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Do technostress, support and engagement measures capture distinct constructs? A multi-site validity evaluation in Ghanaian Colleges of Education

Do technostress, support and engagement measures capture distinct constructs? A multi-site validity evaluation in Ghanaian Colleges of Education

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Abstract
This study evaluated whether questionnaire items written to measure technology-related demands (overload, complexity and intrusion), institutional and instructor support, technology-related strain, academic engagement and perceived academic progress represent distinct constructs among students of Ghanaian Colleges of Education, and how far the associations among these constructs can be interpreted. Students from nine randomly selected Colleges of Education (N = 845; voluntary participation) completed a cross-sectional online questionnaire with 38 five-point items. Ordinal confirmatory factor analysis, reliability and discriminant validity indices, nested alternative models, a response style model, clustering diagnostics and an exploratory structural equation model were estimated. The eight-factor model fitted inadequately (CFI = .881; RMSEA = .074). Overload, complexity and intrusion correlated .856 to .869, the two support factors .871, and engagement and progress .905; combining the three demand factors reduced CFI by only .007. Strain correlated most strongly with intrusion (r = .711) and complexity (r = .683), and engagement with instructor support (r = .784). In the structural model, four of eight expected paths had the expected sign and three were reversed, a pattern consistent with collinearity among the predictors. Students were not sampled at random, colleges contributed unequal numbers of students, and all data were self-reported at one time point. The item sets need revision before they are used to test demands-resources models with students of Colleges of Education. Colleges should treat technology-related demands as one combined burden and give priority to instructors' guidance and responsiveness when planning support for technology-supported learning.

Introduction

Colleges of Education in Ghana now run much of their teaching, communication and assessment through digital systems. Students use these systems for three broad purposes: communication (institutional email and academic messaging groups), access to learning content (learning-management systems, online-class platforms and digital libraries) and assessment and

administration (online assessment and student-information systems). The systems can widen access to materials and support independent study, but they also place demands on students who often study with a smartphone, on shared devices and with costly or unreliable connectivity (Aidoo & Chebure, 2024; Debrah et al., 2021).

Research on technostress shows that technology can create demands that relate to strain and lower productivity among employees (Ragu-Nathan et al., 2008; Tarafdar et al., 2007) and among university students (Upadhyaya & Vrinda, 2021; Wang et al., 2020). Study demands-resources (SD-R) theory places such demands alongside the resources that institutions and instructors provide (Bakker & Mostert, 2024; Lesener et al., 2020). Two gaps limit the use of this work in Ghanaian teacher education. First, studies of technology in Colleges of Education have described infrastructure and implementation problems (Aidoo & Chebure, 2024; Debrah et al., 2021) but have not measured technostress, strain or engagement among student teachers. Second, technostress measures were developed for employees, and it has not been shown that their dimensions remain distinct when the items are written for students in a low-resource setting. If the dimensions cannot be separated, path estimates that link one demand to strain or engagement cannot be interpreted, and decisions about which demand to address would rest on a measurement artefact.

The aim of this study was to evaluate whether 38 questionnaire items intended to measure eight technology-related constructs form distinct factors among students of nine Ghanaian Colleges of Education, and to determine how far the associations among those constructs that SD-R theory predicts can be interpreted given the measurement evidence. The study contributes item-level evidence on where the constructs overlap, tests of whether the overlap reflects response-style or institution membership, and an exploratory check of SD-R expectations bounded by that evidence.

The data come from the same survey as a companion study that classified students' open-ended recommendations (Amponsah et al., 2026, manuscript submitted for publication). The companion study analysed only the open-ended item (J2); the present study analyses only the 38 closed-ended items, and neither study reports results from the other. All 845 retained respondents met the self-reported age-confirmation eligibility criterion and were therefore used for this analysis.

The quantitative SEM sample was derived independently of the open-ended methodological-pilot sample; we did not use the 846 usable responses reported in the companion to define the SEM sample.

Technology-related demands among students

Technostress research conceptualises some technology characteristics as creators of stress rather than as neutral tools (Ayyagari et al., 2011; Ragu-Nathan et al., 2008; Tarafdar et al., 2007). In student settings, overload appears as the volume and pace of digital coursework, notifications and messages; complexity as the time and skill needed to learn platforms and solve technical problems; and intrusion as academic messaging and platform checking that extend into rest and family time. The items in this study follow these meanings (Appendix A). For example, TO3 concerns notifications that interrupt planned study time, TC3 concerns frequent platform updates, and TI2 concerns pressure to check academic messages outside planned study hours.

Ragu-Nathan et al. (2008) described five creators, of which this study retained three. Techno-insecurity, the fear of losing one's job to technology or to more skilled colleagues, has no direct counterpart for students. Techno-uncertainty, the constant change of systems, is partly represented by the complexity item on platform updates (TC3). This is why techno-insecurity and techno-uncertainty were left out.

