CROSS-CULTURAL ADAPTATION OF THE STUDENTS' SUSTAINABLE ENGAGEMENT IN E-LEARNING SCALE INTO TURKISH: AN EVALUATION OF PSYCHOMETRIC PROPERTIES

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ABSTRACT

This study aims to adapt the six-factor "Students' Sustainable Engagement in E-Learning Scale" (SSE-eL-S) developed by Lee et al. (2019) from English to Turkish language and culture and validate its psychometric properties to be conducted as a reliable research instrument. It was designed with a three-step approach involving translation and cross-cultural adaptation, pre-testing, and field testing. First, the SSE-eL-S was cross-culturally adapted to the Turkish language and culture with forward and backward translation as well as functional, conceptual, and linguistic assessment. Subsequently, in the pre-testing phase, the English and Turkish versions of the scale were administered to a sample of 43 university students, and paired sample t-tests with Pearson correlation analyses were conducted to ensure content equivalence and reliability. In the field testing phase, data were collected from two independent student samples. Exploratory factor analysis and internal consistency analysis were applied to the first group (n=226), resulting in a four-factor structure. Confirmatory factor analysis was subsequently performed on the second group (n=206) to validate the factor structure. The model exhibited acceptable fit indices (χ^2/df=2.065; CFI=0.934; IFI=0.935; RMSEA=0.072), and internal consistency coefficients ranged between 0.799 and 0.936. Furthermore, convergent and discriminant validity were confirmed through AVE, CR, MSV, and Fornell-Larcker analyses. The finalized Turkish version consisted of 20 items categorized into four factors: psychological motivation, peer collaboration, cognitive problem-solving, and learning management. The adapted SSE-eL-S provides a reliable and valid tool to measure sustainable student engagement in e-learning environments in higher education.

Keywords: Student engagement, e-learning, scale adaptation, higher education, sustainability.

INTRODUCTION

E-learning has predominantly become a part of undergraduate students' experiences in higher education settings in the post-pandemic period. As the instructional medium, e-learning has been preferred by universities due to its benefits in convenience and flexibility (Dewi, 2010; Jabeen et al., 2015; Singh, 2024), cost-efficiency (Kumaravel & Manoharan, 2010), technology-driven approach to learning (Dong Chiong & Fu, 2020; Singh, 2024), and student learning outcomes (Amane et al., 2023). However, engaging students in online learning settings, as a critical component in e-learning, has been challenging (Vermeulen & Volman, 2024), and specific attention should be taken to investigate student engagement in online learning because of the limitations of e-learning in terms of engagement, communication, and interactions with peers, instructors, and institutional resources (Meyer, 2014; Shah & Barkas, 2018).

Student engagement refers to "how involved or interested students appear to be in their learning and how connected they are to their classes, their institutions, and each other" (Axelson & Flick, 2010, p. 38). Conceptually, it involves cognitive, behavioral, and affective engagement in educational settings (Franklin-Guy & Schnorr, 2016; Trowler, 2013; Verdeflor et al., 2024). Cognitive engagement represents the mental effort and strategies that learners employ to understand and master the content, and it encompasses the integration of various learning strategies, maintaining motivation during the learning process (Richardson & Newby, 2006). As Karatas et al. (2014) indicated, motivation and learning strategies are closely linked in university students' learning processes. Because of its relationship with critical thinking, problem-solving, and independent learning skills, cognitive engagement is a significant requirement in e-learning settings to ensure an active learning environment (Elsayary, 2023). Effective cognitive engagement requires meaningful interaction with the learning content that can be facilitated through well-designed e-learning platforms encouraging active learning and critical thinking (Da Silva Gomes De Oliveira & Nunes, 2011; Hussin et al., 2019).

Behavioral engagement refers to "[students'] effort, persistence, attentiveness, and participation" in learning (Benabbes et al., 2023, p. 70914). In e-learning, it involves participation in academic activities, including attending classes, completing assignments, tasks, tests and quizzes, and engaging in discussions on the learning platforms (Nawi et al. 2021; Trowler, 2013). Behavioral engagement in e-learning settings can be influenced by several factors, such as the quality of digital content (Cholisoh et al., 2024), interactive and adaptive tools (Poondej & Lerdpornkulrat, 2019), and feedback and support mechanisms (Ali Krishan et al., 2023; Cholisoh et al., 2024). Accordingly, to increase behavioral engagement in e-learning, high-quality digital content is necessarily integrated into interactive and adaptive tools on the platforms that measure student performance based on their individual needs.

Affective engagement refers to students' emotional investment in learning, such as their motivation, interest, satisfaction, and sense of belonging (D'Errico et al., 2016; Franklin-Guy & Schnorr, 2016). It is affected by both positive and negative emotions experienced by students in e-learning environments; thus, negative emotions across e-learning activities, particularly in synchronous classes, need to be navigated with appropriate implementations by instructors (D'Errico et al., 2016). Students involved in e-learning need to develop positive emotions about their learning process, whether synchronous or asynchronous, and learn how to regulate the adverse emotional drawbacks to increase their affective engagement. As indicated by Daher et al. (2021), communication channels used in synchronous lectures, discussion forums, and assignments help students in higher education develop more positive emotions, and their affective engagement is influenced positively by different types of interactivities in digital learning environments.

