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Techno-stressors in Social and Institutional Contexts among Metropolitan Costa Rican University Students

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Abstract

The growing presence of digital systems in higher education has reshaped how students engage with academic technologies, exposing them to new forms of technology-related strain. In this study, we examine technostress among university students in Costa Rica and validate a refined three-factor structure of the Technostress Scale for University Students (TS4US). A total of 279 students participated in a cross sectional survey, and the 19 item scale was analyzed through exploratory and confirmatory factor analyses using polychoric correlations and robust estimation methods. The resulting model demonstrated solid psychometric properties and achieved robust goodness-of-fit indicators. Its three dimensions, Perceived Technological Overload and Complexity, Lack of Social Support for the Use of Information Technologies, and Insufficient Institutional Support and Digital Culture, capture the multidimensional nature of technostress in digitally mediated learning environments. Sociodemographic analyses indicated that contextual and organizational variables, particularly educational journey and employment status, were more strongly associated with technostress than individual demographic characteristics. The results underscore that technostress is shaped by broader organizational conditions and emphasize the role of institutional practices in fostering healthier digital learning environments. The study expands regional evidence on the TS4US and underscores the need to integrate human centered strategies into sustainable digital transformation processes in higher education.

1. Introduction

The rapid expansion of digital infrastructures across higher education has altered the ways in which teaching and learning are organized, incorporating virtual environments, asynchronous formats, and hybrid arrangements that redefine students' academic interactions. Such transformations stem from long-term technological developments, particularly the widespread adoption of information and communication technologies (ICT) and were intensified by the disruptions caused by the COVID-19 pandemic, which reshaped pedagogical practices and institutional routines [1–3]. Previous research indicates that the incorporation of digital technologies can support more flexible learning pathways, strengthen academic performance, and reinforce institutional commitments to Sustainable Development Goal 4, which promotes equitable access to quality education [4–6]. At the same time, the growing reliance on digital systems may generate psychological tension for both students and instructors, particularly when technological requirements surpass users' skills or when institutional support is limited.

Against this backdrop, technostress has emerged as a key construct for examining how sustained interaction with digital technologies shapes users' psychological states and behavioral responses. Following Brod's early characterization of technostress as a modern adaptive disorder, subsequent scholarship has broadened and refined the construct [7]. Salanova et al. [8] conceptualize technostress as an adverse psychological condition associated with actual or perceived ICT demands, typically expressed through strain, fatigue, and resistant or avoidant attitudes toward technology. In the information systems literature, Tarafdar et al. [9–11] proposed five core techno-stressors (overload, complexity, invasion, insecurity, and uncertainty), that account for the ways in which digital technologies may disrupt users' wellbeing and hinder academic or occupational functioning. Beyond its pedagogical implications, the expansion of digital infrastructures in higher education represents a broader process of social change, reshaping how students relate to institutions, access knowledge, and participating in academic life. These transformations alter patterns of interaction, redistribute responsibilities between individuals and organizations, and generate new forms of inequality linked to digital access, competencies, and institutional support. Understanding technostress therefore requires situating it within these wider sociotechnical shifts, where digitalization becomes a driver of both opportunity and strain in contemporary higher education systems.

The COVID-19 pandemic accelerated these processes across Latin America, prompting a rapid shift toward digital learning in contexts marked by uneven access to connectivity, technological resources, and digital competencies [1]. Consequently, interest in technostress grew within the region, as empirical studies documented notable strain among educators [12–14] and university students [15–17]. Research on sustainable education highlights that digital transformation should integrate pedagogical and psychological dimensions, fostering learning environments that prevent excessive technological demands and support student wellbeing [18–19]. In this context, technostress has become a critical dimension of digital well-being, as it reflects how students experience the psychological, cognitive, and emotional consequences of sustained engagement with academic technologies. Understanding technostress therefore contributes to broader discussions on digital well-being in higher education, where the benefits of technological innovation must be balanced against the risks of overload, fragmentation, and unequal access to support.

A further conceptual foundation for understanding technostress comes from person–environment fit models, originally formulated by French et al. [20], Caplan [21], and Caplan and Van Harrison [22]. These frameworks argue that stress arises when the requirements imposed by the environment surpass individuals' abilities, or when personal needs cannot be satisfied with the resources at hand. When applied to digital settings, this perspective highlights tensions that emerge from misalignments between technological demands, users' digital competencies, institutional expectations, and the support systems provided by educational organizations. Building on this approach, Wang and Li [23] adapted the person–environment fit perspective to the study of technostress in higher education, outlining a multidimensional structure that has guided subsequent efforts to design and validate psychometric measures.

These dynamics also highlight the importance of digital governance in higher education, as institutional decisions regarding platform adoption, technological standards, communication practices, and support systems shape the conditions under which students engage with digital environments. Technostress therefore emerges not only from individual competencies or technological complexity but also from the ways institutions govern their digital transformation processes.

Along this trajectory, Vega-Muñoz et al. [24] introduced the Technostress Scale for University Students (TS4US) in Chile, reporting a three-factor configuration —Abilities–Demands Techno-Educational, Needs–Supplies Resources, and Person–People Factor—that demonstrated satisfactory model fit and internal reliability. Subsequently, Araya-Ugarte et al. [19] tested an adapted version of the instrument in Peru, yielding a two-factor, thirteen-item solution that supported the scale's relevance across different Latin American higher education contexts. Despite these advances, empirical work on technostress in Latin

America is still geographically limited, which restricts broader regional comparisons and makes it difficult to assess the robustness of the TS4US across diverse sociotechnical settings. This gap also constrains the instrument's potential to inform institutional strategies aimed at strengthening students' digital experiences and support systems.

To contribute new evidence to this line of research, the present study examines the factorial structure of the TS4US among university students in Costa Rica, a setting that has not previously been analyzed using this instrument. By doing so, the study broadens the geographic coverage of prior validations, evaluates the instrument's behavior within a specific Costa Rican sociotechnical context, and adds to the emerging body of Latin American research on technostress among university students. The results offer guidance for institutions seeking to strengthen academic support systems, enhance students' digital competencies, and promote healthier digital learning conditions, in line with broader discussions on public health and sustainable organizational practices.

By examining technostress within this broader landscape of digital transformation and social change, the present study contributes to understanding how institutional practices, technological infrastructures, and students lived experiences intersect to shape emerging forms of digital strain. In doing so, the study positions technostress as a key determinant of students' digital well-being, highlighting how institutional support, social resources, and platform design influence their capacity to engage healthily with digital learning environments. At the same time, the analysis adopts a digital governance perspective, emphasizing how institutional structures, policies, and decision-making processes shape students' experiences of digital transformation and their ability to adapt to evolving academic technologies. Together, these perspectives situate technostress as a sociotechnical phenomenon that reflects the interplay between individual capacities, organizational practices, and the governance of digital ecosystems in higher education.

2. Materials and Methods

2.1. Participants

The research was carried out in Costa Rica's Greater Metropolitan Area and focused on examining technostress among undergraduate students enrolled in Business Administration programs. These programs, offered by the Technological Institute of Costa Rica (TEC), span two to five academic years and serve a total enrollment of 2,067 students in the Greater Metropolitan Area, of whom 1,143 are men (55.30%) and 924 are women (44.70%) [25]. The final sample consisted of 279 undergraduate students, with 56% identifying as men and 44% as women. Participants were enrolled across the first to fifth years of their respective programs (technician, high school diploma, or bachelor's degree). A non-probabilistic convenience sampling strategy was used, seeking diversity in gender, study schedule, and instructional modality. Eligibility criteria required active enrollment in the School of Business Administration at TEC and the absence of cognitive or physical conditions that could interfere with understanding or completing the questionnaire.