There are also reasons to expect that the creators may not separate empirically. Tarafdar et al. (2007) and Ragu-Nathan et al. (2008) modelled the creators as first-order dimensions of a second-order technostress construct, which assumes that they share substantial common variance. In

student samples, the creators have shown different associations with outcomes: among first-year students at a South African university of technology, complexity was associated with lower academic commitment, uncertainty with higher commitment, and invasion with neither (Mangundu, 2023). Such dimension-specific differences can be interpreted only if the dimensions are measured distinctly. The present study therefore treats separability as a question to be tested and compares the three-factor representation with a single technology-demand factor and with second-order, bifactor, and exploratory alternatives.

Institutional and instructor support

Institutional and instructor support may provide important resources. Institutions may support students through access to devices, internet connectivity, training, technical assistance, and effective learning platforms. Instructors may assist students through guidance, responsiveness, clarification, and help with digital learning activities. Among students taking online courses, Saleem et al. (2024) found that support from instructors and support from the university each weakened the negative association between technostress and the quality of online learning. Whether students distinguish the two sources of support is less clear, and overlap among engagement-related and support-related measures has to be tested empirically (Amerstorfer & Freiin von Münster-Kistner, 2021; Zilvinskis et al., 2017).

Strain, academic engagement and perceived academic progress

Strain refers to psychological responses to stressors such as exhaustion, tension and frustration (Ayyagari et al., 2011); technostress research uses the term techno-strain when technology is the source (Salanova et al., 2013). Academic engagement has been defined as a positive state of vigour, dedication and absorption in study (Schaufeli et al., 2002) and as behavioural, emotional and cognitive involvement in learning (Fredricks et al., 2004). The engagement items in this study refer to participation, focus, time organisation, persistence and timely submission in technology-based tasks (Appendix A). They correspond to the behavioural strand described by Fredricks et al. (2004), restricted to technology-supported learning, and do not cover vigour, dedication or absorption; the construct is therefore labelled technology-related study engagement (engagement) in this paper. Perceived academic progress (progress) refers to students' judgements that they understand course material, keep up with requirements and meet their learning goals. Two of its four items (PP1 and PP3) concern understanding of, and confidence in, technology-mediated coursework, which is close to academic self-efficacy, a strong correlate of university performance (Richardson et al., 2012). Overlap between the engagement and progress items was therefore plausible before the data were analysed.

Technology-supported learning in Ghanaian Colleges of Education

Studies of Colleges of Education report poor connectivity, high data costs, inadequate equipment, limited technical support, and difficulties implementing online teaching and learning (Aidoo & Chebure, 2024; Debrah et al., 2021). These conditions may bear on each construct. Poor connectivity and high data costs lengthen the time needed to download materials and answer messages, which may add to overload, and push study tasks into whatever hours a connection is available, which may add to intrusion. Limited equipment and training make platforms harder to use (complexity). Where technical support is limited, institutional support is weaker and instructors may become students' main source of help with technology. The two studies cited describe infrastructure and implementation; neither measured technostress, strain or engagement.

Theoretical framework

SD-R theory proposes two processes (Bakker & Mostert, 2024; Lesener et al., 2020; Salmela-Aro & Upadyaya, 2014). In the health-impairment process, study demands increase strain, and strain reduces engagement. In the motivational process, resources increase engagement; resources may

also reduce strain, directly or by buffering demands, although job demands-resources research treats this link as weaker than the link between resources and engagement (Bakker & Demerouti,

2017). The theory also expects engaged students to perform better, which is why perceived progress was specified as an outcome of engagement.

These propositions gave eight directional expectations, specified before the models were estimated: technology-related overload (E1), complexity (E2) and intrusion (E3) relate positively to strain; institutional support (E4) and instructor support (E5) relate negatively to strain; strain relates negatively to engagement (E6); and institutional support (E7) and instructor support (E8) relate positively to engagement. Direct paths from demands to engagement were not specified, because SD-R places the effect of demands on engagement mainly through strain and because the sign of a direct path is uncertain when demands can be experienced as either challenges or hindrances (Tarafdar et al., 2019). Progress was regressed on strain and engagement only.

Figure 1 shows the specified model. Because the data are cross-sectional, the arrows express the direction assumed by the theory; the estimates are conditional associations and cannot establish temporal order. Whether the expectations can be evaluated depends on the measurement results: if the demand factors or the support factors are not distinct, their separate path coefficients cannot be interpreted. The measurement evaluation is therefore the primary analysis, and the structural model is reported as an exploratory check. Three research questions guided the study:

RQ1. Do the 38 items support eight distinct constructs, and do the demand, support, and engagement-progress factors show discriminant validity?

RQ2. Is the overlap among factors explained by item content, a common response-style or institution membership?

