10 items were all larger than 0.70 and did not load on other factors. This suggests that the 10 items in the scale demonstrated sufficient discriminant validity (Chin, Marcolin, & Newsted, 2003). The average variance extracted for the factor was 0.70, which exceeds 0.50 (Hair et al., 2010). Thus, the convergent validity of the scale was supported. Furthermore, the Cronbach's alpha value of the scale was 0.95, indicating high internal consistency. To sum up, the results of the pilot study suggest that the technostress scale with 10 items had sufficient validity and reliability for further analysis.

Table 3
Factor analysis outcomes of the pilot and main study for the P-E fit scale of technostress

Items	Pilot study (N = 120)		Main study (N = 300)	
	Factor loadings	M(SD)	Factor loadings	M(SD)
ADT1	0.80	1.83 (1.02)	0.76	1.83 (1.08)
ADT2	0.88	1.84 (1.12)	0.81	2.03 (1.08)
ADT3	0.86	2.00 (1.12)	0.83	2.11 (1.08)
ADT4	0.87	2.00 (1.09)	0.85	2.07 (1.08)
ADT5	0.86	1.77 (1.15)	0.80	1.93 (1.08)
NST1	0.76	1.76 (1.08)	0.64	1.70 (1.02)
NST3	0.83	1.73 (1.03)	0.78	1.88 (1.07)
NST4	0.87	1.89 (1.14)	0.79	2.14 (1.08)
NST5	0.85	1.99 (1.10)	0.80	2.16 (1.08)
NST6	0.81	1.58 (1.03)	0.77	1.82 (1.07)
Cronbach's alpha	0.95		0.93	
AVE	0.70		0.61	

Note. ADT = abilities-demands misfit; NST = needs-supplies misfit; AVE = average variance extracted

Main study

Analysis procedure

The main study was performed on the data of the remaining 300 participants obtained from the first round of data collection. The purpose of the main study was to verify the factor structure of the revised scale attained from the pilot study and ensure its uni-dimensionality and measurement invariance using both factor analysis and the Rasch model. EFA was first carried out using the dataset. Subsequently, confirmatory factor analysis (CFA) was conducted to confirm the results of EFA. The first-order 1-factor model of technostress was assessed using the following criteria (Cangur & Ercan, 2015; Hooper, Coughlan, & Mullen, 2008; Hu & Bentler, 1999) for its goodness of fit: (a) the normed chi-square (χ^2/df), which should be between 2.0 to 5.0; (b) the comparative fit index (CFI), which should be $\geq$ 0.90; (c) normed fit index (NFI), which is expected to be $\geq$ 0.90; (d) standardised root mean square residual (SRMR), which is expected to be < 0.05, and (e) root mean square error of approximation (RMSEA), which should be $\leq$ 0.08.

For the Rasch analysis, the *eRm* package in R language (Mair & Hatzinger, 2007) was used to perform the following functions: the Martin-Löf test, the Bond-and-Fox pathway map, local independence test, differential item functioning (DIF), item infit and outfit, and information indices. Specifically, the Martin-Löf test splits items under study into two or more subsets and examine whether the subsets of items constitute a Rasch model (Glas & Verhelst, 1995). The Bond-and-Fox pathway map (Bond & Fox, 2007) presents the location of each item against its infit *t*-statistics. Items with an infit *t*-statistic beyond the range from -2 to +2 logit should be removed. Local independence test requires that items of a scale not be related to each other; otherwise, parameter estimation may be biased, thus affecting the uni-dimensionality of the scale (Bond & Fox, 2007).

DIF happens when participants with similar abilities or endorsability do not respond to the same items of an instrument with similar probability. As prior studies (Marchiori et al., 2019; Yan et al., 2013) have debated over possible differences between males and females in relation to technostress and effects of participants' willingness in the use of technology on technostress, this study decided to further examine these two factors with regard to DIF. Item infit (information-weighted fit) and outfit (outlier-sensitive fit) are calculated based on items' mean square (MSQ) of standardised residuals (Bond & Fox, 2007). Acceptable values for both infit and outfit vary from 0.7 to 1.3, with the value of 1 suggesting a perfect fit (Smith, Rush, Fallowfield, Velikova, & Sharpe, 2008). Finally, information indices, including Akaike's information criterion (AIC), Bayesian information criterion (BIC), and consistent AIC (cAIC), provide criteria for model selection. Normally, lower values of the information indices suggest better approximation toward the true model (Vrieze, 2012).

