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How remote leaning during crisis affect technostress levels experienced by academicians

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Abstract

Despite the extensive coverage in the literature, limited attention has been paid to the investigation of technostress among academicians who work under special circumstances, such as occupation, and might have different psychological states due to those conditions. To fill this gap, this study examined the level and factorial structure of technostress among 573 Palestinian academicians who worked in a more-than-seventy-years occupied country, and with the addition of the COVID-19 pandemic. A sequential mixed method approach with confirmatory and exploratory factor analysis was used to explore the technostress factors and to measure their level among the academicians. The obtained findings indicated that the four factors of (1) schedule overload, (2) complexity, (3) uncertainty and uselessness, and (4) invasion and compulsion formed the model of techno-stressors among Palestinian academicians. This can help various stakeholders (researchers, policy makers, practitioners, etc.) to design the needed interventions accordingly and reduce the technostress among academicians; hence, enhancing the latter's teaching practices and experiences.

Keywords Remote learning · Occupied Palestine · COVID-19 · Technostress · Academicians

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1 Introduction

Information and Communication Technologies (ICT) are crucial in achieving the Sustainable Development Goals (SDGs) promoted by the United Nations (UN), as their implementation can help to enhance different domains of development, such as education and health (Jones et al., 2017). Therefore, several organizations and universities have started conducting various ICT training to equip different stakeholders, including teachers, students, and administrators, with the needed ICT competencies (Ali, 2020; Sife et al., 2007). Despite the beneficial changes, the implementation of ICT in organizations can also negatively impact the workplace (Gaudioso et al., 2017). Particularly during the COVID-19 pandemic, where homes became the workplace of all people, including academicians, and learning became remote (Kaushik & Guleria, 2020). Therefore, academicians had to be well-prepared for the new teaching environment and gain the needed competencies to manage virtual classrooms (Albrahim, 2020). In this context, several studies (Christian et al., 2020; Tarafdar et al., 2019) revealed that the use of technology in an unplanned situation, like the case of the COVID-19 pandemic, can have a negative impact, including the increase in stress level. The findings of these aforementioned studies further revealed that heavy workload and working insecurity environment could form a type of technostress that negatively impacts teaching performance. Technostress is a phenomenon introduced by Brod (1984) and is considered as the perceived stress caused by the utilization of an information technology that someone is unfamiliar with. Li and Wang (2021) highlighted that techno-insecurity and techno-complexity have a negative impact on teachers' performance in online learning environments.

Despite the increasing benefits of technology in different aspects of life, there have been increasing demands among researchers to understand the negative impact of using ICT during the COVID-19 pandemic (Almazova et al., 2020). Technostress has been widely studied in the literature in different contexts before the COVID-19 pandemic and its impact on employees in different organizations (Tarafdar et al., 2019; La Torre et al., 2019). However, there is a shortage of empirical studies that examined the impact of technostress on academicians during the pandemic period (Penado Abilleira et al., 2021). In the Arab region and specifically in Palestine (the context of this study), no study to the best of our knowledge was focused on the investigation of technostress level among Palestinian academicians during the pandemic. The motivation for focusing on Palestine is because it is unique as a research context; It has been under occupation for the last 70 years, and this has negatively impacted its education system. The pandemic was an additional crisis for Palestinian academicians that came with long years of closure, movement restrictions, and lack of salaries, which contributed as additional factors that intensified the different levels of technostress experience (Khlaif et al., 2022). Therefore, it is worth investigating how remote learning, under the occupation and COVID-19 pandemic, could affect the technostress level of Palestinian academicians. Specifically, this study extends the current literature and answers the following research questions. The findings of this study can contribute to the educational technology field by understanding how academicians with special circumstances, i.e., under occupation, might behave when using technology for remote education.

RQ1. What is the factorial structure of technostress among academicians in Palestinian higher education institutions?
RQ2. What is the technostress level among academicians in Palestinian higher education institutions?
RQ3. Do demographic variables affect the technostress level among academicians in Palestinian higher education institutions?

2 Literature review

The utilization of technology can come with several technical difficulties that lead to frustration and technostress (Stadin et al., 2021). Taser et al. (2021) stated that technostress is caused by the use of technology, and it is related to negative feelings like anxiety. A similar definition of technostress was drawn by Steelman and Soror (2017), who defined it as a psychological state caused by the failure to deal with the current needs brought by technology. Verkijika (2019) described technostress as any unhealthy status caused by various challenges to coping with new technologies, including addiction and stress. Technostress is a psychological state which is framed by cognitive symptoms, such as poor level of concentration and irritability (La Torre et al., 2020). It is usually a result of nonconformity between people and the surrounding technological environment (Wang et al., 2020b). Torres (2021) believed that technostress is a phenomenon that has multiple negative effects on individuals as it generates exhaustion.

In education, previous studies defined technostress as a pressure generated from the use of technology and the skills and knowledge required to integrate technology effectively in teaching practices (Coklar et al., 2016; Jena, 2015; Tarafdar et al., 2010). Joo et al. (2016) stated that technostress has a negative impact on instructors' intention to accept and integrate ICT in teaching. Chou and Chou (2021) proved that technostress, self-efficacy, and school support are related to online teaching adoption. Oksanen et al. (2021) showed that the increase in social media communication in education could predict higher technostress. Qi (2019) further added that technostress could cause insufficient self-efficacy, job insecurity, work-home conflict, information overload, and privacy concerns.