RQ3. Given the measurement evidence, how far do the associations among technology-related demands, support, strain and engagement agree with the SD-R expectations E1-E8?

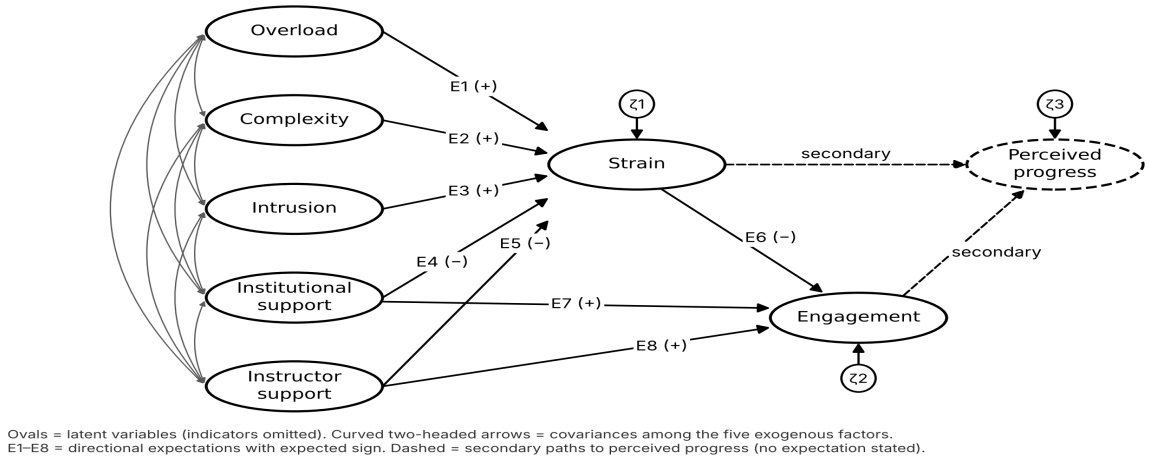


Figure 1: Specified model with the expected sign of each path

Note. Ovals denote latent variables; indicators are omitted (see Appendix A). Curved two-headed arrows denote the estimated covariances among the five exogenous factors; ζ denotes disturbances. Dashed paths to perceived progress are secondary. Arrows show the direction assumed by SD-R theory, not temporal or causal order.2.

Method

Design and participants

The study used a cross-sectional survey design. Of 874 submitted records, 845 met the two eligibility criteria: self-reported current registration as a student (item S1) and confirmation of being at least 18 years old (item S2). The 29 excluded records answered No to S1. Participants came from nine Colleges of Education, which contributed 353, 213, 140, 71, 36, 26, 2, 2, and 2 respondents; institutions are identified only by codes (Supplementary Table S9).

Recruitment and data collection

The questionnaire was administered online through Google Forms between 16 August and 17 September 2026. The nine colleges were selected at random from the list of public Colleges of Education in Ghana by simple random draw. Tutors in each selected college shared the questionnaire link with their students, and no incentive was offered. Participation was voluntary, and all participants gave electronic informed consent before starting the questionnaire. Participation differed widely across colleges, and three colleges contributed two respondents each. Because tutors distributed the link, the number of students who received it is not known, and a response rate cannot be calculated. The questionnaire had no attention-check items, so careless responding was screened statistically in the data screening section.

Instrument

The closed-ended section had 38 items (Appendix A): overload (TO1-TO4), complexity (TC1-TC4), intrusion (TI1-TI4), strain (TS1-TS7), institutional support (IS1-IS5), instructor support (INS1-INS5), engagement (AE1-AE5) and progress (PP1-PP4). Each item had five response options coded 1 to 5 and labelled Each item had five response options coded 1 to 5 and labelled 1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree. All items within a construct were worded in the same direction, and none were reverse-keyed. The items were developed by the research team for this study. The items were reviewed by experts before use. Item J1 asked for the student's overall grade band and was used only descriptively. Item J2 was an open-ended question inviting recommendations; it was analysed in the companion study and not here. The 38 items had nine missing values, all on TI4 (1.07% of respondents).

Data screening

Duplicates were defined as records identical on all closed-ended demographic, study, device, and item responses; six candidate records in three groups were found. Following recommendations for detecting careless responding (Curran, 2016; Meade & Craig, 2012), we flagged records with identical responses on all 38 items (constant responding, $n = 54$) and records with a within-person response variance below 0.10 (near-zero variance, $n = 13$). The 73 flagged records did not overlap. They were retained in the primary analysis, and their influence was assessed by re-estimating the models without them.

Analysis

Analyses used lavaan 0.6-17 (Rosseel, 2012) and semTools 0.5-6 in R 4.3.3. Items were treated as ordered categorical, and models were estimated with robust diagonally weighted least squares (WLSMV), which performs better than robust maximum likelihood with five-category items (Li, 2016; Rhemtulla et al., 2012). Factors were identified by fixing their variances to 1 (std.lv = TRUE). Missing values were handled pairwise, which assumes that they are missing completely at random; with nine missing values on one item, the assumption has little influence on the estimates.