Results of the main study

Findings of exploratory factor analysis and confirmatory factor analysis
EFA was first performed on the refined scale using the data of 300 participants. The first-order 1-factor structure with 10 items was substantiated. The 10 items were jointly loaded on one factor, which explained 61.44% of the total variance. As shown in Table 3, the factor loadings of the 10 items were all above 0.70, except for NST1. However, as the deletion of NST1 did not greatly improve the explanatory power of the factor obtained from EFA and the inclusion of it could enrich the scale's conceptual interpretability, NST1 was kept for further analysis.

As the 10 items were not loaded on other factors, the refined scale demonstrated sufficient discriminant validity. The average variance extracted for the single factor was 0.61, suggesting adequate convergent validity. In addition, the Cronbach's alpha value of the refined scale was 0.93, which indicated a high internal consistency. Subsequently, CFA was performed to verify the factor structure obtained from EFA. The results of CFA confirmed the first-order 1-factor structure of the scale with 10 items. Specifically, χ^2/df = 3.33, CFI = 0.96, NFI = 0.95, SRMR = 0.04, and RMSEA = 0.08, indicating good model fit.

Findings of the Rasch analysis (first round)
As the polytomous response data was used in this study, the rating scale model was adopted for the Rasch analysis. The Martin-Löf test did not find violation of the model assumption of uni-dimensionality, χ^2 (399) = 382.12, p = 0.72 > 0.05. However, as indicated in the Bond-and-Fox pathway map (Appendix A), ADT2, ADT3, ADT4, and NST1 were located beyond the -2 to +2 logit and thus might be mis-fitting items, requiring further assessment of them. In addition, the local independence test was performed using Ponocny's (2001) function of T_{11}. The result indicated that the one-tailed p value for the scale was 0.00, which is lower than 0.05, therefore violating the assumption of local independence.

The DIF analysis using Ponocny's (2001) test of T_{10} was first conducted with gender as a splitting criterion to examine whether male and female students with similar abilities might differ in their responses to the technostress scale. The results did not identify a significant difference, p = 0.36 (one-tailed) > 0.05. Then, students' willingness to participate in technology-enhanced learning was chosen as another splitting criterion. No significant difference was found between students who joined technology-involved learning willingly and unwillingly, p = 0.18 (one-tailed) > 0.05. With regard to the item infit and outfit, as shown in Table 4, the infit and outfit values of most items were in the acceptable range of 0.70 to 1.30, except for ADT4 (infit MSQ = 0.69; outfit MSQ = 0.69) and NST1 (infit MSQ = 1.45; outfit MSQ = 1.31), which were likely to be mis-fitting items.

Table 4
Infit and outfit values and information criteria for the two rounds of the Rasch analysis

Items		Rasch model (first round)		Rasch model (second round)	
		Outfit MSQ	Infit MSQ	Outfit MSQ	Infit MSQ
ADT1		1.02	1.02	1.00	1.01
ADT2		0.82	0.80	0.90	0.85
ADT3		0.78	0.78	0.85	0.84
ADT4		0.69	0.69	n/a	n/a
ADT5		0.82	0.84	0.89	0.89
NST1		1.45	1.31	n/a	n/a
NST3		0.91	0.91	0.92	0.91
NST4		0.90	0.89	0.85	0.85
NST5		0.90	0.86	0.82	0.81
NST6		0.97	0.96	0.93	0.92
Information	AIC	4858.71		3645.35	
criteria	BIC	4903.15		3682.39	
	cAIC	4915.15		3692.39	

Note. ADT = abilities-demands misfit; NST = needs-supplies misfit; MSQ = mean square; n/a= not available

Overall, the P-E fit scale of technostress with ten items showed measurement invariance across university students of different demographics. Nevertheless, the first round of the Rasch analysis did not find strong evidence to support the psychometric property of uni-dimensionality. Based on the result of the Bond-and-Fox pathway map and the values of item infit and outfit, ADT4 and NST1 were identified as mis-fitting items and should be removed from the technostress scale.

Findings of the Rasch analysis (second round)
Another round of the Rasch analysis was conducted on the technostress scale with 8 items after excluding ADT4 and NST1. The Martin-Löf test still did not find violation of the model assumption of uni-dimensionality, χ^2 (255) = 268.69, *p*= 0.27 > 0.05. The local independence test revealed that the one-tailed *p* value for the scale was 0.00 < 0.05, thus implying a possible issue of local dependence among remaining 8 items in the P-E fit scale of technostress. However, the assumption of the Rasch model was not fundamentally violated in relation to local dependence (Wang & Wilson, 2005).