Several researchers documented technology integration in higher education in different fields (Nepo, 2017; Wood et al., 2018). However, studies of mandatory technology adoption and technostress in public and higher education institutions settings (i.e., like the case of the COVID-19 pandemic, where teachers were forced to use technology for remote education) are limited. Tarafdar et al. (2007) pointed out that technostress is not well understood and defined as a phenomenon, and more investigation should look for "how and why" using ICT causes various demands on individuals, especially in education. Additionally, no study, to the best of our knowledge, has investigated the technostress among Arab academicians, particularly Palestine, which is the main context of this study and is considered with a special circumstance of under territorial occupation. Traxler et al. (2019) stated that unlike most neighboring countries in the world, academicians in the occupied territories of Palestine face extraordinary conditions and challenges. Therefore, it is worth investigating to study the technostress level of Palestinian academicians during the COVID-19 pandemic and the factors that might have been affecting it. This study can contribute to the body of knowledge by covering this gap, as no previous studies in the literature have conducted similar investigations.

3 Methods

A sequential mixed method approach was used to identify the structural factors of technostress among Palestinian academicians through three phases. In the first phase, a qualitative method was utilized, where an online focus group discussion using the Zoom platform was conducted to explore the academic technostress experienced while using new technology in their teaching and tasks (Rose et al., 1998). Focus group is frequently used as a qualitative approach to explore in-depth information about social issues from purposely selected people (Nyumba et al., 2018). The purpose of this initial phase was to explore technostress from the lived experiences of academicians by sharing their stories with other group members. Lastly, the second and third phases of the research involved the use of quantitative methods to process the data collected from a survey disseminated in the study.

3.1 Participants

The participants in the focus group session were 30 Palestinian academicians from eight universities with a mean age of 46.6 years (SD = 10.13, range = 26—65 years old). These academicians were selected using the convenience sampling method, where the authors contacted the deanships of scientific research in all Palestinian universities in the West Bank and Gaza Strip via email. Afterward, the Zoom invitation link to the focus group session was distributed to the academicians upon requests from these faculties.

In the second phase, a quantitative method of exploratory factor analysis (EFA) was utilized on the convenience sample of (245) Palestinian academicians from eight Palestinian universities with a mean age of 47.3 years old (SD = 11.50, range = 26—65 years old). Subsequently, the third phase followed another quantitative approach, where the confirmatory factor analysis (CFA) was used on the convenience sample of (328) Palestinian academicians from eight Palestinian universities with a mean age of 45.6 years old (SD = 14.18, range = 28—65 years old). The authors tested the differences in age means of the three samples (focus group, sample of CFA, and sample of EFA), and no significant differences were found ($F=1.210$, $p=.299$). In addition, the authors tested the differences in proportions of the three samples regarding gender, place of residence, education, faculty, university, and experience in technology. The chi-square test results showed no significant differences in the three groups in terms of demographic variables, namely gender ($\chi^2=0.184$, $p=.912$), place of residence ($\chi^2=1.484$, $p=.829$), education ($\chi^2=0.179$, $p=.996$), faculty ($\chi^2=0.076$, $p=.962$), university ($\chi^2=6.125$, $p=.633$), and experience in technology ($\chi^2=0.656$, $p=.999$). This indicates that the three samples had similar demographical backgrounds.

The sample sizes in the second (EFA) and third (CFA) phases of the study were deemed to be sufficient for the analyses since a sample size of 100–150 is considered the minimum sample size for conducting either EFA or CFA (Stevens, 2012). However, the big difference between EFA and CFA sample sizes may affect the precision of the results or lead to different factor loading.

In summary, the current study used cross-sectional survey data and the study sample consisted of 573 participants (phases 2 + 3) with a mean age of 44.7 years old (SD = 15.12, range = 27—65 years old). All of the respondents were academicians in eight Palestinian universities. They voluntarily participated in this study as the questionnaire was prepared online and disseminated through the official university channels (e.g., official website, Facebook page, etc.), as well as through the professional network of the authors. The questionnaire was administered online as it was difficult to reach participants physically because of the social distancing due to the COVID-19 pandemic. For the same reason, the researchers used the convenience sampling technique, which is a nonprobability sample, where people are easily sampled as they are "convenient" sources of information for researchers (Lavrakas, 2008).

Table 1 shows the frequencies and percentages for the demographic variables of the participants due to the three phases and the test of differences in proportions in the three samples.

3.2 Research instruments

3.2.1 Focus group

Three focus group sessions were a one-hour (for each session) recorded online discussion with 30 participants. The purpose was to explore the lived experience of the participants with technostress and allow them to talk about their stories and discuss the factors between the participants in-depth and insights (Yin, 2013). Two researchers moderated the flow of the discussion while another two researchers took notes and summarized the discussions with the Palestinian academicians. The early part of the session was marked by one of the moderators who posted the first prompt of, "*Using new technology needs more time and effort; what do you think (about this)? Please give examples from your lived experience*". There was a discussion among the participants during the session. Afterward, the second moderator generated new questions based on the first discussion, such as, "*Why*

Table 1 Descriptive statistics of the participants in the three phases and the test of differences in proportions in the three samples