Phase 1: measurement evaluation (RQ1 and RQ2). We estimated the eight-factor confirmatory factor analysis (CFA) and judged fit against CFI and TLI ≥ .95, RMSEA ≤ .06, and SRMR ≤ .08 (Hu & Bentler, 1999); CFI and TLI values below .90 were regarded as inadequate. Reliability was assessed with ordinal alpha and composite reliability (CR), and convergent validity with average variance

extracted (AVE ≥ .50; Fornell & Larcker, 1981). Discriminant validity was assessed with the Fornell-Larcker criterion, latent correlations, and the heterotrait-monotrait ratio (HTMT; thresholds .85 and .90; Henseler et al., 2015). HTMT percentile intervals were obtained from 2,000 bootstrap draws resampled within institutions, with failed draws logged. We compared the eight-factor model with four restricted alternatives (one technology-demand factor, one support factor, one engagement-progress factor, and a single-factor). Merging factors is equivalent to fixing their correlation at 1, so these models are nested in the eight-factor model and were compared with scaled chi-square difference tests; a decrease in CFI larger than .01 was treated as meaningful (Cheung & Rensvold, 2002). For the demand items, we also estimated a second-order technostress factor, a bifactor model (Reise, 2012), and an exploratory structural equation model (ESEM) with geomin rotation (Marsh et al., 2014). For RQ2, we examined item content, modification indices and residual correlations; added a random-intercept factor to the eight-factor model to represent acquiescence (Maydeu-Olivares & Coffman, 2006; Podsakoff et al., 2003); and tested measurement invariance across sex. Finally, the sample was split at random: exploratory factor analysis with parallel analysis was run in one half and the CFA in the other.

Clustering. Students were nested in nine institutions of very unequal size. Multilevel structural equation models give unreliable estimates with so few clusters (McNeish & Stapleton, 2016), so we computed intraclass correlations (ICCs) and design effects, re-estimated the models without the three institutions that contributed two respondents each, entered institution as a set of fixed-effect dummy variables, and compared conventional with cluster-robust standard errors.

Phase 2: exploratory structural check (RQ3). The model in Figure 1 was estimated with the eight-factor measurement model and with a reduced model that combined the three demand factors. Collinearity among the five exogenous factors was assessed from their latent correlation matrix: approximate variance inflation factors were 4.18 to 5.72, and the condition number was 30.86, values above the commonly used thresholds of 5 and 30. Because Phase 1 showed that neither the demand factors nor the support factors were distinct, the model was also estimated with a parsimonious four-factor measurement model (one technology-demand factor, one support factor, strain and engagement; progress omitted). Indirect associations were computed as products of paths. To examine the reversed signs, we estimated models with one predictor at a time and with predictors entered sequentially, and models with study-mode, device-access difficulty, sex, and year of study as covariates. Sensitivity analyses excluded, in turn, constant responders, near-zero-variance responders, duplicate candidates, all 73 flagged records, and the largest institution.

Sample size. With 637 degrees of freedom and N = 845, the power of the test of close fit (RMSEA = .05 against RMSEA = .08) exceeds .999 (MacCallum et al., 1996). The eight-factor CFA has 218 free parameters (38 loadings, 152 thresholds and 28 factor correlations), giving 3.9 respondents per parameter. The sample was therefore adequate for model-level tests, although the large number of thresholds and the unequal clusters limit the precision of individual estimates.

Results

Participants

Table 1 describes the sample. Most participants were male (69.35%), in their first-year (47.57%), studied mostly face-to-face (80.47%), and used a smartphone as their main device (92.07%); 9.70% reported that access to a device was often difficult. Age: mean age =23.34, SD-29; range=29.

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Table 1: Participant characteristics (N = 845)

Characteristic	Category	n (%)
Sex	Female	259 (30.65%)
	Male	586 (69.35%)
Programme level	Year 1	402 (47.57%)
	Year 2	181 (21.42%)
	Year 3	116 (13.73%)
	Year 4 or above	146 (17.28%)
Main study-mode	Mostly face-to-face	680 (80.47%)
	Blended/hybrid	136 (16.09%)
	Mostly online/distance	26 (3.08%)
	Other/unclear	3 (0.36%)
Main device	Smartphone	778 (92.07%)
	Laptop	46 (5.44%)
	Tablet	10 (1.18%)
	Desktop computer	7 (0.83%)
	Shared/public computer	3 (0.36%)
	No device available	1 (0.12%)
Device-access	Own device	662 (78.34%)
	Shared or institutional device	101 (11.95%)
	Access often difficult	82 (9.70%)
Age (years)	M (SD); range	23.34(3.44);29

Note. All variables had 845 valid responses. Open-text entries were harmonised for description only:"online" was grouped with mostly online/distance;"iPhone" and"Mobile phone" entries are recorded as Smartphone and provide a combined total of 650 with smartphone;" No device available for me" with no device available; and institutional, public and shared-device responses with shared or institutional device. Three study-mode entries could not be classified. Percentages describe this sample only.