2.2. Context

Costa Rica is considered an upper-middle-income nation according to World Bank classifications and has an estimated population of approximately 5.25 million inhabitants. The country's demographic composition shows a relatively mature population: around one-fifth of residents are younger than 15, close to two-thirds fall within the working-age range (15–64), and roughly one in ten are 65 or older, yielding a median age near 35 years. This demographic configuration supports sustained economic activity, yet it also signals growing demands on health and social protection systems as the population continues to age. Urbanization levels are high, with over 80% of residents concentrated in metropolitan zones—especially the San José area, which serves as the country's principal political, economic, and administrative hub. Although Costa Rica is noted for its political stability, comprehensive social programs, and extensive access to education and healthcare, it continues to face issues such as income inequality, labor informality, and the integration of migrant populations, particularly from neighboring countries, which shape internal mobility patterns and broader migration dynamics [26].

2.3. Instruments

Technostress was assessed using the Technostress Scale for University Students (TS4US), a 19-item instrument previously validated in Latin American higher education contexts (see Appendix A). Items were rated on a five-point Likert-type scale, with response options spanning from "strongly disagree" to "strongly agree." The survey was delivered online and completed individually by participants after providing informed consent. No personally identifiable information was collected. The TS4US was first created and validated in Chile with Spanish-speaking university students, demonstrating strong internal consistency (α = 0.925) and satisfactory psychometric properties, as summarized in Table 1 [24].

Table 1
TS4US and Factor Loading for items in Vega-Muñoz et al. (2022).

Items	V01	V02	V03	V04	V05	V06	V07	V08	V09	V10	V11	V12	V13	V14	V15	V16
Factor Loading	0.732	0.745	0.734	0.696	0.794	0.747	0.924	0.779	0.657	0.894	0.841	0.612	0.535	0.657	0.749	0.629

2.4. Data Analysis and Processing Procedures

The research aim established in the previous section has been accompanied by two types of hypotheses, which are detailed below.

Hypothesis of the factors:

H_{11} . *(Alternative hypothesis): The TS4US scale has a factorial structure composed of three factors that fits the theoretical model well, showing acceptable fit indices in both exploratory and confirmatory factor analysis in undergraduate in Greater Metropolitan Area, Costa Rica.*

H $_{10}$. *(Null hypothesis): The factor structure of the TS4US scale does not fit the theoretical model of three factors, showing significant differences in factor configuration or inadequate fit indices in exploratory and/or confirmatory factor analysis in undergraduate in Greater Metropolitan Area, Costa Rica.*

Hypothesis of the correlations:

H $_{21}$. *(Alternative hypothesis, Expanded): There are significant and differentiated correlations between the sociodemographic variables (gender, age level, educational level, educational journey, educational modality, and employment status) and the TS4US scale factors such that the intensity and direction of technostress scores vary according to the personal and experiential characteristics of undergraduate students in Greater Metropolitan Area, Costa Rica.*

H $_{20}$. *(Null hypothesis, Expanded): There are no statistically significant correlations between the sociodemographic variables and any of the three factors of the TS4US scale, indicating that variations in technostress are independent of students' demographic or experiential characteristics.*

The 19 TS4US items were first analyzed in SPSS 23 (IBM, New York, NY, USA) to evaluate their initial psychometric properties [24, 27]. The analytical process started with a univariate descriptive review, examining variance (> 0), skewness (|≤1|), and kurtosis (|≤1|) [28]. Minor deviations were allowed, especially for kurtosis, where values up to 1.8 were considered acceptable [29]. Measurement quality was assessed through the Measurement of Sampling Adequacy (MSA), derived from the anti-image correlation matrix [30], together with the Kaiser–Meyer–Olkin (KMO) statistic. Bartlett's test of sphericity was used to verify the suitability of the correlation matrix for factor extraction, which justified conducting an exploratory factor analysis (EFA) using the unweighted least squares (ULS) method and Oblimin rotation with Kaiser normalization [31]. ULS was chosen because it performs well with ordinal variables and non-normal distributions, minimizing discrepancies between observed and estimated correlations without applying residual weights. This choice is supported by evidence showing its advantages over maximum likelihood in moderate samples and asymmetric distributions [32–35].

The factor solution obtained from the EFA was then evaluated through confirmatory factor analysis (CFA) conducted in FACTOR version 12.01.02 (Rovira i Virgili University, Tarragona, Spain) [36]. The CFA relied on polychoric correlations and used Hull's method with Robust Unweighted Least Squares (RULS) estimation [37], applying a Normalized Direct Oblimin rotation. The analysis also considered the Measure of Sampling Adequacy (MSA) [38] and retained factors according to communalities, loading strength relative to sample size, and the minimum items-per-factor criterion (MIF) [39–42]. Model fit was evaluated using χ^2/df, RMSEA, AGFI, GFI, CFI, NNFI, and RMSR, as shown in Table 2 [43, 44]. Internal reliability was estimated through Cronbach's alpha, computed in SPSS 23 [45].

Table 2
Validation and reliability parameters.

Sample	Level	Cronbach's Alpha	MIF	χ^2/df	RMSEA	AGFI	GFI	CFI	NNFI	RMSR
≥ 200	Good fit	[0.70, 0.80)	NR	[0, 2]	[0.00, 0.05]	[0.90, 1.00]	[0.95, 1.00]	[0.97, 1.00]	[0.97,1.00]	[0.00, 0.05) ++
	Acceptable fit	[0.80, 0.95)	≥ 3	(2, 3]	(0.05, 0.08]	[0.85, 0.90)	[0.90, 0.95)	[0.95, 0.97)	[0.95,0.97)	[0.05, 0.08] ++

NR: not reported. ++ indicated in Kalkan & Kelecioğlu [44].

After confirming the factorial validity through the CFA, an overall TS4US score was calculated and analyzed in relation to key sociodemographic variables to explore potential differences in technostress levels across student subgroups. For this purpose, weighted technostress scores, derived from the latent factors, were cross-tabulated with the variables Gender (GND), Age Level (AGL), Educational Level (EDL), Educational Journey (EDJ), Educational Modality (EDM), and Employment Status (EMP). Given the categorical nature of these variables, the Freeman–Halton exact test [46] was used as a nonparametric alternative for assessing associations. This test generalizes Fisher's exact procedure to RxC contingency tables, maintaining its probabilistic accuracy while accommodating matrices with more than two categories. As highlighted by Contreras-Cristán and González-Barrios [47], the Freeman–Halton test offers a robust approach for comparing discrete distributions and can also be applied to symmetry assessments in bivariate data through the construction of symmetric contingency matrices. Ruxton and Neuhäuser [48] further note that the Freeman–Halton test is preferable to the χ^2 test when expected frequencies are low, and that its mid-p variant provides better control of type I error while maintaining statistical power. Although SPSS does not explicitly name this procedure as the Freeman–Halton test, it can be executed through the software's exact-tests module for contingency tables, which generates the corresponding exact p-values.

2.5. Ethical Procedures

The study followed the ethical principles of the Declaration of Helsinki for research involving human participants. All students provided written informed consent before completing the questionnaire (see Informed Consent Statement). The research protocol received approval from the corresponding institutional ethics committee, as detailed in the Institutional Review Board Statement included at the end of the manuscript.