	Phase 1 Focusing group	Phase 2 EFA	Phase 3 CFA	χ^2	*df*	*P*-value
Gender	$n_1=30$	$n_2=245$	$n_3=328$			
Male	19 (63.3%)	162 (66.1%)	212 (64.6%)	0.184	2	.912
Female	11 (36.7%)	83 (33.9%)	116 (35.4%)			
Place of residence						
City	21 (70%)	179 (73.1%)	240 (73.2%)	1.484	4	.829
Village	7 (23.3%)	59 (24.1%)	79 (24.1%)			
Camp	2 (6.7%)	7 (2.9%)	9 (2.7%)			
Education						
Bachelor	2 (6.7%)	14 (5.7%)	18 (5.5%)	0.179	4	.996
Master	9 (30%)	73 (29.8%)	102 (31.1%)			
Ph.D	19 (63.3%)	158 (64.5%)	208 (63.4%)			
Faculty						
Humanities	16 (53.3%)	125 (51%)	170 (51.8%)	0.076	2	.962
Natural science	14 (46.7%)	120 (49%)	158 (48.2%			
University						
An-Najah National University	9 (30%)	111 (45.3%)	147 (44.8%)	6.125	14	.633
Birzeit University	3 (10%)	20 (8.2%)	24 (8.2%)			
Open Quds University	7 (23.3%)	29 (29.5%)	41 (12.5%)			
Arab American University	2 (6.7%)	14 (5.7%)	20 (6.1%)			
Quds University	2 (6.7%)	16 (6.5%)	21 (6.4%)			
Islamic University of Gaza	3 (30%)	22 (9%)	34 (10.4%)			
Alaqsa University	3 (30%)	21 (8.6%)	24 (7.3%)			
Hebron University	1 (3.3%)	12 (4.9%)	14 (4.3%)			
Experience in technology						
Excellent	6 (20%)	44 (18%)	60 (18.3.3%)	0.656	8	.999
Very Good	9 (30%)	72 (29.4%)	95 (29%)			
Good	10 (33.3%)	78 (31.8%)	104 (31.7%)			
Average	2 (6.7%)	25 (10.2%)	36 (11%)			
Poor	3 (10%)	26 (10.6%)	33 (10.1%)			

do you need more time to use a new technology?". Consecutively, another question was posted by the first moderator, "*describe your experience with using new technology in your teaching*". These kinds of questions and prompts were used to facilitate and direct the discussion into the scope of the study and to encourage participants to participate in the discussion (Redmond & Curtis, 2009).

Recruiting the participants for focus group sessions

- The researchers sent an invitation to the e-learning centers to nominate faculty members who have experience in teaching online and using platforms for online teaching. Therefore, 30 participants were nominated from the universities. The participants from each university was stated in Table 1. The thirty participants were divided into three focus group based on the recommendation of Vaughn et al. (1996) that participants in a focus group session is up to 12.

3.2.2 Survey tool

We used the findings of the focus group session to develop a quantitative survey called the Palestinian Techno-Stress Scale (PTSS). Guided by the findings of previous studies and the findings of the qualitative phase, the researchers created an items pool composed of 50 items. The PTSS is a 5-point Likert scale questionnaire (5 = very much like me vs 1 = not at all like me) which was used to assess the level of technostress in the teaching process during COVID-19. It was adapted based on several technostress scales in the literature (Fischer et al., 2019; Lee et al., 2016; Nimrod, 2018), as well as based on the inputs of several academicians. In this case, Palestine (the study context) has special and unique factors (as explained in the research gap section) compared to those contexts in the literature where technostress was assessed, i.e., Palestinian academicians might have different factors that cause them stressed or might also cope with stress differently. The initial pool of 50 items was reduced to 42 items after validating the instrument (see Instrument validity and reliability section). The validated Techno-Stress Scale is presented in Appendix.

These items reflected four initial components: (a) F1: *overload*, which refers to doing their tasks faster and quickly by using technology; (b) F2: *invasion and compulsion*, which refers to emerging new technology/upgrade technology and using it obligatory; (c) F3: *complexity*, which refers to difficult to use a new technology or to learn about using it; and (d) F4: *uncertainty and uselessness*, which refer to lack of knowing the value of technology and not sure about achieving the outcomes of using new technology.

3.3 Data analyses

To validate PTSS, EFA was conducted by principal component analysis with Promax rotation using SPSS (version 23). The Promax rotation method is an oblique one that offers the unique contribution of each factor to the variance of each variable (Karimikia, 2017). Furthermore, the Promax rotation method was utilized because the factors were expected to be correlated (see Table 7). The Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy and the Bartlett test were also used. In order to specify the estimation method in CFA, multivariate normality and outliers were checked. Univariate normality was utilized for the multivariate normality inspection (Kline, 2015). Skew and kurtosis were utilized to examine univariate normality (Kline, 2015). To investigate whether the variable of interest has significant skew or kurtosis, Kline (2015) recommended dividing the skewness or kurtosis value by its corresponding standard error. This ratio is interpreted as a z-test of skew or kurtosis. Ratios greater than 1.96 would have a p-value less than .05, and ratios greater than 2.58 would have a p-value less than .01, indicating significant skewness or kurtosis. On the other hand, outliers are very unusual or extreme cases that can bias the results. The cases can be univariate or multivariate outliers. Univariate outliers have extreme scores on one variable and can be detected by examining z-scores; cases with z-scores greater than 3.0 in absolute value are unusual and may be outliers (Kline, 2015). Moreover, Mahalanobis distance was used to identify multivariate outliers. A p-value less than .001 ($p < .001$) is recommended for statistical significance in this multivariate outlier test (Kline, 2015). AMOS 22 was used to inspect multivariate outliers of the data. Furthermore, to validate the measurement scale, structural equation modeling (SEM) with CFA was conducted by utilizing the maximum likelihood estimation method (ML) in AMOS 22.