Measurement model and discriminant validity (RQ1)

The eight-factor CFA fitted inadequately: $\chi^2(637) = 3570.074$, CFI = .881, TLI = .869, RMSEA = .074, 90% CI [.071, .076], SRMR = .061. CFI and TLI were below .90, whereas SRMR was within the conventional limit. Item means ranged from 2.38 to 3.80 and standard deviations from 1.09 to 1.36 (Supplementary Table S13). Standardised loadings ranged from .560 (TO1) to .905 (AE2). Ordinal alpha and CR exceeded .80 for every construct except overload, and AVE exceeded .50 for every construct except overload (AVE = .415; Table 2).

Only strain met the Fornell-Larcker criterion (Table 2). Five HTMT point estimates exceeded .85: overload-complexity (.874), overload-intrusion (.886), complexity-intrusion (.875), institutional-instructor support (.880), and engagement-progress (.914); the corresponding latent correlations were .867, .856, .869, .871, and .905. In the original 200-draw bootstrap, only the engagement-progress interval lay wholly above .85 ([.877, .947]).

Table 3 compares the eight-factor model with the alternatives. Combining the three demand factors reduced CFI by .007, below the .01 criterion, so the three demand factors could not be distinguished empirically. Combining the two support factors reduced CFI by .011 and combining engagement with progress by .012, and the single-factor model fitted far worse (ΔCFI = .349). Excluding the progress factor changed no structural coefficient by more than .025 and left the demand and support overlap unchanged (Supplementary Table S16).

Table 2: Measurement model: reliability, convergent and discriminant validity (eight-factor CFA)

Construct	Items	Loadings	Ord. α	CR	AVE	√AVE	Highest latent r	Highest HTMT
Overload	TO1-TO4	.560-.710	.728	.738	.415	.644	.867 (Complexity)	.886 (Intrusion)
Complexity	TC1-TC4	.721-.789	.834	.840	.568	.754	.869 (Intrusion)	.875 (Intrusion)
Intrusion	TI1-TI4	.700-.744	.813	.819	.531	.729	.869 (Complexity)	.886 (Overload)
Strain	TS1-TS7	.707-.792	.885	.898	.556	.746	.711 (Intrusion)	.734 (Intrusion)
Institutional support	IS1-IS5	.740-.818	.880	.883	.601	.775	.871 (Instructor)	.880 (Instructor)
Instructor support	INS1-INS5	.844-.872	.931	.935	.741	.861	.871 (Institutional)	.880 (Institutional)
Engagement	AE1-AE5	.783-.905	.929	.932	.734	.857	.905 (Progress)	.914 (Progress)
Progress	PP1-PP4	.835-.904	.921	.924	.752	.867	.905 (Engagement)	.914 (Engagement)

Note. Loadings are standardised. CR = composite reliability; AVE = average variance extracted. The Fornell-Larcker criterion is met when √AVE exceeds the construct's highest latent correlation. HTMT = heterotrait-monotrait ratio. Item-level loadings, thresholds and descriptives are in Supplementary Tables S1, S8 and S13.

Table 3: Comparison of alternative measurement models

Model	χ^2 (df)	CFI	TLI	RMSEA [90% CI]	SRMR	ΔCFI
Eight-factor (comparator)	3570.074 (637)	.881	.869	.074 [.071, .076]	.061	—
One technology-demand factor	3648.702 (650)	.874	.863	.075 [.073, .078]	.064	.007
One support factor	3756.452 (644)	.870	.858	.077 [.074, .079]	.063	.011
Engagement and progress combined	3677.892 (644)	.869	.857	.077 [.074, .079]	.062	.012
Single-factor	16693.191 (665)	.532	.506	.143 [.141, .145]	.162	.349

Note. All models were estimated with WLSMV; χ^2 values are scaled and shifted. $\Delta\chi^2$ = scaled chi-square difference test against the eight-factor model; ΔCFI = CFI of the eight-factor model minus CFI of the alternative. The four-factor model omits the progress items and is therefore not nested in the eight-factor model.

Sources of overlap (RQ2)

Item content (Appendix A) shows overlap across constructs. TO3 (notifications interrupt planned study time) and TO4 (expected to respond to messages quickly) are close to TI2 (pressure to check messages outside planned study hours). IS1 and INS1 both concern clear guidance on technology, and IS2 and INS3 both concern timely help. TS6 (harder to concentrate) mirrors AE2 (remain focused), TO1 (difficult to keep up with academic tasks) mirrors PP2 (keeping up with requirements), and TC4 (worry about lacking the skills) is the reverse of PP3 (confidence in performing well). Strain correlated positively with institutional support (r = .362), instructor support (r = .313), engagement (r = .284) and progress (r = .298) (Supplementary Table S2). Because every item in a construct was keyed in the same direction, these correlations could reflect acquiescence or general exposure to technology.