As a multidimensional concept, student engagement is an extensive phenomenon including cognitive, behavioral, and affective perspectives in learning, which can be challenging in online learning environments. These perspectives within the concept of engagement are dynamic in human nature, and maintaining active student involvement may be more challenging throughout the entire term or within the period the online course is taken. On the other hand, sustainable student engagement in e-learning involves maintaining and improving students' active involvement in online learning activities over time and ensures continued participation and positive learning outcomes (Huda et al., 2022; Pandita & Kiran, 2023; Susanti et al., 2024).

Another significant issue regarding student engagement in e-learning is its measurement depending on the capabilities of the platforms, the online teaching abilities of instructors as well as the quality of digital content offered to students in higher education. Basically, within the limitations of learning management systems (LMS) configured by universities, the data obtained from LMS' tracking systems can be evaluated based on student log-ins, usage patterns, activity performance, etc. (Ahmadi et al., 2023; Holmes, 2018; Hussain et al., 2018). Nevertheless, regarded as part of data analytics, LMS data, despite high-capacity platforms, may not capture real-time engagement covering all three perspectives of cognitive, behavioral, and affective engagement (Balasooriya et al., 2018; Santoni et al., 2023). Hence, online scales can be more functional and effective in measuring student engagement in e-learning.

Notably, the scales measuring student engagement have been generally designed for face-to-face classes rather than e-learning environments (e.g., Heilporn et al., 2024; Schaufeli et al., 2002; Zhoc et al., 2019). On the other hand, the scales measuring student engagement in e-learning are limited in university settings that are expected to be sustainable entities in providing quality education (e.g., Inder, 2022; Lee et al., 2019). Because of the unprecedented exposure to e-learning environments within Turkish universities in the post-pandemic period, it is obvious to effectively measure student engagement as part of achieving quality education in terms of sustainability. Therefore, this study aims to adapt the six-factor "Students' Sustainable Engagement in E-Learning Scale" (SSE-eL-S) developed by Lee et al. (2019) from English to Turkish language and culture and validate its psychometric properties to be conducted as a reliable research instrument.

MEASURES FOR STUDENT ENGAGEMENT

Evaluating student engagement in e-learning is a key to creating effective online learning environments, particularly in higher education. Several instruments have been developed and used to measure student engagement (e.g., Dixson, 2015; Heilporn et al., 2024; Kocak & Goksu, 2023; Lee et al., 2019; Maroco et al., 2016; Zhoc et al., 2019). For instance, Maroco et al. (2016) developed the University Student Engagement Inventory (USEI), including the constructs of cognitive, behavioral, and emotional engagement to assess student engagement in higher education settings. The USEI was validated for different cultures, such as Chinese and Persian versions (Sharif Nia et al., 2023; She et al., 2023). However, it was not developed for e-learning settings. Similarly, the Higher Education Student Engagement Scale (HESES) developed by Zhoc et al. (2019) adopted a broad multidimensional approach. It measured academic, cognitive, social, and affective engagement, yet its design was not tailored to digital environments. Moreover, the Online Student Engagement Scale (OSE) was developed by Dixson (2015), consisting of four factors; namely, skills, emotion, participation, and performance, to measure student engagement in online courses at university. More recent instruments like the Multidimensional Student Engagement in Courses Scale (MSSEC) developed by Heilporn et al. (2024) and the Live Online Class Engagement Scale (LOCES) by Kocak and Goksu (2023) attempted to address engagement across modalities and live digital learning contexts, respectively. Even though these scales link self-reported engagement with measurable online activities, no focus on sustainability has been indicated in the developmental procedures. On the other hand, Lee et al. (2019) developed and validated the SSE-eL-S, including the factors of psychological motivation, peer collaboration, cognitive problem-solving, interaction with instructors, community support, and learning management with a particular focus on sustainability.

Of the existing scales in the literature, the SSE-eL-S was selected to be adapted and validated in the Turkish language and culture after thorough scrutiny and consultation with experts in the field. Several issues were considered in this selection process. First, the existing scales were evaluated in terms of the study context. In this case, e-learning settings for university students were identified as the study context and particularly examined in the existing scales in the literature. Next, those matching the context were evaluated for their items and factor structures. In this respect, linguistic and statistical concerns were considered such as item clarity and factor loadings, and expert opinion was taken for the prospective scales to be adapted to the Turkish language and culture. Finally, practicality was evaluated regarding length, ease of administration, interpretation, and inclusivity.