4 Results

4.1 Instrument validity and reliability

For exploratory factor analysis, the Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy was .95 and the Bartlett test (χ^2 (351) = 4801.60, $p < .001$) indicated significant sampling adequacy for performing EFA. The EFA uncovered a four-factor solution (See Table 2). Factors with eigenvalues lower than 1 and items with factor loading less than .40 were ignored. Items with factor loadings on multiple factors with .30 or more were also eliminated. The obtained four factors (27 items out of 42 items) with an Eigenvalue of more than one explained 66.90% of the total variance. This indicated a good construct validity for the scale. The first factor accounted for 43.44% of the total explained variance, the second factor accounted for 11.49%, the third accounted for 6.84%, and the fourth accounted for 5.14% of the variance. Communalities ranged from .50 to .85. For Factor 1, which consisted of nine items measuring *overload*, Cronbach's alpha was .94. For Factor 2, which consisted of seven items reflecting *complexity*, Cronbach's alpha was .93. For Factor 3, which consisted of seven items reflecting *uncertainty and uselessness*, Cronbach's alpha was .86. Finally, for Factor 4, which consisted of four items measuring *invasion and compulsion*, Cronbach's alpha was .84. For the total scale, including all the 27 items, Cronbach's alpha was reported as .95. This indicated high internal consistency of the scale.

For normality and outliers, the results revealed that all of the skewness and kurtosis values are less than 1.96, which indicate a good evidence that univariate and multivariate normality were present and based on the cut-point of three; there were no univariate outliers. Using the Mahalanobis distance test, seven outliers in the sample ($p < .001$, Kline, 2015) were observed. The percentage of the outlier cases was very small and less than .05% (12/245). Therefore, the researchers preferred to keep all cases, including the outliers, to get realistic results. To conclude, no factors in the suggested scale violated the univariate and multivariate normality assumptions (See Table 3).

Table 2 Factor loadings of each item of the PTSS and the descriptive statistics ($n_1 = 245$)

Items	F1 Overload	F2 Complexity	F 3 Uncertainty and uselessness	F 4 Invasion and compulsion
q15	.815			
q16	.795			
q13	.764			
q14	.753			
q20	.753			
q18	.726			
q11	.710			
q12	.676			
q17	.657			
q28		.875		
q29		.862		
q31		.793		
q42		.773		
q43		.764		
q21		.732		
q30		.713		
q44			.790	
q35			.716	
q34			.685	
q39			.650	
q50			.642	
q46			.635	
q25			.482	
q1				.757
q4				.754
q5				.731
q7				.582
Eigenvalue	11.73	3.10	1.85	1.39
Percent variance	43.44	11.49	6.84	5.14
Mean	3.13	2.16	3.40	2.38
Standard deviation	0.65	0.88	0.76	1.04

For every respondent, average scores were computed in each factor since there are differing numbers of items per factor. Furthermore, the researchers calculated the means and standard deviations of PTSS and its domains according to demographic variables, and in this phase, no significant differences in PTSS and its domains according to demographic variables were discovered since the main objective of this study was to ensure the stability of the factorial structure of technostress among Palestinian academicians in EFA and CFA (see Table 4).

Table 3 Skewness, kurtosis Indices, and z-scores for the PTSS

Factor	Skewness	S.E	Ratio	Kurtosis	S.E	Ratio	Min.*	Max.**
F1	-0.058	0.156	-0.372	-0.514	0.31	-1.658	-1.92	1.92
F2	0.111	0.156	0.712	0.506	0.31	1.632	-1.18	2.45
F3	-0.241	0.156	-1.545	-0.469	0.31	-1.513	-2.68	1.84
F4	0.135	0.156	0.865	-0.468	0.31	-1.510	-1.50	2.68
PTSS	0.07	0.156	0.449	-0.375	0.31	-1.210	-2.24	2.90

F1: Overload, F2: Complexity, F3: Uncertainty and Uselessness, and F4: Invasion and Compulsion, S.E.: Standard Error

* Min.: Minimum z-score, Max**: Maximum z-score

Based on the normality and outlier results, the ML method was a good choice (Kline, 2015) since the data did not violate the assumptions of SEM. Accordingly, the ML method was used to estimate the parameters of the study variables.

Confirmatory Factor Analysis (CFA) was performed to test the validation of PTSS resulted in EFA. The analysis measures variables related to the latent factors by factor loading estimates. When each measured variable loads highly on a specified factor and has smaller loadings on other factors, it is then associated with the highest loading factor (Murtagh & Heck, 2012). In CFA, the investigator specifies both the number of factors and which measured variables will load highly on a particular factor (Murtagh & Heck, 2012). In this study, CFA was used to confirm the existence of the four-factor structure fit of the PTSS, namely: *overload*, *complexity*, *uncertainty and uselessness*, and *invasion and compulsion*. Therefore, the data collected in the second phase was analyzed using CFA with the ML method.

The first CFA result on the model in the original form showed that some of the fit indexes were not within the acceptable limits. Therefore, the Modification Indexes were used to correct the fit indexes. Modification Indexes suggested some changes to improve the measurement model.

As shown in Table 5, the measurement model revealed good model fit (χ^2 (306) = 801.06, $p < .001$, CMIN/df = 2.62, SRMR = .09, RMSEA = .07, CFI = .92, TLI = .91, and AGFI = .81) in accordance with the recommended criteria in the relevant literature (Kline, 2015; Tabachnick et al., 2007). The goodness-of-fit (GFI) index was .81, which failed to meet the recommended minimum value of .90. The small value discrepancies of 0.05 for GFI led us to believe that the model fit was reasonable and adequate for assessing the results of the measurement model. The diagram of CFA is shown in Fig. 1. The results of Cronbach alpha coefficients were obtained for PTSS ($\alpha = .95$) and its subscales; *overload* ($\alpha = .94$), *complexity* ($\alpha = .93$), *uncertainty and uselessness* ($\alpha = .83$), and *invasion and compulsion* ($\alpha = .83$), demonstrating an internal consistency of PTSS. The validated PTSS is presented in Appendix.