Exploratory structural check (RQ3)

The eight-factor structural model fitted much like the CFA: $\chi^2(645) = 3630.106$, CFI = .878, TLI = .867, RMSEA = .074, 90% CI [.072, .077], SRMR = .062. Table 4 evaluates each expectation. Four estimates had the expected sign (E2, E3, E5, and E8). Three were opposite to expectation: overload → strain (E1, β = −.258), institutional support → strain (E4, β = .456) and strain → engagement (E6, β = .078). One had the expected sign but a confidence interval that included zero (E7, β = .048, 95% CI [−.056, .152]). The model accounted for 57.4% of the variance in strain and 68.2% in engagement.

The reversed signs have two different sources (Supplementary Table S2). Overload and instructor support correlated positively with strain at the bivariate level (*r* = .624 and .313), so their negative coefficients are sign reversals produced by conditioning on highly correlated predictors. Institutional support and engagement were already positively correlated with strain (*r* = .362 and .284), so these positive coefficients are present in the bivariate data and cannot be attributed to suppression. Entered one at a time, each predictor was positively associated with strain (latent *r* = .624 for overload, .683 for complexity, .711 for intrusion, .362 for institutional support and .313 for instructor support). Standardised regression weights computed from the latent correlation matrix of the eight-factor CFA show where the overload coefficient changes sign: .624 with overload alone, .128 after complexity was added, −.085 after intrusion, −.215 after institutional support and −.221 after instructor support. The sign therefore reverses once the other two demand factors, with which overload correlates .856 to .867, are held constant. These weights come from the CFA correlations and differ slightly from the SEM estimates, which re-estimate the measurement model.

The unstandardised indirect products through strain were positive for complexity (0.030, 95% CI [0.005, 0.055]) and intrusion (0.054, [0.013, 0.096]) and indistinguishable from zero for overload (−0.031, [−0.068, 0.006]) (Supplementary Table S5). Their positive sign follows from the positive strain → engagement path, which is opposite to E6.

Table 4: Structural estimates and evaluation of the expectations E1-E8

Path	Expected	Eight-factor β [95% CI]	Evaluation	One demand factor β
Panel A. Specified model (Figure 1)				
Overload → Strain	E1 (+)	−.258 [−.507, −.010]	Opposite	—
Complexity → Strain	E2 (+)	.352 [.176, .527]	Consistent	—
Intrusion → Strain	E3 (+)	.595 [.414, .775]	Consistent	—
Technology-demand → Strain	—	—	—	.696
Institutional support → Strain	E4 (−)	.456 [.268, .644]	Opposite	.315
Instructor support → Strain	E5 (−)	−.332 [−.506, −.158]	Consistent	−.267
Strain → Engagement	E6 (−)	.078 [.025, .130]	Opposite	.075
Institutional support → Engagement	E7 (+)	.048 [−.056, .152]	Expected sign; CI includes 0	.062
Instructor support → Engagement	E8 (+)	.758 [.669, .846]	Consistent	.745
Strain → Progress	secondary	.024 [−.014, .062]	—	.025
Engagement → Progress	secondary	.929 [.910, .947]	—	.928
Overload → Strain → Engagement (B)	—	−0.031 [−0.068, 0.006]	—	—
Complexity → Strain → Engagement (B)	—	0.030 [0.005, 0.055]	—	—
Intrusion → Strain → Engagement (B)	—	0.054 [0.013, 0.096]	—	—
R^2 Strain; Engagement		.574; .682		
CFI; RMSEA		.878; .074		.871; .076
Panel B. Parsimonious four-factor model	Expected	Four-factor β [95% CI]	+ institution fixed effects (n = 839)	+ random intercept / + covariates

Note. β = standardised coefficient with 95% delta-method confidence interval. Intervals and p values do not adjust for clustering; results with institution fixed effects and with cluster-robust standard errors are given in Panel B and the sensitivity analyses. Panel A, one-factor demand column: the three demand factors are combined into one technology-demand factor (β = .696 for technology-demand → strain). Paths to progress are secondary because engagement and progress were not distinct (r = .905). Complete unstandardised estimates are in Supplementary Table S4.