METHODS

Research Design

To obtain a reliable research instrument measuring sustainable student engagement in e-learning within Turkish university settings, this study sought to adapt the SSE-eL-S developed by Lee et al. (2019) from English to Turkish language and culture and validate its factor structure to be conducted in future studies. Accordingly, the present research was designed with a three-step approach including translation and cross-cultural adaptation, pre-testing, and field testing as illustrated in Figure 1.

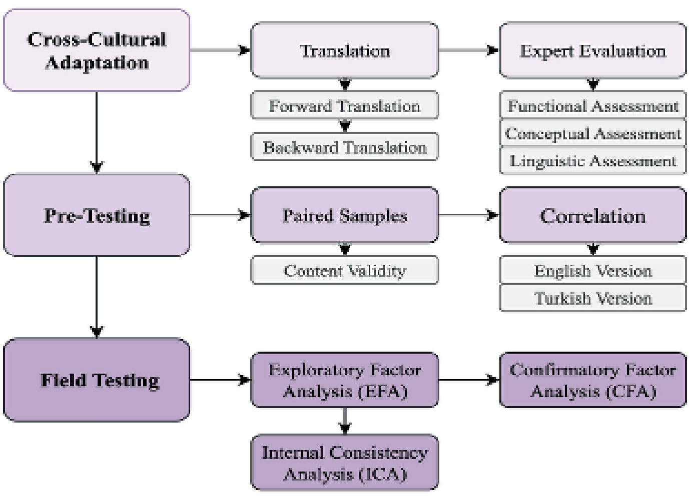

Figure 1. Research model

As displayed in Figure 1, in the first phase, the SSE-eL-S was cross-culturally adapted into the Turkish language and culture with forward and backward translation in addition to the functional, conceptual, and linguistic assessment of the translated version. Subsequently, pre-testing was conducted to ensure content validity with paired samples and correlation analyses on the original and translated versions. Finally, in the psychometric evaluation processes, the finalized form in Turkish was tested in the field through exploratory factor analysis (EFA), internal consistency analysis (ICA), and confirmatory factor analysis (CFA), which were applied to examine the factor structure and internal consistency coefficients of the scale.

Participants

The participants in this study were selected in three different groups through different sampling strategies depending on the study phase. Group 1 was the pre-test group in which the Turkish and English forms were administered intermittently to the same students. Therefore, Group 1 (n=43) was chosen through purposeful sampling based on having a minimum B2 level of English proficiency, as they were required to complete both the English and Turkish versions of the instrument to examine linguistic and conceptual equivalence. Group 2 (n=226) and Group 3 (n=206) in the field testing were selected through convenience sampling from undergraduate students across various faculties at Turkish universities. These two groups participated in the EFA and CFA, respectively, ensuring independent samples for structural validation. The demographic characteristics of all three groups are presented in Table 1.

Table 1. Sample profile

Demographics	Group 1 (Pre-Testing)		Group 2 (Field Testing – EFA)		Group 3 (Field Testing – CFA)	
	N	%	N	%	N	%
Gender						
Female	26	60.5%	163	72.1%	143	69.4%
Male	17	39.5%	63	27.9%	63	30.6%
Age						
$\bar{X} \pm SD$	20.53 ± 4.605		22.36 ± 4.036		22.30 ± 3.794	
Year of Education						
Freshman	25	58.1%	83	36.7%	67	32.5%
Sophomore	10	23.3%	64	28.3%	56	27.2%
Junior	3	7.0%	34	15.0%	44	21.4%
Senior	5	11.6%	45	19.9%	39	18.9%
Number of Online Courses						
1-10	N/A	N/A	54	23.9%	44	21.4%
11-20	N/A	N/A	64	28.3%	68	33.0%
21+	N/A	N/A	108	47.8%	94	45.6%
Faculty of						
Engineering	26	60.5%	32	14.2%	26	12.6%
Architecture	11	25.6%	5	2.2%	3	1.5%
Science and Literature	3	7.0%	23	10.2%	18	8.7%
Management	3	7.0%	12	5.3%	17	8.3%
Agriculture	N/A	N/A	6	2.7%	2	1.0%
Communication	N/A	N/A	5	2.2%	3	1.5%
Economy	N/A	N/A	19	8.4%	19	9.2%
Education	N/A	N/A	52	23.0%	59	28.6%
Fine Arts	N/A	N/A	7	3.1%	9	4.4%
Health Sciences	N/A	N/A	56	24.8%	44	21.4%
Law	N/A	N/A	9	4.0%	6	2.9%
Satisfaction with Online Courses						
$\bar{X} \pm SD$	N/A	N/A	3.15 ± 1.153		3.14 ± 1.093	

N/A: Not applicable.