Table 4 Means and standard deviations for PTSS and its domains according to demographic variables ($n_1 = 245$)

Demographic variables			Overload	Complexity	Uncertainty	Invasion	PTSS
Gender	Male	Mean	2.86	2.02	3.33	2.46	2.71
		S.D	0.99	0.83	0.88	0.93	0.74
	Female	Mean	3.26	2.02	3.46	2.39	2.86
		S.D	1.09	0.93	0.90	0.99	0.81
Place of residence	City	Mean	2.96	1.99	3.38	2.40	2.73
		S.D	1.04	0.83	0.88	0.95	0.76
	Village	Mean	3.07	2.05	3.37	2.56	2.81
		S.D	1.07	0.91	0.91	0.98	0.82
	Camp	Mean	3.51	2.49	3.27	2.39	3.02
		S.D	0.88	1.24	0.76	0.93	0.78
Education	Bachelor	Mean	3.23	2.37	3.35	2.63	2.95
		S.D	1.19	0.89	1.07	1.34	0.98
	Master	Mean	3.20	2.12	3.51	2.45	2.89
		S.D	1.05	0.86	0.93	0.93	0.78
	Ph.D	Mean	2.89	1.95	3.31	2.42	2.68
		S.D	1.01	0.85	0.84	0.93	0.74
Faculty	Humanities	Mean	3.08	2.16	3.37	2.46	2.82
		S.D	1.01	0.85	0.86	0.90	0.72
	Natural sciences	Mean	2.92	1.88	3.37	2.42	2.69
		S.D	1.07	0.85	0.91	1.01	0.82

Table 4 (continued)

Demographic variables			Overload	Complexity	Uncertainty	Invasion	PTSS
University	An-Najah National University	Mean	3.07	2.01	3.40	2.55	2.80
		S.D	1.02	0.83	0.85	1.02	0.76
	Birzeit University	Mean	3.06	1.99	3.49	2.50	2.81
		S.D	1.37	1.03	0.99	0.96	0.93
	Open Quds University	Mean	3.11	2.03	3.30	2.55	2.80
		S.D	0.99	0.72	0.84	0.84	0.69
	Arab American University	Mean	2.83	2.11	3.57	2.34	2.76
		S.D	1.16	0.70	0.70	0.92	0.76
	Quds University	Mean	2.99	1.82	3.46	2.17	2.69
		S.D	0.83	0.88	0.69	0.56	0.58
	Islamic University of Gaza	Mean	2.69	1.84	3.04	2.27	2.50
		S.D	0.98	1.02	0.99	0.98	0.78
	Alaqsa University	Mean	2.62	2.33	3.31	2.06	2.64
		S.D	0.93	1.06	0.96	0.88	0.86
	Hebron University	Mean	3.41	2.13	3.45	2.52	2.96
		S.D	1.08	0.68	1.21	1.03	0.86

Table 4 (continued)

Demographic variables			Overload	Complexity	Uncertainty	Invasion	PTSS
Experience in technology	Excellent	Mean	2.91	2.34	3.31	2.72	2.83
		S.D	0.85	0.99	0.84	0.97	0.70
	Very Good	Mean	3.12	2.21	3.71	2.76	2.98
		S.D	1.06	0.94	0.85	0.94	0.81
	Good	Mean	2.90	2.18	3.25	2.43	2.73
		S.D	1.02	0.90	0.75	0.94	0.76
	Average	Mean	3.11	1.95	3.53	2.36	2.81
		S.D	1.10	0.78	0.90	0.93	0.77
	Poor	Mean	2.97	1.57	3.19	2.24	2.56
		S.D	1.10	0.60	1.06	0.98	0.79

Table 5 Model fit indices for the measurement model ($n_2 = 328$)

Fit indices	Recommended value	Measurement model	Decision
Relative chi-square (CMIN/df)	< 3	2.62	Accepted
Root mean squared error of approximation (RMSEA)	≤ .08	.07	Accepted
Standardized root mean square residual (SRMR)	< 10	.09	Accepted
Goodness of fit index (GFI)	≥ .90	.85	Rejected
Adjusted goodness of fit (AGFI)	≥ .80	.81	Accepted
Tucker–Lewis index (TLI)	≥ .90	.91	Accepted
Comparative fit index (CFI)	≥ .90	.92	Accepted