3. Results

3.1. Sample Characterization

The Technostress Scale for University Students (TS4US) [24] was administered during the second academic semester of 2025, yielding a final sample of 279 valid participants, which exceeds the recommended minimum for conducting factorial analyses in medium-sized samples (≥ 200) [49]. The sociodemographic distribution of the respondents is presented in Table 3.

Regarding gender, 44% of the students identified as female and 56% as male. In terms of age, 30% were 20 years old or younger, 53% fell within the 21–30 age range, and 17% were over 30. With respect to educational level, 35% were enrolled in technician programs, 41% in high-school diploma programs, and 24% in bachelor's degree programs.

A slight majority of students reported attending classes in the evening (56%), compared with 44% in daytime schedules. Concerning instructional modality, 56% studied face-to-face, 14% followed blended learning, and 30% participated in fully virtual programs. Finally, 62% of the sample indicated that they were not employed at the time of the survey, while 38% combined their studies with paid work.

Table 3
Students sample characterization.

Sociodemographic Variables	**Level (number code)**	***n***	***n*%**
Gender (GND)	Female (1) *	123	44%
	Male (2)	156	56%
Age level (AGL)	AGL ≤ 20 (1)	85	30%
	20 < AGL ≤ 30 (2)	147	53%
	30 < AGL (3)	47	17%
Educational level (EDL)	Technician (1)	97	35%
	High School Diploma (2)	116	41%
	Bachelor's Degree (3)	66	34%
Educational journey (EDJ)	Daytime (1)	124	44%
	Nighttime (2)	155	56%
Educational modality (EDM)	Face-to-face (1)	156	56%
	Blended learning (2)	39	14%
	Virtual (3)	84	30%
Employment status (EMP)	Unemployed (1)	172	62%
	Employed (2)	107	38%

* The numbers in parentheses (°) correspond to the values assigned in the database.

3.2. Validation through Exploratory and Confirmatory Factor Analysis

The analysis began by examining whether the three-factor structure previously identified by Vega-Muñoz et al. [24] in Chile could also be observed in the Costa Rican sample. The univariate descriptive statistics indicated that all 19 ordinal items displayed non-zero variance, confirming their contribution to the shared variance of the instrument. Skewness and kurtosis values fell within acceptable ranges for ordinal data, as shown in Table 4, supporting the suitability of the items for subsequent factor analysis.

Table 4
Univariate descriptive statistical analysis.

Variables	N	Mean	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
V01	279	2.18	0.973	0.525	0.146	-0.332	0.291
V02	279	2.05	0.980	0.892	0.146	0.309	0.291
V03	279	1.82	0.917	1.256	0.146	1.164	0.291
V04	279	1.81	0.888	1.297	0.146	1.378	0.291
V05	279	1.98	1.126	1.055	0.146	0.453	0.291
V06	279	2.01	1.011	0.963	0.146	0.440	0.291
V07	279	2.07	1.110	0.934	0.146	0.255	0.291
V08	279	2.10	1.134	0.807	0.146	0.121	0.291
V09	279	1.98	1.028	0.940	0.146	0.334	0.291
V10	279	1.87	.990	1.078	0.146	0.593	0.291
V11	279	2.58	1.632	0.327	0.146	-0.997	0.291
V12	279	2.41	1.610	0.475	0.146	-0.910	0.291
V13	279	2.41	1.436	0.517	0.146	-0.710	0.291
V14	279	2.09	1.194	0.828	0.146	0.001	0.291
V15	279	2.11	1.053	0.829	0.146	0.312	0.291
V16	279	1.96	1.099	0.898	0.146	-0.026	0.291
V17	279	2.11	1.260	0.710	0.146	-0.377	0.291
V18	279	2.04	1.099	0.796	0.146	-0.030	0.291
V19	279	2.20	1.418	0.708	0.146	-0.501	0.291
Valid N (listwise)	279						

* Variables that satisfy the pre-established parameters of standard deviation, skewness, and kurtosis.

Given these conditions, all 19 items were retained for the exploratory factor analysis (EFA). The scree plot (Fig. 1) shows a clear inflection point at an eigenvalue of 1.031, which closely aligns with the Kaiser criterion (eigenvalue ≥ 1). This convergence supports the extraction of three latent factors for the purposes of this study. It is important to note that this three-factor configuration is specific to the present dataset and does not represent an officially standardized version of the TS4US.

The EFA results are summarized in Table 5. The analysis yielded a Cronbach's alpha of 0.934, indicating excellent internal consistency. Sampling adequacy was confirmed by a KMO value of 0.925, and Bartlett's test of sphericity was significant ($\chi^2 = 3247.949$, $df = 171$, $p < 0.001$), demonstrating that the correlation matrix was appropriate for factor extraction. The three-factor solution accounted for 56.277% of the total variance, and each factor met the recommended minimum of three items per factor [39, 41, 49]. The anti-image correlation matrix is provided in Appendix A (Table A1).

Elbow point indicated in red and clipping line (eigenvalue = 1) in red dashed line.

The scree plot in Fig. 1 shows that the elbow point (eigenvalue 1.031) practically coincides with the clipping line (eigenvalue = 1), which is the only good alternative for latent variables, setting the number of factors at 3.

Table 5
Exploratory factor analysis for three factors.

KMO and Bartlett's Test			
Kaiser–Meyer–Olkin Measure of Sampling Adequacy.			0.925
Bartlett's Test of Sphericity		Approx. Chi-Square	3247.949
		Degree of freedom	171
		Significance	0.000
Pattern Matrix [a]			
ID	Factor 1 (F1)	Factor 2 (F2)	Factor 3 (F3)
V01	0.734		
V02	0.794		
V03	0.815		
V04	0.769		
V05	0.681		
V06	0.741		
V07	0.562		
V08	0.636		
V09	0.746		
V10	0.434		
V11		0.799	
V12		0.776	
V13		0.863	
V14		0.652	
V15		0.522	
V16		0.352	
V17			-0.641
V18			-0.653
V19			-0.618
Eigenvalue	8.409	1.672	0.612
% of Variance	44.255	8.801	3.221
Cumulative %	44.255	53.056	56.277
Factor Correlation Matrix [b]			
Factor	1	2	3
1	1.000	0.516	-0.588
2	0.516	1.000	-0.558
3	-0.588	-0.558	1.000

[a] Extraction Method: Unweighted Least Squares. Rotation Method: Oblimin with Kaiser Normalization. Rotation converged in 6 iterations. [b] Extraction Method: Unweighted Least Squares. Rotation Method: Oblimin with Kaiser Normalization.

A confirmatory factor analysis (CFA) was subsequently conducted using the FACTOR software to evaluate the adequacy of the three-factor model. The Measure of Sampling Adequacy (MSA) [38] indicated that no items required removal, as all 90% confidence intervals exceeded the minimum threshold of 0.50. The CFA produced a KMO of 0.921, and Bartlett's test remained highly significant ($\chi^2 = 3118.1$, df = 171, p = 0.000010), confirming the suitability of the polychoric correlation matrix for model estimation.

Using the Hull method, the CFA supported the retention of three latent factors, consistent with the EFA results. The rotated loading matrix is presented in Table 6, showing clear and interpretable item–factor associations. Overall, the combined EFA and CFA findings provide strong evidence for the validity of a three-factor structure of the TS4US in the Costa Rican context.

Table 6
Confirmatory factor analysis for three factors.