Regarding the gender distributions, the proportions of women and men were found to be 60.5% and 39.5% in Group 1, 72.1% and 27.9% in Group 2, and 69.4% and 30.6% in Group 3, respectively. The mean age of the participants was 20.53 (±4.605) in Group 1, 22.36 (±4.036) in Group 2, and 22.30 (±3.794) in Group 3. In terms of year of education, 58.1% of the participants were freshmen in Group 1 (n=25), while this rate decreased to 36.7% in Group 2 (n=83) and 32.5% in Group 3 (n=67). Only 7% of the respondents were in their junior year in Group 1 (n=3), whereas this rate increased to 15% in Group 2 (n=34) and 21.4% in Group 3 (n=44). The online course experiences of the participants in Group 2 and Group 3 were also evaluated concerning the number of courses they had already taken to ensure their background in the field testing. Accordingly, 47.8% of the participants in Group 2 stated that they had attended 21 or more online courses at their universities (n=108); this rate was 45.6% in Group 3 (n=94). Regarding the distribution of participants by faculty, the students of the faculty of engineering constituted the highest proportion with 60.5% in Group 1 (n=26), while this rate decreased to 14.2% in Group 2 (n=32) and 12.6% in Group 3 (n=26). On the other hand, the faculties of education and health sciences had higher representation rates with 23% (n=52) and 24.8% (n=56) in Group 2; similarly, 28.6% (n=56) and 21.4% (n=44) in Group 3, respectively. Finally, the level of satisfaction with online courses was determined as 3.15 (±1.153) in Group 2 and 3.14 (±1.093) in Group 3.

Research Instrument

The questionnaire consisted of two sections: demographics and the SSE-eL-S. In the demographics, university students were asked about their gender, age, year of education, and faculty for all the groups. Besides, the number of online courses taken and students' satisfaction with online courses were assessed for Groups 2 and 3. Students' level of satisfaction with online courses was measured in a single question with a five-point Likert scale: (1) very satisfied, (2) satisfied, (3) unsure, (4) dissatisfied, and (5) very dissatisfied; therefore, higher scores indicate lower satisfaction.

Subsequently, the SSE-eL-S was configured in the questionnaire. It was originally developed by Lee et al. (2019) in English with a total of 25 items in six factors: (1) psychological motivation (PM) with six items (1, 2, 3, 4, 5, and 6), (2) peer collaboration (PC) with five items (7, 8, 9, 10, and 11), (3) cognitive problem solving (CPS) with five items (12, 13, 14, 15, and 16), (4) interactions with instructors (IwI) with two items (17 and 18), (5) community support (CS) with three items (19, 20, and 21), and (6) learning management (LM) with four items (22, 23, 24, and 25). A five-point Likert scale was used as (1) strongly disagree, (2) disagree, (3) neither agree nor disagree, (4) agree, and (5) strongly agree. The reliability coefficients of the SSE-eL-S factors were calculated at 0.896 for PM, 0.876 for PC, 0.825 for CPS, 0.758 for IwI, 0.819 for CS, and 0.717 for LM (Lee et al., 2019).

Procedures

After determining the cross-cultural adaptation of the SSE-eL-S, first, the permission for scientific and ethical compliance was confirmed by the Board of Ethics for Human Studies in Social Sciences and Humanities to conduct the study, documented on 25.12.2023 with project number 440. Subsequently, official permission was requested via e-mail from Professor Song Hae-Deok, one of the authors of the scale, from the Department of Education at Chung-Ang University in Seoul, Republic of Korea. Following the permissions taken before data collection, translation and cross-cultural adaptation were processed with experts in the field. Accordingly, two bilingual experts in the field of educational sciences conducted the forward translation process from English to Turkish, and two other bilingual experts performed backward translation from Turkish to English.

After the translation process was over, the cross-cultural evaluation of the Turkish version was performed in terms of functional, conceptual, and linguistic equivalence, and the SSE-eL-S was finalized for pre-testing. In the phase of pre-testing, the final version of the SSE-eL-S was configured on a platform along with the original version separately to be tested with a time interval for correlation via paired samples. Finally, in the field testing, the final form of the SSE-eL-S was performed to test its psychometric properties through EFA, ICA, and CFA. The respondents in the pre-testing in Group 1 and the field testing in Groups 2 and 3 consented to their voluntary participation in the research.

Data Analysis

In the cross-cultural adaptation, translation outputs were evaluated through a trichotomous rating scale (TRS) by four expert raters (ER); accordingly, the translated version was assessed as "it is not clear", "item needs some revision", or "very clear" (Cruchinho et al., 2024; Rodrigues et al., 2017). Based on the feedback received from the ERs over the TRS, the items were revised if applicable. Following the translation process, cross-cultural principles were assessed functionally, conceptually, and linguistically by six field and linguistic experts with a range from 1.00 (not equivalent) to 5.00 (fully equivalent) (Salamanca-Sanabria et al., 2019).

In the pre-testing phase, both the original and translated versions of the scale were administered to the target population with a time interval to assess content validity and reliability. Content validity was ensured by evaluating the clarity and relevance of the items, while reliability was measured through internal consistency. The paired sample t-test and Pearson correlation analysis were employed to evaluate the consistency between the English and Turkish versions of the scale.