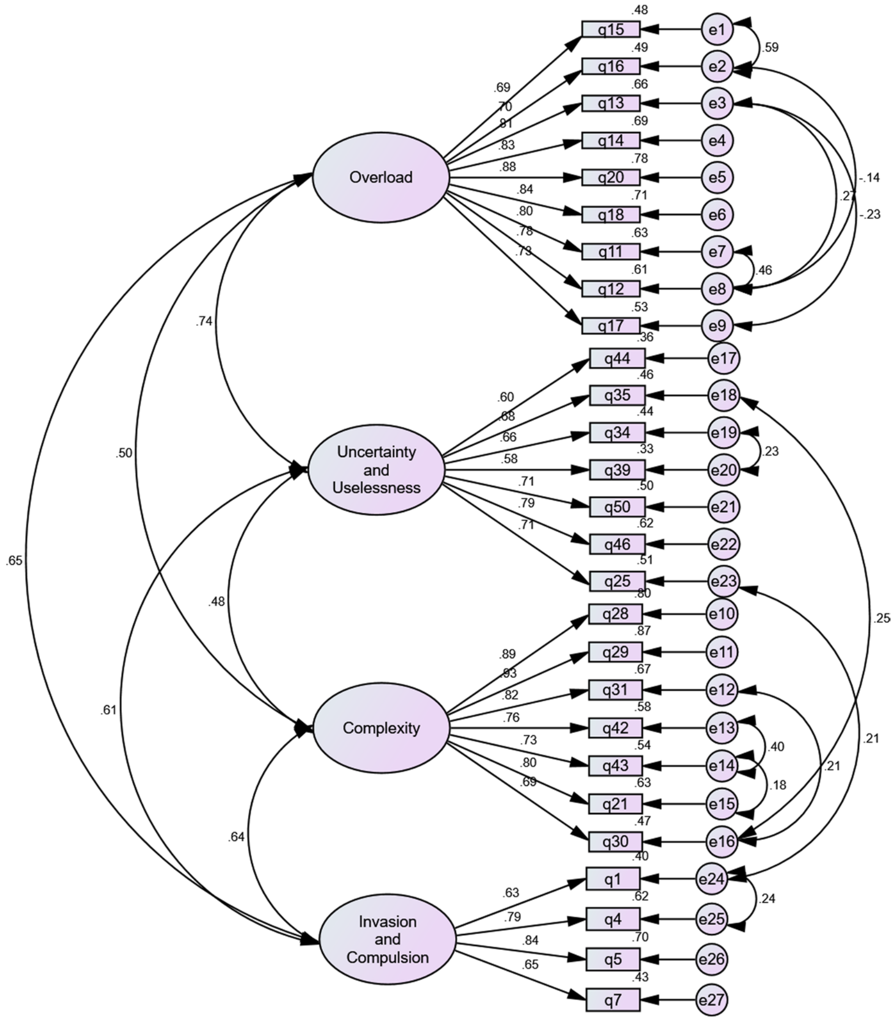

Fig. 1 Measurement model

4.2 Technostress level among academicians in the higher education institutions in palestine

In order to assess the Palestinian academicians' responses related to PTSS, the PTSS scores of each domain and the total score with the appropriate cut-point value, based on the mid-point between the minimum and the maximum values, were compared. Since PTSS and its domains were measured using 5-point Likert-type statements, the scores ranged between 1 and 5. Accordingly, a cut point of 3 was considered as a hypothetical mean. One-sample t-test was then conducted to test if, based on the sample means, one can confidently conclude that PTSS scores and its domains are above or below the scale mid-point. Table 6 shows the one-sample t-test results.

As illustrated in Table 6, the results indicated that there is a positive, significant difference ($p < 0.01$) between Uncertainty and Uselessness domain scores and its corresponding cut point value, in benefit to sample scores. In other words, there is a high level of *uncertainty and uselessness* among Palestinian academicians, which likely causes them technostress. On the other hand, there is a negative, significant difference ($p < 0.01$) between *complexity* and *invasion and compulsion* domains scores and PTSS scores and the corresponding cut point value, in benefit to the hypothetical mean. In other words, there are low levels of *complexity* and *invasion and compulsion* total scores of PTSS among Palestinian academicians, which do not likely cause them technostress. Furthermore, there is a positive, insignificant difference ($p > .05$) between *overload* domain scores and its corresponding cut point value, which indicates that there is a mild level of *overload* among Palestinian academicians that likely causes them technostress.

4.3 Effects of the demographic variables

Descriptive statistics of the PTSS means and standard deviations were calculated. In order to determine whether the PTSS means have a significant difference across gender, place of residence, education, faculty, university, and experience in technology, six-way MANOVA was conducted where the PTSS scores were considered as the dependent variables, and the demographic scores were considered as the

Table 6 Results of one sample t-test for the differences between PTSS and its domains means and the hypothetical mean of 3 ($n = 328$)

Domains	Means	Standard deviations	t-value	*P*-value
Overload	3.02	1.05	0.492	0.623
Complexity	2.02	0.87	-20.47	0.0001**
Uncertainty and Uselessness	3.38	0.88	7.85	0.0001**
Invasion and Compulsion	2.44	0.94	-10.69	0.0001**
PTSS (total score)	2.77	0.77	-5.35	0.0001**

** *p < .01*

Table 7 Correlations among all variables ($n = 328$)

Study variables	Overload	Complexity	Uncertainty and uselessness	Invasion and compulsion
Overload	1			
Complexity	.484**	1		
Uncertainty and Uselessness	.648**	.444**	1	
Invasion and Compulsion	.571**	.568**	.533**	1

** *p* < .01

independent variables. Preliminary tests were conducted to check assumptions of multicollinearity and homogeneity of variance for all dependent variables. In order to test the absence of multicollinearity between the study variables, Pearson correlation coefficients were computed to investigate the pattern of correlations between the study variables because conducting MANOVA requires that the dependent variables should all be moderately related, and any correlation over .80 indicates the presence of multicollinearity (Tabachnick et al., 2007). Therefore, correlation coefficients between dependent variables were checked (See Table 7).

As shown in Table 7, all correlation coefficients had moderate values, which indicate the absence of multicollinearity among the study variables. The assumptions of homogeneity of variances were assessed. Levene's test was used to verify the equality of variances in all dependent variables. Levene's test results revealed that the homogeneity of variances was met ($p > .05$).

The results indicated that there were no violations of the MANOVA assumptions. According to Tabachnick et al. (2007), an effect size based on eta-squared that is $\eta_p^2 = .01$ corresponds to a small effect, an effect size that is $\eta_p^2 = .09$ corresponds to a medium effect, and an effect size that is $\eta_p^2 = .25$ represents a large effect (See Table 8).