Sensitivity analyses

Removing flagged records changed fit little (CFI = .868 without all 73 flagged records; Supplementary Table S3). Instructor support → engagement (β = .726 to .774) and institutional support → strain (β = .321 to .456) kept their signs in every analysis (Supplementary Table S4). The strain → engagement path did not hold: β = .053 (p = .074) without constant responders and β = .049 (p = .111) without all flagged records. Overload → strain could not be distinguished from zero without duplicate candidates (β = −.228, p = .074) or without the largest institution (β = −.174, p = .207), and instructor support → strain could not be distinguished from zero without the largest institution (β = −.175, p = .079); that model also fitted worse (CFI = .839, N = 492). The indirect products for complexity and intrusion could not be distinguished from zero without constant responders (p = .108 and .096) or without all flagged records (p = .145 and .134; Supplementary Table S5).

Discussion

The 38 items did not support eight distinct constructs. In these data, the three technostress creators, the two sources of support, and engagement and progress each behaved as a single construct, and the overall fit of the eight-factor model was inadequate. Strain was the only construct that met the Fornell-Larcker criterion, and the demand factors were clearly distinct from the support factors (latent r = .305 to .479). Of the eight SD-R expectations, four were consistent with the data, three were reversed, and one could not be distinguished from zero. The reversal for overload (E1) arose from collinearity among the predictors, whereas the reversals for institutional support (E4) and strain → engagement (E6) were already present in the bivariate correlations.

The high overlap among the technostress creators is consistent with the way the creators were first modelled, as facets of one second-order construct (Ragu-Nathan et al., 2008; Tarafdar et al., 2007). Students' technology demands come from a small set of platforms and messaging groups, which may make overload, complexity and intrusion harder to separate than in workplaces. Mangundu (2023) reported different associations for different creators among South African first-year students; the present results suggest that such differences should be checked against the discriminant validity of the measures before they are interpreted. The strong associations of the demand factors with strain (r = .624 to .711) agree with studies that link technostress to poorer academic outcomes among university students (Upadhyaya & Vrinda, 2021; Wang et al., 2020).

The support results agree with Saleem et al. (2024), who found that both instructor and university support mattered for students' online learning. Students in the present sample did not separate the two sources, possibly because instructors deliver much of the technical guidance in colleges with few technical staff. The positive association of institutional support with strain is not what SD-R predicts (Bakker & Mostert, 2024). One explanation is exposure: students who use more digital systems may encounter both more support and more strain. A second is acquiescence, since all items in each construct were keyed in the same direction (Podsakoff et al., 2003). The random-intercept model tests the second explanation in the sources overlap section; the first could not be tested because the questionnaire did not measure frequency of technology-use.

The small positive association between strain and engagement departs from the negative association found in demands-resources research with students (Salmela-Aro & Upadyaya, 2014), and it did not survive the removal of flagged records. Tarafdar et al. (2019) distinguish techno

eustress from techno-distress; students who engage more with technology-based tasks may also report more strain because they spend more time on them. The overlap between engagement and progress is consistent with the item content. Two of the four progress items concern understanding and confidence, which are close to academic self-efficacy (Richardson et al., 2012), and the engagement items describe behaviour in technology-based tasks; neither set measures the vigour, dedication and absorption described by Schaufeli et al. (2002).

Implications

Theoretical. Tests of SD-R with technology-specific measures require demand and resource measures that are empirically distinct; otherwise the paths for individual demands or resources cannot be interpreted. In this population, a single technology-demand factor, or a second-order technostress factor, is the more defensible representation.

Methodological. Researchers who adapt technostress measures for students should report response anchors and item sources, include reverse-keyed and attention-check items, and avoid demand items that repeat outcome content ("keeping up" appears in both an overload item and a progress item). Discriminant validity should be tested with HTMT intervals and nested model comparisons before structural paths are estimated, and where few institutions take part, institution should be built into the sampling design.

Practical. The latent correlations, which do not depend on separating the demand dimensions, offer some guidance to Colleges of Education. Strain was most closely associated with intrusion (r = .711) and complexity (r = .683), and engagement with instructor support (r = .784). Colleges could set expectations about when students must respond to academic messages, announce platform changes in advance, provide platform orientation at the start of each semester, and help instructors give clear directions and timely responses on technology-based tasks. The 9.70% of students who reported that access to a device was often difficult, and the 11.95% who relied on shared or institutional devices, indicate where access support is needed. These suggestions rest on cross-sectional associations and should be evaluated before they are adopted as policy.

Limitations and future research

Although the colleges were selected at random, students chose whether to take part, and the colleges contributed very unequal numbers, so the findings describe this sample and may not generalise to all Colleges of Education. All data were self-reported at one time point, which allows for common-method bias and prevents conclusions about temporal order. The verbal response anchors and the sources of the items were not documented, which limits comparison with other studies. The questionnaire had no reverse-keyed items, attention checks, or measure of technology-use intensity. Future studies should revise the items through cognitive interviews with student teachers, recruit enough institutions with planned sample sizes for multilevel models, measure exposure to technology directly, and use externally recorded academic outcomes in place of perceived progress.