During the field-testing phase, psychometric validation was conducted using EFA, ICA, and CFA. EFA was performed to identify the underlying factor structure of the adapted scale. The Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity confirmed the suitability of the data for factor analysis. Initially, a five-factor structure was identified, but after removing certain items, a four-factor structure emerged, explaining 67.004% of the total variance. The factors were labeled based on the items they contained, and high factor loadings indicated strong correlations with the relevant factors. Internal consistency was assessed using Cronbach's alpha, with all factors showing high reliability. All the descriptive analyses along with paired sample t-test, Pearson correlation, KMO, Bartlett's test of sphericity, EFA, ICA, and CFA were performed on the collected data by using SPSS v26.0 and IBM AMOS v24.0. Convergent and discriminant validity analyses were performed with the Master Validity Tool of IBM AMOS v24.0.

FINDINGS

Translation and Cross-Cultural Adaptation of the SSE-eL-S

The items of the SSE-eL-S were translated using a forward and backward translation by four independent bilingual experts in the field. Accordingly, first, 25 items in the SSE-eL-S were translated from English to Turkish to keep the meaning of the items rather than a literal word-for-word translation. Then, the translated items were translated backward from Turkish and English to ensure the quality. After forward and backward translation, the ERs compared the translated versions with the original scale to resolve ambiguities, cultural differences, or misinterpretations. The translation outputs were evaluated with the TRS, as presented in Table 2.

Table 2 . Evaluation of clarity in the translated items

TRS Items	ER1	ER2	ER3	ER4
	n	n	n	n
It is not clear	N/A	N/A	N/A	N/A
Item needs some revision	8	6	5	7
Very clear	17	19	20	18
TOTAL	25	25	25	25

N/A: Not applicable.

As indicated in Table 2, no items were found unclear with the consensus of all the ERs. However, several items were recommended for some minor revisions (n=8 for ER1; n=6 for ER2; n=5 for ER3; n=7 for ER4). The majority of the translated items were identified as "very clear" (n=17 for ER1; n=19 for ER2; n=20 for ER3; n=18 for ER4).

Subsequently, cross-cultural principles in the revised translated items were assessed in terms of functional, conceptual, and linguistic equivalence by three field experts (FE) and three linguistic experts (LE) with a range from 1.00 (not equivalent) to 5.00 (fully equivalent). The results are presented with mean scores (M) and standard deviation (SD) in Table 3.

Table 3 . Evaluation of cross-cultural principles in the translated items

Cross-cultural principles	Field Experts (n=3)		Linguistic Experts (n=3)		Combined (n=6)	
	M_{FE}	SD	M_{LE}	SD	M_C	SD
Functional equivalence	4.96	0.28	4.78	0.36	4.84	0.37
Conceptual equivalence	4.80	0.44	4.65	0.53	4.71	0.49
Linguistic equivalence	4.37	0.65	4.40	0.60	4.40	0.62

In Table 3, the evaluation of cross-cultural principles in the translated items was organized with the ratings of field experts (n=3) and linguistic experts (n=3) with the combined assessment (n=6) scores. Accordingly, functional equivalence received the highest mean scores across all the groups (M_{FE}=4.96; M_{LE}=4.78; M_C=4.84). These findings pointed out a strong agreement that the translated items effectively serve the same function as the original items. Regarding conceptual equivalence, it was rated slightly lower than functional equivalence (M_{FE}=4.80; M_{LE}=4.65; M_C=4.71). Despite the overall agreement among the experts, the standard deviations were calculated slightly higher, which shows minor variations in expert ratings in the conceptual consistency of the translated items. Finally, linguistic equivalence received the lowest ratings among all the groups (M_{FE}=4.37; M_{LE}=4.40; M_C=4.40), which suggests that there were more concerns regarding linguistic issues and phrasing compared to functional and conceptual equivalence, even though the translated items were found largely accurate. In light of these values, it is notable that all the mean scores were detected to be more than 4.30 on a five-point scale, and the standard deviations calculated ranged from 0.28 to 0.65, which are relatively low and show no major discrepancies among the experts. Therefore, it can be concluded that the translated items are of high quality and successfully adapted to the Turkish language and culture.

Pre-Testing of the Adapted SSE-eL-S

To assess the consistency between the English (ENG) and Turkish (TR) versions of the adapted SSE-eL-S, a paired sample t-test was performed on SPSS v26.0 along with Pearson correlation analysis. At this phase, the data intermittently gathered from Group 1 (n=43) were used for pre-testing analyses. Consistency between the English and Turkish versions is indicated by a statistically insignificant result in the paired sample t-test; in other words, no significant difference should be found between the two versions. Additionally, a high Pearson correlation coefficient is required to confirm a strong positive relationship, which will further support the equivalence of the adapted SSE-eL-S. The results of pre-testing are displayed in Table 4.