Table 8 shows the results of six-way MANOVA for PTSS and its domains; Overload, Complexity, Uncertainty and Uselessness, and Invasion and Compulsion. The MANOVA revealed a significant multivariate effect for gender (male = 1,

Table 8 Results of Wilks' Lambda of the effect of study variables on technostress ($n = 328$)

Independent variables	Wilks' Lambda	F-value	*P*-value	Partial eta squared
Gender	.945	4.46	.002**	.055
Place Of Residence	.963	1.45	.171	.019
Education	.934	2.67	.007**	.034
Faculty	.955	3.62	.007**	.045
University	.966	1.42	.193	.017
Experience In Technology	.800	4.44	.000**	.054

* *p* < . 05; ** *p* < .01

female = 2), Wilks' lambda = .945, $F_{4,307} = 4.46$, $p < 0.01$, $\eta_p^2 = .055$, significant multivariate effect for education, Wilks' lambda = .934, $F_{8,\ 614} = 2.67$, $p < 0.01$, $\eta_p^2 = .034$, significant multivariate effect for faculty, Wilks' lambda = .955, $F_{4,307} = 3.62$, $p < 0.01$, $\eta_p^2 = .045$, and significant multivariate effect for experience in technology, Wilks' lambda = .800, $F_{16,939} = 4.44$, $p < 0.01$, $\eta_p^2 = .054$. On the other hand, place of residence and university had no significant multivariate effects.

The overall MANOVA, descriptive statistics, and LSD post hoc test revealed that there is a statistically significant small effect of gender in overload ($F_{1,\ 327} = 6.95$, $p > 0.01$, $\eta_p^2 = .022$), specifically for females. MANOVA also revealed a statistically significant small effect of education in *complexity* ($F_{2,\ 326} = 5.80$, $p > 0.01$, $\eta_p^2 = .036$), specifically for the bachelor's degree. MANOVA further revealed a statistically significant small effect of faculty in *overload* ($F_{1,\ 327} = 3.96$, $p > 0.05$, $\eta_p^2 = .013$) and in Complexity ($F_{1,\ 327} = 10.65$, $p > 0.01$, $\eta_p^2 = .033$), specifically for humanities faculties. Finally, MANOVA revealed a statistically significant small effect of experience in technology in *complexity* ($F_{4,\ 324} = 9.51$, $p > 0.01$, $\eta_p^2 = .11$), *uncertainty and uselessness* ($F_{4,\ 324} = 2.70$, $p > 0.05$, $\eta_p^2 = .034$), and *invasion and compulsion* ($F_{4,\ 324} = 2.62$, $p > 0.05$, $\eta_p^2 = .033$), specifically for less than excellent

Table 9 Results of MANOVA of the effect of study variables on technostress ($n = 328$)

Source	Dependent variable	F	*P*-value	Partial eta squared
Gender	Overload	6.951	.009**	.022
	Complexity	.002	.968	.000
	Uncertainty and Uselessness	.393	.531	.001
	Invasion and Compulsion	1.227	.269	.004
	PTSS	1.331	.249	.004
Education	Overload	.564	.569	.004
	Complexity	5.798	.003**	.036
	Uncertainty and Uselessness	.429	.651	.003
	Invasion and Compulsion	.426	.653	.003
	PTSS	1.022	.361	.007
Faculty	Overload	3.956	.048*	.013
	Complexity	10.646	.001**	.033
	Uncertainty and Uselessness	.369	.544	.001
	Invasion and Compulsion	.999	.318	.003
	PTSS	4.650	.032*	.015
Experience in technology	Overload	.749	.560	.010
	Complexity	9.514	.000**	.109
	Uncertainty and Uselessness	2.696	.031*	.034
	Invasion and Compulsion	2.624	.035*	.033
	PTSS	2.275	.061	.029

$^*p < .05$; $^{**}p < .01$

experiences. Meanwhile, independent variables did not affect the remaining dependent variables (see Table 9).

5 Discussions

This research explores a new model for technostress structure in the Palestinian context, and the reported findings presented two new factors that differ from the previous models (Dong et al., 2020; Özgür, 2020) that are related to the cultural backgrounds, which are *uncertainty and uselessness* and *invasion and compulsion,* which could be discussed and used in the future to measure technostress and this could be considered as an additional added value of this research. We believe that these two new factors emerged due to the unique research context, namely Palestine, as Palestinian academicians have been living in crisis for over 70 years in terms of occupation, on top of the education system, which has been neglecting teacher training. In terms of *invasion and compulsion,* it is related to the general policy of decision-makers who believe that using technology mitigates daily challenges, but without collecting and analyzing teachers' opinions. This new model could be suitable for conflict zones and people in crisis situations, where people have a combination of stress from different factors that can either eliminate each other or increase stress levels.

The results also show that there is a high level of *uncertainty and uselessness* among Palestinian academicians due to the negative impact of the COVID-19 pandemic. This was in line with the findings of Dahabiyeh et al. (2022) in terms of uncertainty in the mandatory use of new technology during a crisis. Based on the findings of Dahabiyeh et al. (2022), uncertainty, as one of the technostress drivers, has a negative impact on online teaching, exhaustion, and teachers' productivity. Moreover, perceiving the benefits and usefulness of a new technology may reduce the technostress, as reported by Wang et al. (2020a), which is inconsistent with the findings of this present study. The findings of this contradiction could be explained partially by the instability created by the crisis, especially since the COVID-19 virus has increased the fear factor among people (including academicians), as no one can tell about its impact and future progression (Tuan, 2022). Despite the fact that academicians have high education levels, they still suffered like others from this technostress and were able to express their fear and feelings, which is congruent with previous studies, such as Baabdullah et al. (2022), Camarena and Fusi (2022), and Li and Wang (2021). Technostress level varies as people get used to the pandemic and have been trained to use technology, and this was shown in the study results as the level of technostress is medium.