The DIF analysis with gender and willingness in joining technology-enhanced learning as two splitting criteria did not find any significant difference, with *p* = 0.21 (one-tailed) > 0.05 for the former and *p* = 0.10 (one-tailed) > 0.05 for the latter. As to the item infit and outfit values, Table 4 indicates that all the values of the 8 items were in the acceptable range of 0.70 to 1.30, therefore suggesting strong fit with the Rasch model. In addition, Table 4 presents the information criteria, including AIC, BIC, and cAIC, for the Rasch analysis on the P-E fit scale of technostress with 18 items and 8 items, respectively. It is obvious that the values of the information criteria in the technostress scale with 8 items were lower than those in the scale with 10 items, implying that the P-E fit scale of technostress with 8 items was more desirable. The Wright map generated in the second round of the Rasch analysis was attached as Appendix B in the supplementary document and suggested that the 8 items almost covered the whole range of participants' agreeability with the items.

To sum up, based on the findings of EFA, CFA, and two rounds of the Rasch analysis, the first-order 1-factor technostress scale with 8 items was psychometrical robust, demonstrating high internal consistency, validity, uni-dimensionality, and measurement invariance across participants of different demographics.

External validation: Relationships between technostress and university students' personality

The refined technostress scale with 8 items achieved from the main study was administered to university students in another university, where valid responses from 200 university students were obtained. As the Big Five personality scale (Appendix C) has been validated in many situations and has been widely used in previous studies (e.g., Hsiao, 2017; Landers & Lounsbury, 2006), it was used here to collect data related to students' personality information. Table 5 presents the psychometric properties of the Big Five personality scale. It shows that technostress was negatively associated with extraversion, agreeableness, conscientiousness, and openness to experience, while being positively associated with neuroticism.

Table 5
The psychometric properties of the Big-five personality scale and technostress (N =200)

	Cronbach's alpha	Correlation				
		Tec	Ext	Agr	Con	Neu
Technostress (Tec)	0.93					
Extraversion (Ext)	0.92	-0.22**				
Agreeableness (Agr)	0.71	-0.35**	0.14*			
Conscientiousness (Con)	0.73	-0.35**	0.23**	0.51**		
Neuroticism (Neu)	0.72	0.42**	-0.35**	-0.33**	-0.54**	
Openness to experience	0.85	-0.23**	0.57**	0.32**	0.34**	-0.25**

Note. * *p* < 0.05; ** *p* < 0.01

Multilevel regression analyses were further performed using lme4 package in R (Bates, Mächler, Bolker, & Walker, 2014) using the sample of 200 participants to examine how university students' personality traits were related to technostress. Participants' age and gender were entered at Step 1. The null model explained

3% of the variance in university students' technostress. At Step 2, the five traits in the Big Five personality scale were entered. The full model accounted for 25% variance of the variance in technostress. As shown in Table 6, compared with the null model, the information indices, including AIC and BIC, decreased substantially in the full model $\chi^2(5) = 52.59$, $p < 0.001$, indicating an improved approximation toward the true model. Among the five traits in the Big Five personality scale, although extraversion, conscientiousness, and openness to experience was negatively related to technostress (Table 5), only agreeableness showed a significant negative association with technostress (Table 6). Contrastingly, neuroticism demonstrated a significant positive association with technostress.

Table 6
Results of multilevel regression analysis for The Big-five personality and technostress (N =200)

Predictor	β	t	AIC	BIC	R^2
Step 1: Null model			531.19	547.68	0.03
Intercept	-1.54	-1.08			
Gender	-0.06	-0.33			
Age	0.18*	2.34			
Step 2: Full model			488.60	521.58	0.22
Intercept	0.15	0.11			
Gender	-0.24	-1.39			
Age	0.12	1.72			
Extraversion	-0.04	-0.57			
Agreeableness	-0.275*	-2.58			
Conscientiousness	-0.09	-0.89			
Neuroticism	0.34***	3.84			
Openness to experience	-0.05	-0.53			

Note. * $p < 0.05$; *** $p < 0.001$

Discussion

The aim of this study was to develop a P-E fit scale of technostress to measure university students' technostress in technology-enhanced learning. To accomplish this aim, an initial scale with 13 items was built following the theoretical framework of P-E fit and drawing upon prior studies related to technostress. The initial scale was refined based on the feedback from an expert panel and five participants to ensure its face validity, wording, and clarity. Subsequently, the refined scale was validated through a pilot study, a main study, and an external validation using factor analysis, the Rasch analysis, and multilevel linear regression. Eventually, a P-E fit scale of technostress with 8 items was obtained (Table 1). It has robust psychometric properties, including high internal consistency, validity, uni-dimensionality, and measurement invariance across university students of different demographics.