Table 4 . Paired sample t-test and correlation analysis between the original and adapted versions

Pairs	Versions of Constructs	M	SD	t	p	Correlation	Sig.
Pair 1	ENG-PM & TR-PM	-0.06202	0.66371	-0.613	0.543	0.763	0.000
Pair 2	ENG-PC & TR-PC	0.12558	0.52739	1.561	0.126	0.789	0.000
Pair 3	ENG-CPS & TR-CPS	-0.00930	0.32937	-0.185	0.854	0.921	0.000
Pair 4	ENG-IwI & TR-IwI	0.19767	0.53607	2.418	**0.020**	0.891	0.000
Pair 5	ENG-CS & TR-CS	0.22480	0.33111	4.452	**0.000**	0.953	0.000
Pair 6	ENG-LM & TR-LM	0.01163	0.35336	0.216	0.830	0.914	0.000

According to the paired sample t-test results, statistically significant differences were found between ENG-IwI and TR-IwI (p=0.020) and between ENG-CS and TR-CS (p=0.000), which shows an issue in the adaptation of IwI and CS dimensions in the original scale to the Turkish language and culture. In other pairings (ENG-PM & TR-PM; ENG-PC & TR-PC; ENG-CPS & TR-CPS; ENG-LM & TR-LM), no significant differences were observed (p>0.05). Regarding the Pearson correlation results, significant correlations were detected between all pairings (p=0.000). The correlation coefficients were quite high, which indicates a strong relationship between the two forms. In other words, it can be concluded that the adapted SSE-eL-S reliably reflects the original scale.

Exploratory Factor Analysis and Reliability of the Adapted SSE-eL-S

In the field testing, different factor analyses were conducted on SPSS v26.0 for Group 2 (n=226). First, the Kaiser-Meyer-Olkin (KMO) sampling adequacy test was performed, and the value was calculated as 0.902, which shows that the data set is quite suitable for EFA with Varimax rotation. Varimax, as an orthogonal rotation method, was selected to facilitate the interpretability of the factor solution by maximizing the variance of squared loadings across variables for each factor because this method is appropriate when factors are assumed to be uncorrelated, which aligns with the theoretical framework in this study that treats the constructs as conceptually distinct (Tabachnick & Fidell, 2013). In addition, Bartlett's test of sphericity was found significant and $\chi 2=3366.077$ (df=300; p<0.001). Based on these findings, there was a sufficient correlation between the variables, and factor analysis can be performed. As a result of the first analysis, a five-factor structure was obtained. However, since the variables CS1, CS2, IwI1, and IwI2 loaded significantly on more than one factor, the load differences between these factors were less than 0.200, and PM4 remained alone in the fifth factor, these items were removed from the analysis, and the EFA was repeated.

In the second factor analysis, the Kaiser-Meyer-Olkin (KMO) sampling adequacy test value was calculated as 0.894, which shows that the data set is still very suitable for EFA. Moreover, Bartlett's test of sphericity remained significant and $\chi 2=2664.378$ (df=190; p<0.001). These findings confirmed a sufficient correlation between the variables for factor analysis, and the EFA results are presented in Table 5.

Table 5. EFA results of the adapted SSE-eL-S

Kaiser-Meyer-Olkin Measure of Sampling Adequacy				0.894
Bartlett's Test of Sphericity Approx. Chi-Square				2664.378
			df	190
			Sig.	0.000
Rotated Component Matrix[a]	**F1**	**F2**	**F3**	**F4**
PM3	0.863			
PM1	0.861			
PM2	0.858			
PM6	0.843			
PM5	0.818			
PC2		0.869		
PC3		0.824		
PC1		0.731		
PC4		0.708		
CS3		0.647		
PC5		0.576		
CPS3			0.816	
CPS2			0.756	
CPS1			0.725	
CPS4			0.641	
CPS5			0.623	
LM3				0.759
LM2				0.756
LM4				0.726
LM1				0.626
Eigenvalues	7.641	2.785	1.809	1.166
Total Variance Explained	38.205	52.131	61.176	67.004
Cronbach's Alpha	0.936	0.847	0.846	0.799

As a result of the repeated EFA analysis, a four-factor structure was obtained, explaining 67.004% of the total variance. The labels of the factors were kept the same as the original SSE-eL-S. Accordingly, PM (F1) included five items in PM, PC (F2) consisted of five items in PC but one item in CS, CPS (F3) comprised five items in CPS, and LM (F4) included four items in LM. Concerning the PC construct, the item originally in the CS dimension, "I frequently interact with other students in my online classes", fell under PC in the adapted version. In Turkish culture, it was perceived as part of peer collaboration, and as its meaning meets the PC construct, the label was not changed and kept as PC for F2. The factor loadings of each item were generally high, ranging from 0.576 to 0.869, which indicates that the items showed strong correlations with the relevant factors. Regarding the reliability of each factor in the adapted SSE-eL-S, Cronbach's alpha was assessed, and all the factors confirmed high internal consistency ($\alpha PM=0.936$; $\alpha PC=0.847$; $\alpha CPS=0.846$; $\alpha LM=0.799$). It can be concluded that the items within each factor reliably measure the same construct.