KMO and Bartlett's Test			
Kaiser–Meyer–Olkin Measure of Sampling Adequacy. (confidence interval 90%)			0.921 (0.800; 0.905)
Bartlett's Test of Sphericity	Approx. Chi-Square		3118.1
	Degree of freedom		171
	Significance		0.000010
Rotated Loading Matrix			
Variable (Item)	Factor 1 (F1)	Factor 2 (F2)	Factor 3 (F3)
V01		0.791	
V02		0.824	
V03		0.863	
V04		0.817	
V05		0.745	
V06		0.770	
V07		0.614	
V08		0.695	
V09		0.813	
V10		0.509	
V11			0.824
V12			0.815
V13			0.902
V14			0.703
V15			0.574
V16			0.402
V17	0.693		
V18	0.717		
V19	0.662		
Explained Variance	0.546	0.105	0.051
Cumulative Variance	0.546	0.651	0.702
Eigenvalue	10.371	2.003	0.960
Inter Factor Correlation Matrix			
Factor	F1	F2	F3
F1	1.000		
F2	0.632	1.000	
F3	0.601	0.568	1.000

Table 7 sets out the proposed model results for the χ^2/df, RMSEA, AGFI, GFI, CFI, NNFI (TLI), and RMSR indicators by FACTOR software with a good fit. The proposed 3-factor model shows a clearly superior fit compared to the original 3-factor contrast model reported by Vega-Muñoz et al. [24]. Although both models exhibit excellent internal reliability (α = 0.934 and α = 0.925, respectively), the goodness-of-fit indices reveal substantial differences:

- The sample size of the proposed model (n = 279) is substantially smaller than that of the contrast model (n = 848), yet it still achieves superior fit indices. This indicates that the proposed structure is not only more parsimonious but also more stable and efficient, even under more demanding conditions.
- The χ^2/df of the proposed model (0.82) falls well within the expected range for a good fit, whereas the contrast model reaches 2.74, a value that is acceptable but considerably higher and closer to the upper limit of adequacy.
- The RMSEA of the proposed model (0.040, ci 0.011–0.047) indicates a strong fit, clearly outperforming the contrast model (0.072, ci 0.064–0.079), whose value lies only within the acceptable range and approaches the threshold of poor fit.

- The incremental and absolute fit indices (CFI, NNFI, GFI, AGFI) are consistently higher in the proposed model, with values above 0.99 in most cases. In contrast, the original model shows lower performance, with several indices positioned near the minimum acceptable threshold (≈ 0.97–0.98).
- The RMSR also favors the proposed model (0.045 vs. 0.047), reflecting a slightly lower level of standardized residuals and a more precise representation of the covariance structure.

Thus, although both models demonstrate reliability, the proposed three-factor model provides a more robust, parsimonious, and theoretically coherent fit. These results confirm that the refined factor structure captures the underlying dimensions of the construct more effectively than the previously reported configuration.

Table 7
Validation and reliability versus parameters [43].

Model	Sample	Level	Cronbach's Alpha	MIF	χ^2/df	RMSEA	AGFI	GFI	CFI	NNFI	RMSR
Proposed (3 Factors)	279	-	0.934 **	3	0.82 **,+	0.040 ** ci (0.011 0.047)	0.991 ** ci (0.989 0.995)	0.994 ** ci (0.993 0.997)	0.996 ** ci (0.994 1.000)	0.994 ** ci (0.996 1.001)	0.045 ** ci (0.036 0.048)
Contrast (3 Factors) (Vega-Muñoz et al., 2022)	848	-	0.925 **	3	2.74 * +	0.072 * ci (0.064 0.079)	0.986 ** ci (0.983 0.989)	0.987 ** ci (0.985 0.990)	0.979 ** ci (0.974 0.985)	0.970 ** ci (0.962 0.978)	0.047 ** ci (0.042 0.050)
Parameters	≥ 200	**	[0.80, 0.95)	NR	[0, 2]	[0.00, 0.05]	[0.90, 1.00]	[0.95, 1.00]	[0.97, 1.00]	[0.97, 1.00]	[0.00, 0.05) ++
		*	[0.70, 0.80)	≥ 3	(2, 3]	(0.05, 0.08]	[0.85, 0.90)	[0.90, 0.95)	[0.95, 0.97)	[0.95, 0.97)	[0.05, 0.08] ++

NR: not reported. ** Good fit; * Acceptable fit. + Minimum Fit Function Chi Square. ++ indicated in Kalkan & Kelecioğlu[44].

Finally, Table 8 shows the instrument's internal reliability by SPSS 23 software, with a total Cronbach's Alpha of 93.4% for the set of 19 items (See details in Table 8), and Fig. 2 presents a histogram of the resulting scales: 2a histogram F1, 2b histogram F2, 2c histogram F3, and 2d histogram FT.

Table 8
Reliability statistics.

Scale	Variance	Skewness	Kurtosis	Valid Cases	Number of Items	Cronbach's Alpha
Factor 1	0.978	0.621	−0.236	279	3	0.825 *
Factor 2	0.689	0.727	0.358	279	10	0.921 **
Factor 3	0.922	0.307	−0.518	279	6	0.874 **
Factor Total	0.657	0.446	0.000	279	19	0.934 **

* Cronbach's Alpha > 0.7, ** Cronbach's Alpha > 0.8.

The blue bars represent the frequency distribution of the data grouped into class intervals, while the black dash curve depicts the theoretical normal distribution fitted to the observed data.

Consequently, it is possible to assert that the proposed theoretical model of the factors has empirical validity, showing a clearly differentiated three-factor structure:

- The first factor (F1), Lack of Social Support for the Use of Information Technologies, groups items that reflect the absence of peer support, such as "I do not have enough support from my peers in using information technologies" or "My peers are not positive about the innovative use of information technologies at my university," showing a limited collaborative climate.
- The second factor (F2), Perceived Technological Overload and Complexity, focuses on items associated with excessive demands and operational difficulties, such as "I find it difficult to meet my university's requirements regarding the use of information technology," "I am overwhelmed by the wide variety of information technologies used at my university," or "I find it difficult to keep up with the rapid changes in information technologies," evidencing high levels of demand and complexity.
- Finally, the third factor (F3), Insufficient Institutional Support and Digital Culture, brings together perceptions linked to the lack of organizational resources, such as "My university does not provide me with sufficient training to use information technologies effectively in my academic activities" or "My university does not have a culture that encourages the use of innovative tools such as information technologies," indicating weaknesses in training, incentives, and institutional culture associated with the use of technologies.

3.3. Sociodemographic Associations with Technostress

After validating the three-factor structure of the TS4US, the next step was to examine whether technostress levels varied across key sociodemographic groups. Weighted scores derived from the latent factors were cross-tabulated with the variables Gender (GND), Age Level (AGL), Educational Level (EDL), Educational Journey (EDJ), Educational Modality (EDM), and Employment Status (EMP). Given the categorical nature of these variables and the presence of cells with expected frequencies below five, the Freeman–Halton exact test was used as a nonparametric alternative to the χ^2 test (see Table 9).

Table 9
Freeman–Halton (F-H) extension of Fisher's Exact Tests.