In the pilot study, 3 items (ADT6, AD7, and NST2) that did not satisfy the stipulated item selection criteria were removed. The refined technostress scale with the remaining 10 items was validated in the main study through exploratory factory analysis and confirmatory factor analysis. The scale was further examined using the Rasch analysis for its uni-dimensionality and measurement invariance. The first round of the Rasch analysis showed that 2 items (ADT4 and NST1) were mis-fitting items. After excluding the 2 items from the scale, the quality of the technostress scale with 8 items was improved, indicating that the final scale with 8 items demonstrated better psychometric properties.

Nevertheless, in both rounds of the Rasch analysis, the test for local independence among the scale items did not generate satisfactory outcomes. This is understandable and reasonable, as in practical research a certain degree of local dependence is often expected (Wang & Wilson, 2005), however, all 8 items in the final scale were found to measure a common construct of technostress. The differential item functioning test suggested that the technostress scale did not have biases with regard to gender or the willingness of participating students for technology-enhanced learning.

The findings of the multilevel linear regression using the data from the finalised technostress scale and the Big Five personality scale, were largely consistent with prior studies. Particularly, the result of agreeableness for negatively predicting technostress, which was in line with Krishnan (2017) who found that people scoring high on agreeableness tended to perceived technostress positively, as they demonstrate

strong characteristics of friendly compliance and social adaptability. Srivastava et al. (2015) also indicated that agreeable persons are more likely to accept and use new technology even without sufficient skills. Therefore, they may have a lower possibility of suffering from technostress than other students. In addition, the result of neuroticism positively predicting technostress also resonates with previous studies (Landers & Lounsbury, 2006; Srivastava et al., 2015). They found that individuals scoring high on neuroticism tend to show anxiousness and hostility to new things (e.g., new technology) they have not been exposed to before, thus, being more likely to suffer from technostress.

Overall, the 8 items in the final scale (Table 1) are closely in line with the P-E fit theory and jointly measure the latent trait of technostress from both the A-D misfit and N-S misfit as suggested by prior studies (Ayyagari et al., 2011; Edwards et al., 1998; Edwards & Shipp, 2007). Compared with previous scales, such as the computer anxiety rating scale (Heinssen et al., 1987) and the scale measuring senior citizens' technostress (Nimrod, 2018) which were developed solely using classical test theory, the technostress scale developed in the current study is more robust and is more relevant to the population of young university students and the setting of higher education where various new technologies are revolutionising learning and teaching (Nami & Vaezi, 2018).

Contribution

This study contributes to current knowledge of technostress by expanding research on this issue to the student population in higher education as compared with previous studies which mainly focus on the worker population. The P-E fit theory provides a valid and natural framework to investigate the issue of technostress. The development of P-E fit scale of technostress provides a basis for identifying university students who may have problems of adapting to technology-enhanced learning, which increasingly becomes a new learning mode in higher education.

Second, the P-E fit scale of technostress obtained in this study has only 8 items, therefore enabling it to be used conveniently and with efficiency. The scale demonstrates strong psychometric properties, thus being able to provide valid information of technostress for further diagnosis and interventions. The total score of the technostress scale ranges from 0 to 32. The higher the score, the greater the levels of technostress.

Third, this study combined the use of classical test theory and the Rasch model, increasing the possibility of developing a technostress scale with robust psychometric properties. Although classical test theory, such as factor analysis, can identify items with variance that are explained by principal components, it cannot verify their uni-dimensionality (Osborne, Costello, & Kellow, 2008). The combination of factor analysis and the Rasch model enables researchers to obtain the most reliable items first and then identify those with the variance that depends on only one latent factor, namely, the factor of technostress in this study.

Fourth, this study contributes to the literature on relationships between demographics and technostress. University students with different personality traits may experience technology-enhanced learning differently (Krishnan, 2017), thereby having different possibilities of suffering from technostress. Those with more neurotic traits are more likely to suffer from technostress while those with more agreeable characteristics tend to adapt to the use of technology in learning and cope with challenges associated with technology-enhanced learning easily.