The results further show that there was a significant difference between male and female Palestinian academicians in the *overload* factor, favoring females over males. This could be explained by the reality of working women in the old traditions of the Arab region who take care of both loads inside and outside (workplace) the house, while men only concentrate on their workplace. Additionally, women are the main family care and housekeeper in addition to their workload, and during the pandemic, they had to take care of more tasks, such as looking after infected family members, elderly people, and their children (Leavy & Shabel, 2022).

Academicians working in Humanities were more affected and had higher levels of technostress in terms of overload than scientific academicians. This could be due to the fact that scientific persons have more hope and beliefs in science and medical efforts more than people in humanities, so they were hopeful of finding medical solutions in the near time and less worried about the future. Another important reason could be due to the fact that academicians in science and medicine have more experience in using technology in their teaching and daily life than those in humanities. Consequently, they are more skillful and less stressed in adopting technology for their teaching practices. Our findings are in line with Tarafdar et al. (2019). Palestinian academicians, on the other hand, have been under crisis for over 70 years, and this enabled them to build a high level of resilience to cope with the stress exhibited by crises and control their own stress and anxiety levels.

Examining the technostress level among academicians can contribute to the literature in different ways. From a theoretical perspective, it could enrich the ongoing discussions and theories about what could cause technostress among people, in general, and academicians, specifically. From a practical perspective, little is known about what could cause technostress among academicians (Li & Wang, 2021); this study covers this gap by revealing these causal factors. Consequently, researchers and practitioners can make the needed interventions to overcome the technostress issue and facilitate the adoption and implementation of ICT in teaching practices. Finally, as technostress is considered not only an academician's health issue but also a management issue in higher education institutions (Hung et al. 2015; Joo et al. 2016), identifying the factors that lead to exhibiting technostress among academicians could contribute to enhancing university management in terms of ICT adoption and implementation in teaching practices.

6 Practical implications

The key implication of the findings of this study is to redesign the content of the courses in higher education as one of the strategies for social justice (Gill et al., 2023a, b) and to reduce technostress in the next normal (post-COVID-19) (Arslan et al., 2022). Educators in higher education sectors should transfer their learned lessons during the pandemic into their teaching practices post-COVID by changing their pedagogical strategies (Gill et al., 2022).

The Palestinian technostress scale developed in this study could be used by managers, school administrations, and policy makers to identify technostress causal factors in their organizations and could design interventions to reduce technostress and enhance multicultural development in online teaching post-COVID-19 (Gill et al., 2023a, b; Li & Eryong, 2022).

7 Conclusion

This study aims to explore how remote teaching during a crisis affects the level of technostress among Palestinian academicians through the conduct of a mixed-method approach. Palestine as a research context was selected because it is unique compared to other contexts, where academicians have to deal not only with the COVID-19 pandemic but also the territorial occupation. The findings of this study contribute to the body of literature by highlighting two additional factors that could influence the level of technostress, namely, *uselessness* and *compulsion*. Additionally, gender significantly impacts the level of technostress among academicians, where females exhibit higher technostress levels compared to males.

Despite the solid ground of this study, it has several limitations that influence the generalization of the findings. For example, the sample size was limited. In addition, this study did not consider the socio-culture factors of academicians. Conducting more research to explore how to measure the individual traits of technostress will be beneficial by including more participants and also considering other factors. The authors of this study encourage researchers and practitioners to extend this study by using the technostress model in other communities and contexts in order to identify new factors for future research and implications.

Appendix

Items	Very high applicable	High applicable	Moderate applicable	low very	Not applicable
Invasion and compulsion					
I feel annoyed since I am forced to use technology in education in an emergency situation					
I think that technology affects all my life aspects, and this annoys me					
I feel exhausted since technology forced me to change to online distance education					
I feel I lost the ability to class management due to online distance learning					
Overload					
I have no chance for rest and relaxation due to online Distance learning					
I feel very exhausted due to online distance learning since it needs more time and efforts					

Items	Very high applicable	High applicable	Moderate applicable	low very	Not applicable
I had a continuous headache due to working online for long hours					
I lack the ability to sleep due to stress and work pressure in online distance learning					
I suffer from severe pains in my neck, back, and shoulders due to long hours of working online					
I suffer from sight problems due to long hours working online					
I feel irritated all the time due to long hours working online					
I can't concentrate due to long hours working online					
I feel exhausted physically and mentally due to long hours working online					
Complexity					
I have low technical skills, which affect my ability to work online					
I feel tired and stressed due to the fact that I lack computer skills					
I feel upset that I am unable to employ technology in online learning					
I feel annoyed since many teachers lack computer skills					
I feel I am unready to use technology in my teaching					
I have my challenges due to the fact that I can't deal with many applications and soft wares					
I have my challenges due to the fact that I don't know many applications and soft wares terminology					
Uncertainty and uselessness					
I have low job satisfaction due to online distance learning					
I lost interaction with my students and colleagues due to distance online learning					

Items	Very high applicable	High applicable	Moderate applicable	low very	Not applicable
I have a challenge in assessing my students' work					
I feel empathy with my students since they suffer from stress and anxiety due to Online distance learning					
I believe that distance online learning does not suit all topics and subjects					
I am not confident that I am doing my job in the best way due to shifting online					
I feel depressed looking at the computer screen, especially all students' videos, when we are locked down					

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Data availability The datasets generated and/or analyzed during the current study are not publicly available due to the unavailability of permission from the participants and the declaration which informed them that the data would not be published to the public but are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that there is no conflict of interest among them.

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