Variable 1	Variable 2	N of Valid Cases	Value F-H [+]	Significance (2-Sided) [+]	Correlation Evidence
F1	GND	279	1.820	0.797 ci (0.778 0.799)	No
	AGL	279	5.067	0.749 ci (0.738 0.760)	No
	EDL	279	8.079	0.400 ci (0.387 0.413)	No
	EDJ	279	12.079	0.011 ci (0.009 0.014) *	Yes
	EDM	279	5.884	0.644 ci (0.631 0.656)	No
	EMP	279	10.764	0.023 ci (0.019 0.799) *	Yes
F2	GND	279	6.450	0.138 ci (0.130 0.147)	No
	AGL	279	15.313	0.033 ci (0.028 0.037) *	Yes
	EDL	279	5.609	0.719 ci (0.707 0.730)	No
	EDJ	279	8.759	0.047 ci (0.041 0.052) *	Yes
	EDM	279	16.179	0.023 ci (0.019 0.027) *	Yes
	EMP	279	17.447	0.000 ci (0.000 0.001) **	Yes
F3	GND	279	2.876	0.599 ci (0.586 0.611)	No
	AGL	279	7.914	0.412 ci (0.399 0.424)	No
	EDL	279	31.844	0.000 ci (0.000 0.000) **	Yes
	EDJ	279	16.071	0.002 ci (0.001 0.003) **	Yes
	EDM	279	27.803	0.000 ci (0.000 0.001) **	Yes
	EMP	279	17.366	0.001 ci (0.000 0.002) **	Yes
FT	GND	279	3.792	0.420 ci (0.407 0.433)	No
	AGL	279	9.517	0.261 ci (0.250 0.273)	No
	EDL	279	8.174	0.388 ci (0.375 0.400)	No
	EDJ	279	10.276	0.022 ci (0.018 0.026) *	Yes
	EDM	279	11.702	0.136 ci (0.127 0.145)	No
	EMP	279	16.725	0.001 ci (0.000 0.001) **	Yes

* *p*-value < 0.05, ** *p*-value < 0.01, [+] Calculated with Monte Carlo significance based on 10,000 sampled tables with starting seed 2,000,000.

The Freeman–Halton procedure, which extends Fisher's exact test to RxC contingency tables, provides an exact probability estimate for associations in multi-category matrices. This approach is particularly suitable for the present analysis, as it maintains statistical accuracy even when sample sizes are uneven across categories. As noted by Contreras-Cristán and González-Barrios [47], the test is robust for comparing discrete distributions and can also be applied to symmetry assessments in bivariate data. Furthermore, Ruxton and Neuhäuser [48] highlight that the mid-p version of the test offers improved control of type I error without compromising statistical power, making it preferable to χ^2 when expected frequencies are low.

The analysis revealed that most individual demographic variables—such as gender, age, and educational level—did not show statistically significant associations with the three TS4US factors. In contrast, contextual and organizational variables, particularly educational journey (daytime vs. nighttime) and employment status, demonstrated significant differences in technostress scores. These findings suggest that students' experiences of technostress are shaped less by personal characteristics and more by the structural conditions under which they study and work (see Fig. 3).

3.4. Interpretation of the Three-Factor Structure

The combined EFA and CFA results supported a three-factor configuration of the TS4US for the Costa Rican sample. Although this structure is consistent with previous Latin American validations, the specific pattern of item loadings observed in this study reflects the sociotechnical characteristics of the local higher education context. The three factors were therefore interpreted as follows.

3.4.1. Factor 1: Perceived Technological Overload and Complexity.

This dimension groups items associated with the cognitive and operational demands imposed by academic technologies. High loadings on this factor indicate that students experience digital tools as excessive, difficult to manage, or requiring more time and effort than they feel able to invest. The factor captures perceptions of technological saturation, rapid task accumulation, and challenges in navigating institutional platforms—elements that align with the broader notion of techno-overload and techno-complexity described in the literature.

3.4.2. Factor 2: Lack of Social Support for the Use of Information Technologies.

The second factor reflects students' perceptions of insufficient interpersonal support when dealing with academic technologies. Items loading on this dimension point to limited assistance from peers, instructors, or immediate social networks when technological difficulties arise. This factor highlights the relational component of technostress, emphasizing how the absence of collaborative or emotional support can intensify frustration and reduce students' confidence in managing digital demands.

3.4.3 Factor 3: Insufficient Institutional Support and Digital Culture.

The third factor encompasses items related to the institutional environment, including the availability of training, clarity of technological guidelines, and the overall digital culture promoted by the university. High scores on this factor suggest that students perceive gaps in institutional communication, inadequate preparation for digital tasks, or a lack of coherent strategies to facilitate technology-mediated learning. This dimension underscores the organizational roots of technostress and the role of institutional practices in shaping students' digital experiences.

Together, these three factors provide a comprehensive representation of technostress among Costa Rican university students, integrating technological, social, and institutional components. Their configuration reinforces the multidimensional nature of the construct and offers a nuanced basis for interpreting the subsequent analyses of sociodemographic associations.

4. Discussion

The findings of this study provide robust evidence for a three-factor structure of the TS4US among Costa Rican university students, reinforcing the multidimensional nature of technostress previously documented in Latin American and international research. The replication of a configuration encompassing technological overload and complexity, lack of social support, and insufficient institutional support and digital culture aligns with earlier validations conducted in Chile [24] and Peru [19, 50], which similarly emphasized the coexistence of cognitive, relational, and organizational components in students' experiences with academic technologies. Although item loadings vary across contexts, the persistence of these three domains suggests that technostress is shaped by structural features of higher education systems rather than by isolated individual characteristics.

These findings also show that technostress is not merely an individual psychological reaction but a manifestation of broader processes of social change driven by digitalization. As universities incorporate new technological systems, students must adapt to shifting expectations, altered communication norms, and reconfigured academic routines, reshaping the social fabric of higher education and influencing how they participate, collaborate, and construct their academic identities. At the same time, technostress emerges as a central component of students' digital well-being when technological demands exceed their capacities or when support systems are insufficient, digital environments can undermine well-being by generating strain, frustration, and disengagement, whereas coherent institutional support and accessible digital cultures foster healthier and more sustainable forms of engagement. These dynamics are closely tied to the governance of digital transformation within universities, as decisions about platform adoption, communication standards, and the allocation of training and support resources reflect institutional governance practices that directly shape students' digital experiences. When governance structures lack coherence or transparency, students face greater uncertainty and strain, underscoring the need for coordinated institutional strategies that align technological innovation with student well-being and equitable participation.

The prominence of technological overload and complexity in the Costa Rican sample is consistent with studies showing that students frequently perceive digital tools as demanding, time-consuming, or difficult to navigate, particularly when multiple platforms are used simultaneously or when institutional expectations escalate rapidly. Research on digital learning environments has documented similar patterns, with students reporting heightened strain when confronted with rapid technological changes or excessive digital requirements [51, 52]. Recent evidence also indicates that these cognitive demands are intertwined with emotional and behavioral responses, such as fear of missing out, compulsive connectivity, and digital overuse, which intensify students' sense of strain and reduce their capacity for self-regulation [53]. In this regard, the present findings resonate with research demonstrating that technostress is not merely a reaction to technological difficulty but also a manifestation of broader patterns of digital engagement that shape students' academic routines and psychological well-being.

At the same time, the identification of a factor related to social support highlights the interpersonal dimension of technostress. Like what has been reported in Paraguay [54], Italy [55], and India [56], students who lack guidance, peer collaboration, or emotional support tend to experience greater frustration and lower confidence when dealing with digital tasks. This pattern underscores the importance of relational resources in mitigating the negative effects of technology-mediated learning. Studies grounded in transactional stress theory suggest that students who can rely on supportive networks are better equipped to reinterpret technological demands, develop adaptive strategies, and prevent the escalation of strain into burnout or disengagement [56]. The Costa Rican results reinforce this perspective by showing that technostress is not solely a function of technological complexity but also of the social environments in which students navigate digital requirements.