Limitations and future research

The findings of this study should be interpreted with caution. First, the participants in this study came from only two universities, therefore limiting the generalisability of the research findings. For the future, a broader sample is suggested to further validate the P-E fit scale of technostress. Second, culture may also matter in students' experience of technostress in technology-enhanced learning (Krishnan, 2017; Tekinarslan, 2008). This study's participants came from mainland China. Their perceptions of technostress may be different from their counterparts in Western universities. Future research is advised to validate the P-E fit scale of technostress in Western culture for its generalisability. Third, there were unequal numbers of male and female students for each round of data analysis, which may have caused bias in the research findings. This was mainly due to the fact that the two universities generally have more female students than males. However, research in the future is suggested to recruit participants of a relatively even gender distribution to validate the technostress scale in this study and for possible refinements.

Conclusion

As the conventional classroom is continually transformed by new technology and a variety of technology-enhanced learning forms, it is essential to ensure university students are well adapted to changes caused by technology. The development of the P-E fit scale of technostress with robust psychometric properties is an important step in detecting maladapted students and maintaining their psychological wellbeing with an objective of better exploiting benefits associated with technology and increasing students' constructive and active participation in technology-enhanced learning.

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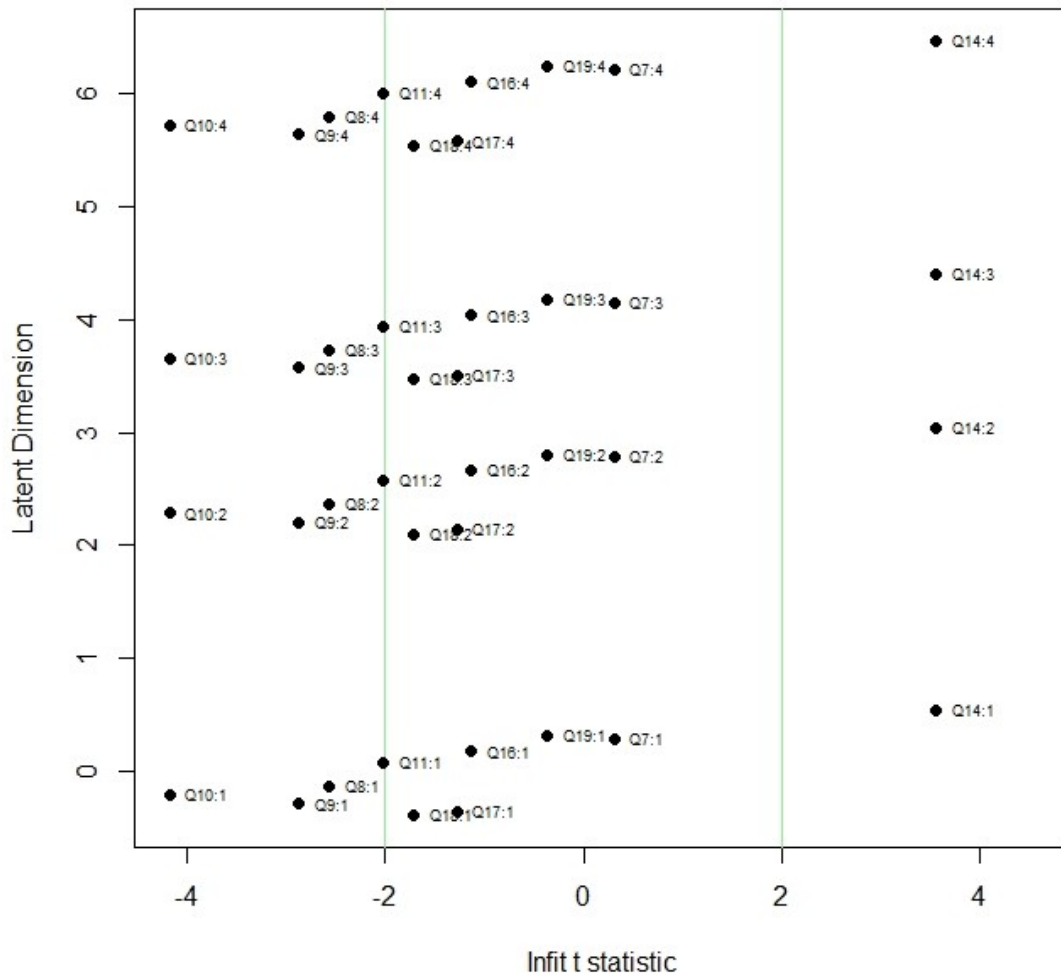
Corresponding author: Wang Xinghua, wangxinghua379@gmail.com