Confirmatory Factor Analysis of the Adapted SSE-eL-S

As the final phase of the field testing, CFA was performed on IBM AMOS v24.0 for Group 3 (n=206). To validate the factor structure of the adapted scale, model fit indices, standardized factor loadings, and error variances were assessed through the indicators of the Chi-Square (χ^2/df), Incremental Fit Index (IFI), Comparative Fit Index (CFI), Goodness of Fit Index (GFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR). The path diagram of the CFA results is depicted in Figure 2.

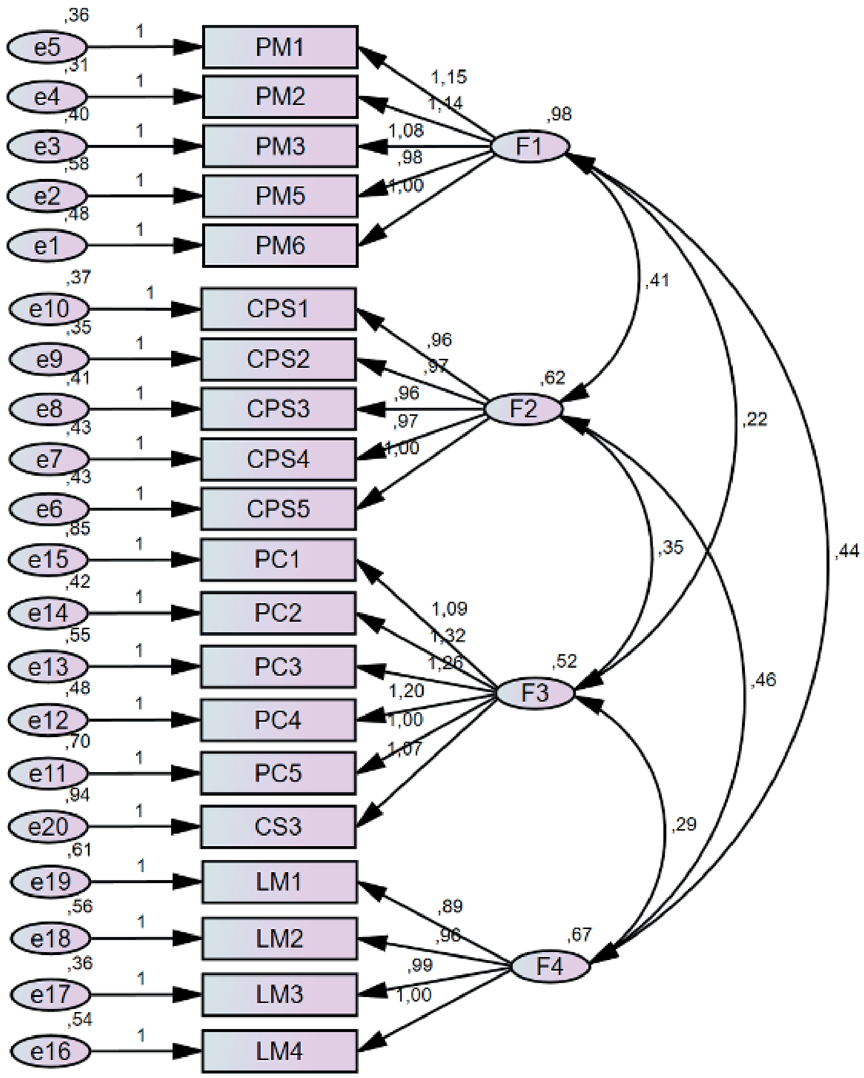

Figure 2. Path diagram of CFA model for the adapted SSE-eL-S

When the model fit indices were evaluated, the x^2/df value was found to be 2.065, and since this value is below 3, it can be concluded that the model showed a good fit (Kline, 2016). IFI, CFI, GFI, and TLI were calculated as 0.935, 0.934, 0.902, and 0.925, respectively. Because these values were in the range of 0.90-0.94, these indices can be evaluated in the acceptable fit category (Hu & Bentler, 1999). Moreover, the RMSEA value was detected as 0.072 in the range of 0.06-0.08, which showed an acceptable fit (Browne & Cudeck, 1993). Finally, the SRMR, which represents the average standardized difference between observed and predicted correlations, was calculated as 0.0617. This value was below the conventional threshold of 0.08, which indicated a good fit (Hu & Bentler, 1999). Overall, it can be interpreted that the model provides an acceptable level of fit. As listed in Appendix A, the adapted SSE-eL-S was validated in 20 items with a four-factor structure of PM, PC, CPS, and LM.

In addition to assessing model fit indices through CFA, convergent and discriminant validity of the adapted SSE-eL-S were evaluated to ensure construct validity as presented in Table 6.