The third factor, reflecting institutional support and digital culture, further demonstrates that technostress is embedded in organizational structures. Consistent with findings from Peru [19], Slovenia [57], and hybrid-learning contexts [58], students in this study reported higher levels of strain when institutional communication was unclear, training opportunities were limited, or digital policies lacked coherence. This aligns with broader analyses of digital transformation in higher education, which emphasize that universities must cultivate supportive digital ecosystems to prevent technology from becoming a source of exclusion or overload [59]. Research on institutional support in other domains, such as sustainability education, similarly shows that organizational practices shape students' engagement, motivation, and capacity to adapt to new demands [60]. The present findings therefore contribute to a growing body of evidence indicating that technostress is not merely an individual challenge but a systemic issue requiring coordinated institutional responses.

From this perspective, institutional support becomes a key mediator of the social changes driven by digital transformation, determining whether new technological arrangements foster inclusion and well-being or instead amplify existing inequalities. When institutions fail to cultivate coherent digital cultures, students experience not only technological strain but also a sense of disconnection from the evolving norms and expectations of academic life. At the same time, institutional support is essential for safeguarding students' digital well-being, as clear communication, accessible training opportunities, and integrated digital ecosystems enable healthier and more sustainable engagement with academic technologies. These dynamics are closely linked to the governance of digital transformation, since digital culture is not merely an emergent property of technological use but the outcome of deliberate institutional choices. Policies that promote interoperability, clarity in digital expectations, and equitable access to support can mitigate technostress, whereas fragmented or poorly communicated governance practices can exacerbate it. The Costa Rican findings illustrate how governance inconsistencies can translate into tangible psychological and academic burdens for students, underscoring the need for coordinated institutional strategies that align technological innovation with equity, well-being, and effective digital governance.

The multidimensional structure identified in this study also aligns with contemporary theoretical perspectives that conceptualize technostress as the result of an interaction between individual capacities, environmental demands, and institutional conditions. From a person–environment fit perspective, the three factors observed in the Costa Rican sample reflect distinct forms of misalignment: technological overload and complexity represent a gap between technological demands and students' digital abilities; lack of social support reflects a mismatch between students' needs for guidance and the assistance available in their interpersonal networks; and insufficient institutional support captures discrepancies between organizational expectations and the resources provided to meet them. Similar interpretations have been advanced in studies conducted in Chile [24], Peru [19], and Italy [55], where technostress emerged when academic technologies exceeded users' competencies or when support systems were fragmented or inconsistent.

Transactional models of stress further illuminate the mechanisms underlying these patterns. Research has shown that students' appraisal of technological demands plays a central role in determining whether digital tools are perceived as threatening, overwhelming, or manageable [52, 56]. The prominence of overload and complexity in the present study suggests that many students interpret academic technologies as stressors that exceed their coping resources, particularly when tasks accumulate rapidly or when platforms require advanced digital skills. This interpretation is consistent with findings from hybrid and virtual learning environments, where students often report heightened strain due to the constant need to adapt to new interfaces, manage multiple communication channels, and maintain continuous online engagement [58, 61].

At the same time, recent research has emphasized that technostress is not exclusively detrimental. Studies incorporating the concept of techno-eustress have shown that, under certain conditions, digital demands can be appraised as challenges that foster motivation, learning, and personal growth [62]. The present results do not directly measure techno-eustress, but the identification of institutional and social support factors suggests that supportive environments may help students reinterpret technological demands more positively. Evidence from studies on digital literacy, self-efficacy, and cognitive flexibility indicates that students with stronger personal resources are better equipped to transform technological challenges into opportunities for development rather than sources of strain [62, 63].

The relational and institutional components identified in this study also resonate with broader discussions on digital culture in higher education. Research from Slovenia [57], Kazakhstan [59], and Europe more broadly [64] has shown that students' experiences with technology are shaped not only by the tools themselves but also by the pedagogical practices, communication norms, and organizational strategies that structure their use. When institutions fail to provide clear guidelines, adequate training, or coherent digital policies, students are more likely to experience uncertainty, frustration, and disengagement. Conversely, environments that promote collaboration, transparency, and digital readiness tend to mitigate technostress and enhance students' sense of competence and belonging.

4.1. Theoretical, Managerial, and Policy Implications

The validation of a three-factor structure strengthens the conceptualization of technostress as a multidimensional construct shaped by cognitive, relational, and institutional dynamics [19, 24]. Managerially, the findings highlight the need for universities to simplify digital ecosystems [51], promote collaborative learning environments [55], and invest in comprehensive digital literacy initiatives [63]. Policy efforts should prioritize platform interoperability, transparent communication, and sustained technical support, particularly in hybrid and virtual modalities where strain tends to intensify [58, 61].

4.2. Limitations

This study used a non-probabilistic sample, limiting generalizability. Its cross-sectional design prevents causal inference, and reliance on self-report measures may introduce bias. Personal resources such as digital literacy, self-efficacy, or resilience, shown to influence technostress [62, 63], were not assessed. Behavioral outcomes such as cyberslacking or digital addiction, documented in recent studies [52, 53], were also not examined.

4.3. Future Research Directions

Future studies should incorporate probabilistic sampling, longitudinal designs, and mixed-methods approaches [65]. Including measures of personal resources and behavioral outcomes would deepen understanding of technostress mechanisms. Comparative institutional analyses could clarify how organizational strategies influence technostress [59], while exploring techno-eustress may offer a more balanced perspective on students' digital experiences [62].

5. Conclusions

This study provides new empirical evidence on technostress among university students in Costa Rica and expands the regional validation of the TS4US by confirming a robust three-factor structure in a previously unexamined sociotechnical context. The results show that students' experiences of technostress arise from the combined influence of technological demands, interpersonal support, and institutional conditions, reinforcing the multidimensional nature of the construct. The factors identified (Perceived Technological Overload and Complexity, Lack of Social Support for the Use of Information Technologies, and Insufficient Institutional Support and Digital Culture), capture distinct yet interconnected sources of strain that shape how students navigate digitally mediated learning environments.

The findings also highlight that technostress is not evenly distributed across the student population. Contextual and organizational variables, particularly educational journey and employment status, were more strongly associated with technostress than individual demographic characteristics. This pattern suggests that students' exposure to digital strain is shaped less by who they are and more by the structural conditions under which they study and work. Such evidence underscores the importance of institutional responsibility in designing coherent digital ecosystems, strengthening communication, and ensuring that technological requirements are aligned with students' competencies and available support systems.

By validating the TS4US in Costa Rica, the study contributes to the consolidation of a regional evidence base that can inform institutional strategies aimed at promoting healthier digital learning environments. The results emphasize the need for universities to adopt human-centered approaches to digital transformation, integrating technological, pedagogical, and psychosocial considerations. As higher education systems continue to expand their digital infrastructures, ensuring that these developments do not inadvertently generate overload, fragmentation, or exclusion becomes essential for advancing equitable and sustainable learning conditions.

More broadly, the study illustrates how digital transformation in higher education constitutes a process of social change that reshapes institutional roles, student expectations, and the distribution of responsibilities within academic communities. Technostress emerges as a key indicator of the tensions inherent in this transition, revealing how technological innovation can simultaneously enable new forms of participation and generate pressures that require thoughtful institutional design. In this context, integrating digital well-being into institutional strategies becomes essential, as expanding technological infrastructures must be accompanied by conditions that allow students to interact with digital systems without experiencing harmful levels of strain. These considerations underscore the need for stronger digital governance frameworks, where coherent practices (encompassing platform integration, communication standards, training policies, and support mechanisms) ensure that digital transformation enhances rather than undermines students' learning conditions and overall well-being.