Appendix A
The Bond-and-Fox pathway map

Note. Q7 = ADT1; Q8 = ADT2; Q9 = ADT3; Q10 = ADT4; Q11 = ADT5; Q14 = NST1; Q16 = NST3; Q17 = NST4; Q18 = NST5; Q19 = NST6

Appendix B
Wright map (person-item map) for the second round of the Rasch analysis

Person-Item Map
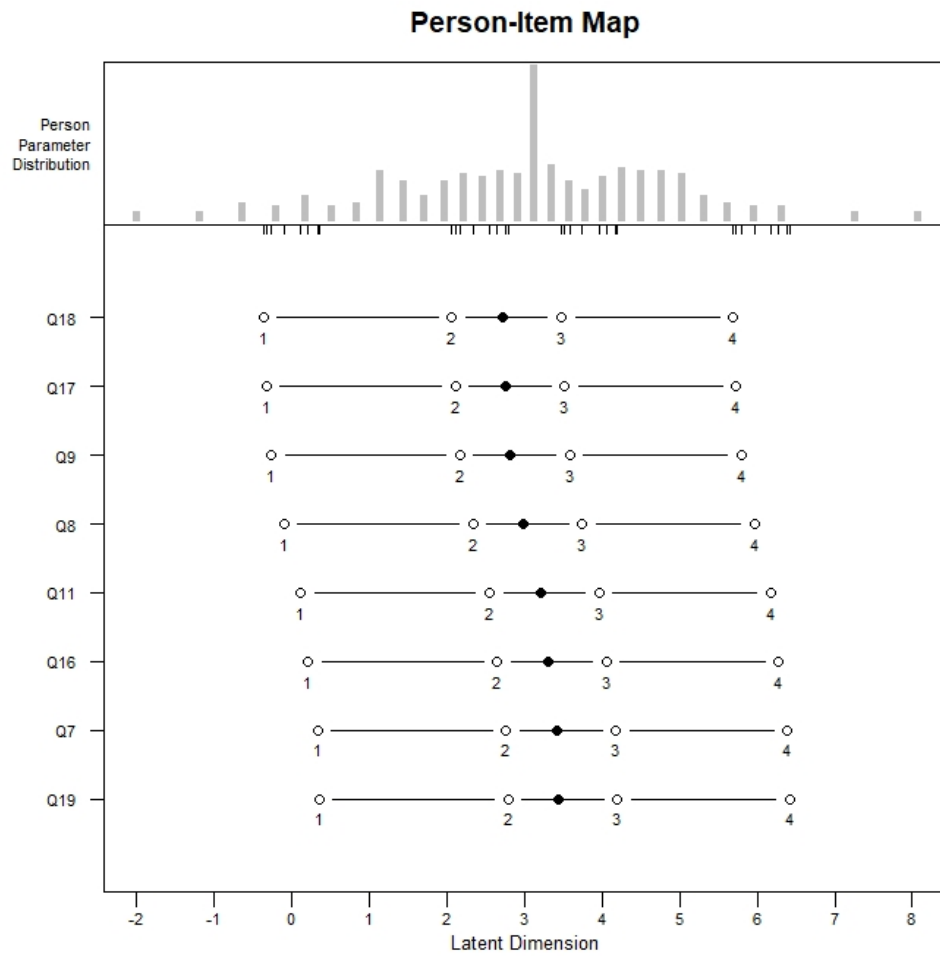
Notes. Q7=ADT1; Q8=ADT2; Q9=ADT3; Q11=ADT5; Q16=NST3; Q17=NST4; Q18=NST5; Q19=NST6

Point 0 in the 5-point scale was not shown in the map because it was not assigned partial credits during calculation.

Appendix C
The Big five personality scale of this study

	I see myself as someone who …
Extraversion	(1) is talkative.
	(2) is full of energy.
	(3) generates a lot of enthusiasm.
	(4) is outgoing, sociable.
Agreeableness	(1) tends to find fault with others. [R]
	(2) starts quarrels with others. [R]
	(3) is sometimes rude to others. [R]
	(4) is generally trusting.
Conscientiousness	(1) can be somewhat careless. [R]
	(2) tends to be disorganized. [R]
	(3) tends to be lazy. [R]
	(4) is easily distracted. [R]
	(5) does a thorough job.
Neuroticism	(1) is depressed, blue.
	(2) gets nervous easily.
	(3) worries a lot.
	(4) can be moody.
Openness to experience	(1) is original, comes up with new ideas.
	(2) is curious about many different things.
	(3) is ingenious, a deep thinker.
	(4) has an active imagination.

Note. R = reversed