Conclusion

The items analysed here measure technology-related strain as a distinct construct, but they do not separate the three technostress creators, institutional from instructor support, or engagement from perceived progress among students of Ghanaian Colleges of Education. The study contributes item-level evidence on where these constructs overlap, tests of two explanations for the overlap, and a check of SD-R expectations bounded by the measurement evidence. Associations between individual demands or supports and strain or engagement should not be interpreted from these measures. A combined technology-demand construct and a combined support construct are more defensible for future work in this setting, and the associations of intrusion and complexity with strain, and of instructor support with engagement, indicate where colleges can act first.

Ethics approval
The University of Cape Coast Institutional Review Board approved the study on 10 January 2026 (IRB/2026/226). Participants provided electronic informed consent by clicking the relevant confirmation before completing the questionnaire. This approval covers both the present and companion papers, and the data collection followed the approved protocol. Permission to approach students was obtained from the principal of each participating College of Education.

Consent to participate
All participants provided electronic informed consent before beginning the questionnaire. Participation was voluntary.

Data protection
The closed-ended analytic dataset used for the SEM contained no direct personal identifiers, including names, telephone numbers, email addresses, or IP addresses. The open-ended J2 responses were excluded from the analytic dataset because some may contain identifying information. Institutions are identified by codes in the article and the Supplementary Information, and institutions with fewer than 30 respondents are merged in any public release. The study complied with the Data Protection Act, 2012 (Act 843) of Ghana.

Data availability
The analysis scripts (including the re-analysis script for this revision), session information, codebook, item wording, and an anonymised dataset, in which institutions are replaced by codes and institutions with fewer than 30 respondents are merged, are deposited in Zenodo (Akaadom et al., 2026).

Statistical declaration
These statistical calculations were done by the research team, and the statistical calculations and their interpretation are found in the supplementary information.

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Do technostress, support and engagement measures capture distinct constructs? A multi-site validity evaluation in Ghanaian Colleges of Education

Appendix A. Item wording

Verbatim wording from the questionnaire (moved from Supplementary Table S7). Response options were coded 1 to 5 and labelled 1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree. All items within a construct were worded in the same direction.

Construct	ID	Wording
Overload	TO1	Digital systems used for my studies make it difficult to keep up with all my academic tasks.
	TO2	Using academic technologies requires me to manage too many activities at the same time.
	TO3	Coursework notifications and messages interrupt the study time I have planned.
	TO4	I feel expected to respond to academic messages more quickly than I can comfortably manage.
Complexity	TC1	I need a great deal of time to learn how to use required academic technologies.
	TC2	I find it difficult to solve technology problems that arise during my studies.
	TC3	Frequent updates or changes to learning platforms make my academic work harder.
	TC4	I worry that I do not have the skills needed to use course technologies effectively.
Intrusion	TI1	Academic technology makes it difficult for me to switch off from studying during my personal time.
	TI2	I feel pressure to check academic platforms or messages outside the study hours I have planned.
	TI3	Technology-related study demands intrude on my rest, family, social, or leisure time.
	TI4	Even when I am not studying, I continue to think about technology-related academic tasks.
Strain	TS1	Technology used for my studies leaves me mentally exhausted.
	TS2	I feel tense when I have to use academic technology for my coursework.
	TS3	Technology-related problems make me feel frustrated while I am studying.
	TS4	I feel overwhelmed by the digital requirements of my studies.
	TS5	I find it difficult to stay calm when an academic platform does not work as expected.
	TS6	Technology use for study makes it harder for me to concentrate on my academic work.
	TS7	After using course technologies for study, I often feel drained.
Institutional support	IS1	My institution provides clear guidance on the academic technologies students are expected to use.
	IS2	I can obtain technical assistance without unreasonable delay when I need it.
	IS3	The institutional digital systems I need for study are generally reliable.
	IS4	My institution provides adequate opportunities to build digital-learning skills.
	IS5	When I have a technology-access problem, I know where to seek support at my institution.
Instructor support	INS1	My instructors give clear directions on how to use technology for course activities.
	INS2	My instructors explain technology-based academic tasks before expecting students to complete them.
	INS3	My instructors respond to technology-related questions within a reasonable time.
	INS4	When technical problems occur, my instructors provide reasonable guidance or alternatives.
	INS5	My instructors use digital communication channels in a clear and predictable way.
Engagement	AE1	I participate actively in learning activities that use academic technology.
	AE2	I remain focused when completing technology-based study tasks.

	AE3	I organise my time so that I can complete digital learning activities.
	AE4	I persist with academic tasks when I encounter technology-related difficulties.
	AE5	I usually complete and submit technology-based academic work by the required deadline.
Progress	PP1	I understand course material delivered through digital technologies.
	PP2	I am keeping up with the academic requirements of my programme.
	PP3	I am confident in my ability to perform well in technology-mediated coursework.
	PP4	I am meeting the learning goals I set for this semester.