Future research should continue to examine technostress across diverse institutional settings and incorporate longitudinal and mixed-methods designs to deepen understanding of how digital demands evolve over time. Strengthening the empirical foundation of technostress research in Latin America will support the development of more responsive, evidence-based policies that enhance students' digital well-being and contribute to the broader goals of sustainable and inclusive higher education.

Abbreviations

AGFI	Adjusted Goodness of Fit Index
AGL	Age Level
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
df	Degrees of Freedom
EDJ	Educational Journey
EDL	Educational Level
EDM	Educational Modality
EFA	Exploratory Factor Analysis
EMP	Employment Status
F1	Factor One
F2	Factor Two
F3	Factor Three
FT	Factor Total
GFI	Goodness of Fit Index
GND	Gender
ICT	Information and Communication Technologies
KMO	Kaiser–Meyer–Olkin
MIF	Minimal Number of Items per Factor
MSA	Measurement of Sampling Adequacy
MSA	Measure of Sampling Adequacy
NNFI	Non-Normed Fit Index
RMSEA	Root Mean Square Error of Approximation
RMSR	Root Mean Square of Residuals
RULS	Robust Unweighted Least Squares
SPSS	Statistical Package for the Social Sciences
TEC	Costa Rican Institute of Technology
TLI	Tucker & Lewis Index
TS4US	Technostress Scale for University Students
ULS	Unweighted Least Squares

Declarations

6.1. Data Available Statement

The following supporting information can be downloaded in Supplementary Materials: TS4USCR.csv.

6.2. Author Contributions

Conceptualization, A.V.-M., J.F.-A., and N.S-G.; methodology, A.V.-C., A.V.-M., J.F.-A., N.C.-B., N.S.-G., and R.L.-E.; software, A.V.-M.; validation, N.S-G., and J.F.-A.; formal analysis, A.V.-M.; investigation, A.V.-C., J.F.-A., J.F.-A., and N.C.-B..; resources, A.V.-M., and N.C.-B.; data curation, A.V.-M..; writing—original draft preparation, A.V.-C., A.V.-M., J.F.-A., N.C.-B., N.S.-G., and R.L.-E.; writing—review and editing, A.V.-C., A.V.-M., J.F.-A., N.C.-B., N.S.-G., and R.L.-E.; visualization, A.V.-M.; supervision, , A.V.-M., and N.S-G.; project administration, J.F.-A., and N.C.-B..; funding acquisition, A.V.-M., N.C.-B., and N.S.-G. All authors have read and agreed to the published version of the manuscript.

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6.4. Ethics statement

6.4.1. Institutional Review Board Statement:

The study was conducted in accordance with the Declaration of Helsinki. This study was reviewed and approved by the Comité Ético Científico of the Universidad Central de Chile for a project funded by the National Agency for Research and Development (ANID). Approval Code: CEC 146/2023. The approval is valid for fieldwork from May 23, 2023, to March 31, 2026.

6.4.2. Informed Consent Statement:

Informed consent was obtained from all subjects involved in the study.

6.4.3. Conflicts of Interest:

The authors declare no conflicts of interest.

6.4.4. Clinical trial number:

Not applicable.

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Figures

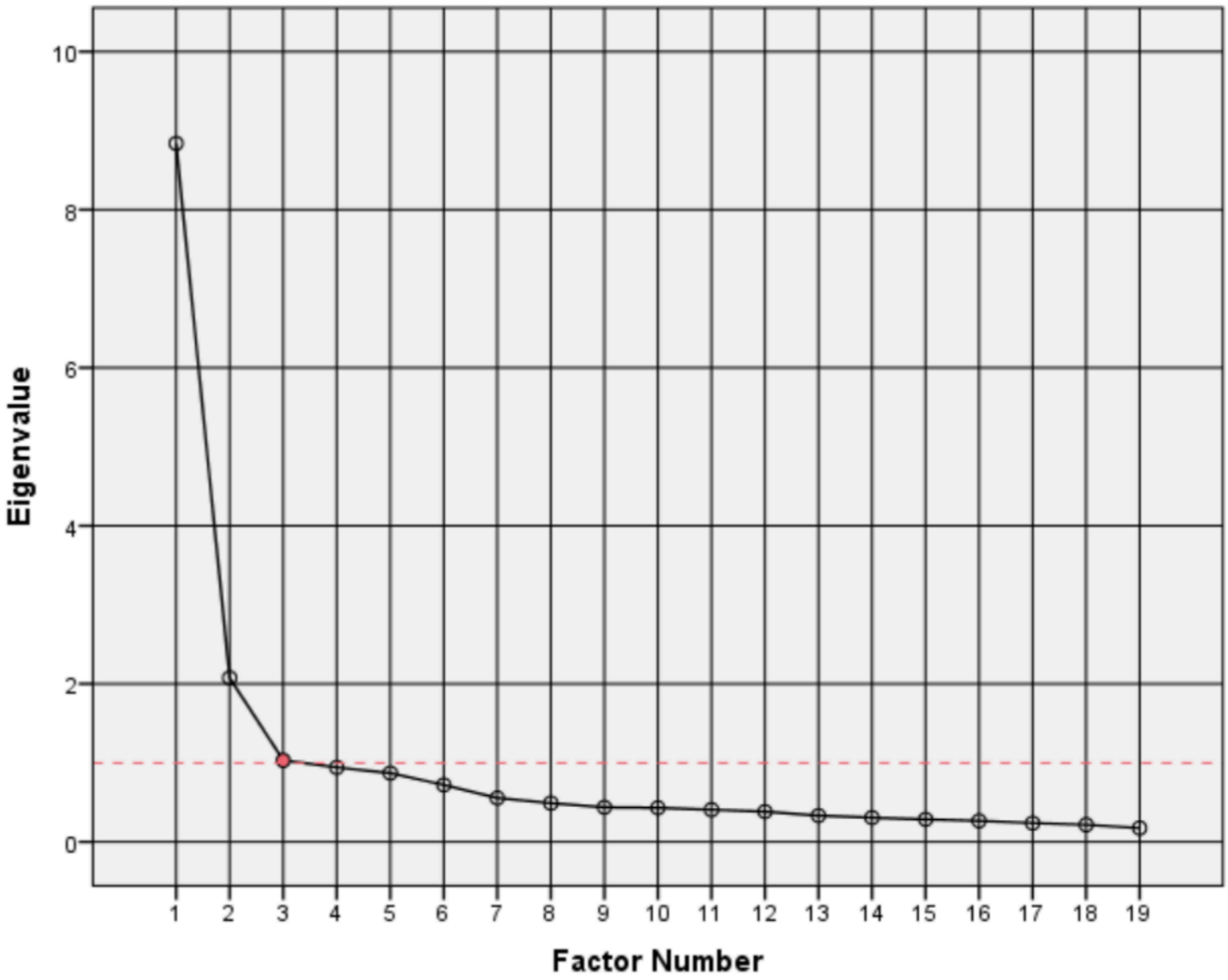
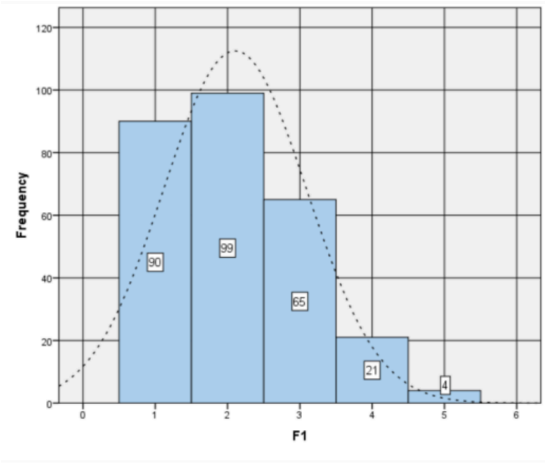


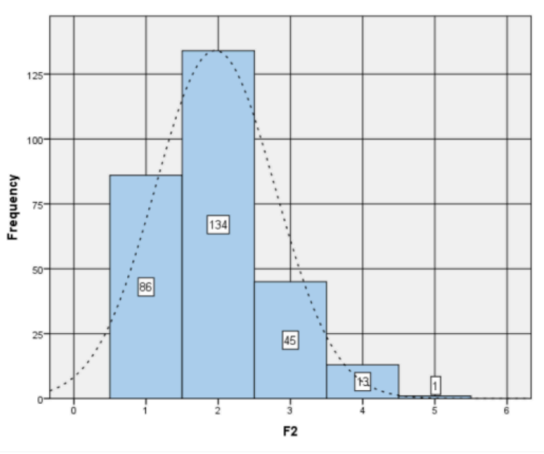
Figure 1

Scree plot.

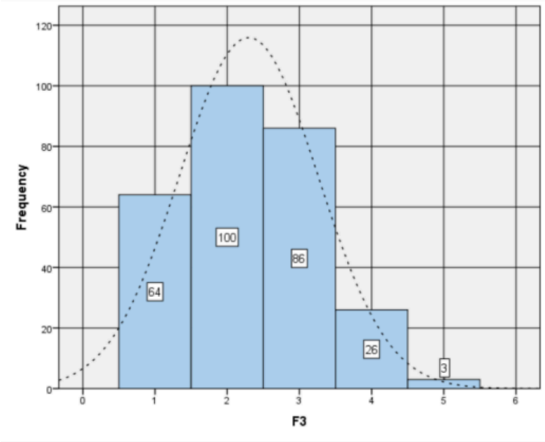
Elbow point indicated in red and clipping line (eigenvalue = 1) in red dashed line.



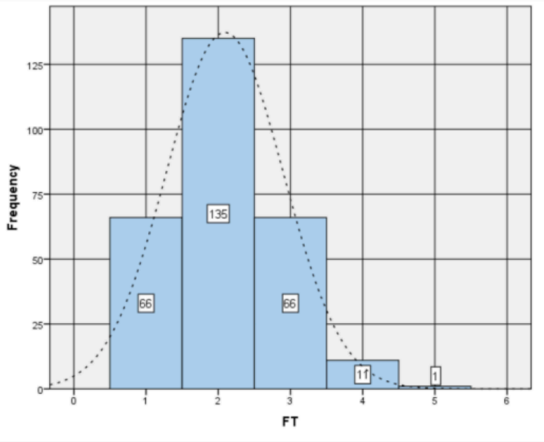
(**a**) Histogram F1. Lack of Social Support for the Use of Information Technologies.



(**b**) Histogram F2. Perceived Technological Overload and Complexity



(**c**) Histogram F3. Insufficient Institutional Support and Digital Culture



(**d**) Histogram FT. Technostress

Figure 2

Histogram of factors in TS4US scale. (**a**) F1, (**b**) F2, (**c**) F3, and (**d**) FT.

The blue bars represent the frequency distribution of the data grouped into class intervals, while the black dash curve depicts the theoretical normal distribution fitted to the observed data.

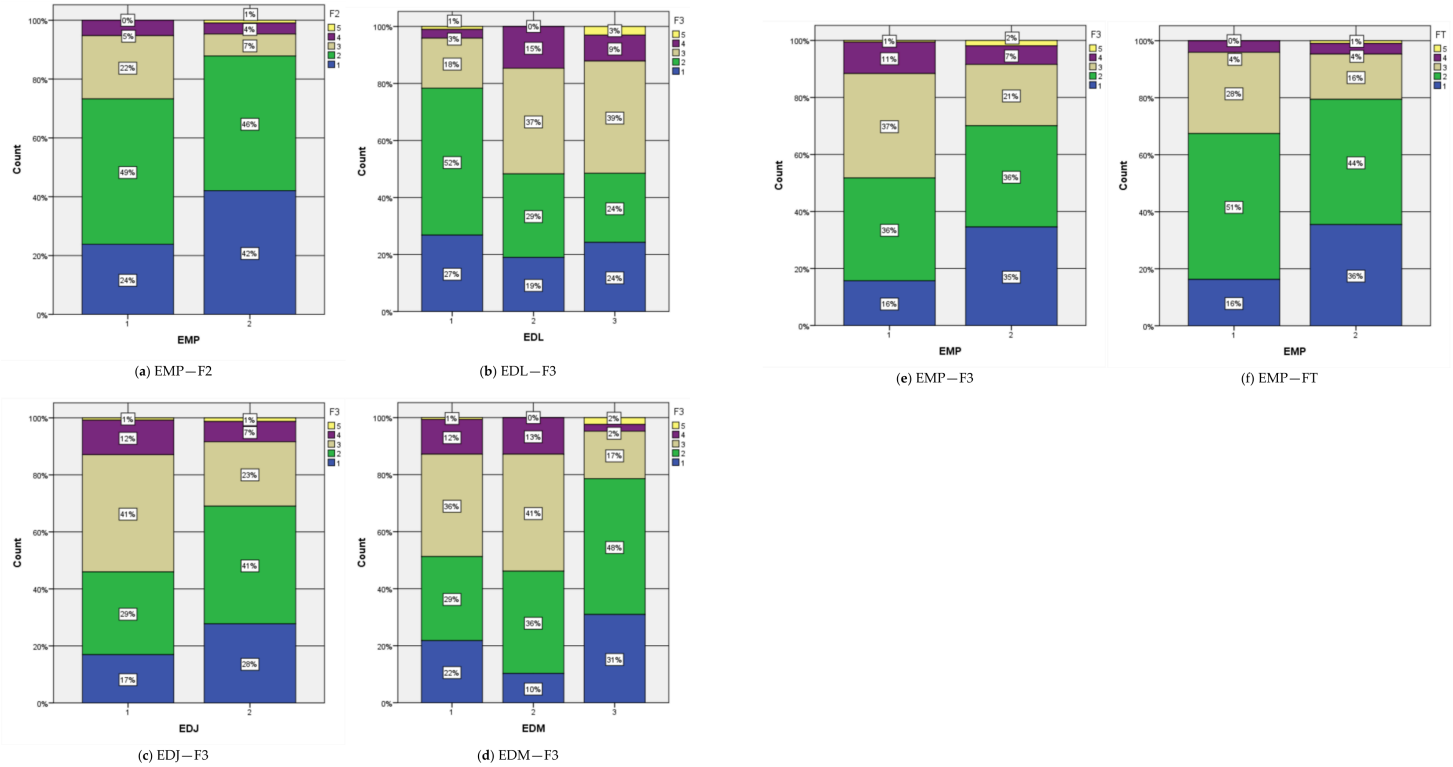


Figure 3

Correlations between (**a**) EMP—F2, (**b**) EDL—F3, (**c**) EDJ—F3, (**d**) EDM—F3, (**e**) EMP—F3, and (f) EMP—FT.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- TS4USCR.csv
- Appendix.docx