Table 6. Convergent and discriminant validity indicators for the adapted SSE-eL-S

Construct	CR	AVE	MSV	MaxR(H)	F1	F2	F3	F4
F1	0.928	0.722	0.296	0.934	0.850			
F2	0.881	0.597	0.503	0.882	0.529***	0.773		
F3	0.865	0.520	0.380	0.879	0.307***	0.616***	0.721	
F4	0.828	0.547	0.503	0.834	0.544***	0.709***	0.494***	0.739

Convergent validity was examined by calculating the Average Variance Extracted (AVE) and Composite Reliability (CR) values for each latent construct. The CR values ranged from 0.828 to 0.928, and all AVE values exceeded the recommended threshold of 0.50, ranging from 0.520 to 0.722, which confirmed that each construct reliably explained the variance of its observed variables (Hu & Bentler, 1999). Discriminant validity was tested using the Fornell-Larcker criterion and Maximum Shared Variance (MSV). In all cases, the AVE values of the latent constructs were greater than their respective MSV values, which indicated that each construct shared more variance with its indicators than with other constructs. Moreover, the squared inter-construct correlations remained below the AVE values, which supported discriminant validity. The results from the Master Validity Tool confirmed that the adapted SSE-eL-S demonstrates satisfactory levels of convergent and discriminant validity, with no concerns regarding multicollinearity or conceptual overlap among constructs (Gaskin & Lim, 2016).

DISCUSSION

In this study, the SSE-eL-S developed by Lee et al. (2019), a reliable research instrument, was validated and adapted from English to the Turkish language and culture to be used to measure sustainable student engagement in e-learning settings in higher education. The results indicated a reliable and valid adaptation of the SSE-eL-S, including 20 items categorized into a four-factor structure in the Turkish version. After the translation and cross-cultural adaptation processes were completed by the experts, pre-testing was performed through paired sample t-tests and correlation analyses. As a form of statistical analysis to assess if there is a significant difference between two identical groups, the paired sample t-test used in pre-testing scale adaptation ensures the consistency and reliability of the adapted scale by comparing the means of the same participants at different times (Park et al., 2020; Xu et al., 2017). In the present study, even though no significant correlations were expected between the original and adapted versions, statistically significant differences were identified in the constructs of IwI and CS. This finding necessitated different factor analyses in the field testing: EFA and CFA.

EFA is commonly used to determine the dimensionality of scales and helps researchers ensure that the items group together meaningfully, which is essential for adapting existing scales to new contexts (Barendse et al., 2015; Phakiti, 2018). As confirmed by the EFA results, the problematic items in IwI and CS needed to be removed to obtain a meaningful four-factor solution, explaining 67.0% of the total variance. In this respect, the dimensionality in the constructs of the adapted SSE-eL-S was statistically validated (Watson, 2017). To confirm the EFA results, CFA was employed on another sample, which ensured that the hypothesized model fit the observed data; in other words, the data supported the expected number of factors and their associated items (Lam, 2024). Finally, the adapted SSE-eL-S was validated in 20 items grouped in the constructs of PM, PC, CPS, and LM.

Compared to the original SSE-eL-S developed by Lee et al. (2019), which included 25 items distributed in six factors, a refined structure was established in the Turkish version with four factors and 20 items. Specifically, the factors existing in the original version, IwI and CS, were not retained in the final Turkish version due to low item loadings and conceptual overlaps with other dimensions. However, four key factors, PM, PC, CPS, and LM, were consistent across both versions, which indicated conceptual equivalence in core dimensions of engagement. Cronbach's alpha coefficients in both studies exceeded the acceptable threshold, which supported reliability in the original and adapted versions. Furthermore, the variance explained by the final models was comparable, as 67.0% in the adapted version and 64.8% in the original. These similarities confirmed the scale's structural stability across cultural contexts.

Student engagement provided sustainably contributes to enhanced academic performance and increased retention rates (Estes, 2016; Kim et al., 2023). Engaged students frequently experience positive emotional and social outcomes, which promote their overall well-being and development (Griffiths et al., 2009). Therefore, practitioners in higher education are recommended to focus on sustainable student engagement in e-learning settings, which may be more challenging (Vermeulen & Volman, 2024). In this respect, the adapted SSE-eL-S contributes to providing sustainable student engagement in e-learning because it is a valid and reliable research tool to measure it, including cognitive, behavioral, and affective engagement (Franklin-Guy & Schnorr, 2016; Trowler, 2013; Verdeflor et al., 2024). As obtained from the EFA and CFA results of the adapted SSE-eL-S, PM, PC, CPS, and LM align with cognitive, behavioral, and affective engagement in e-learning.

The PM construct is closely connected to affective engagement because student motivation influences their emotional investment in online learning through persistence in self-paced courses, willingness to engage with digital content, and their level of satisfaction (D'Errico et al., 2016; Franklin-Guy & Schnorr, 2016). Regarding the second construct in the adapted scale, PC aligns with behavioral engagement in e-learning because active participation in discussion forums, group projects, and virtual study sessions fosters interaction and a sense of community in digital learning environments (Nawi et al., 2021; Trowler, 2013). Moreover, the third construct, CPS, corresponds to cognitive engagement since students must apply higher-order thinking skills to navigate complex tasks, critically analyze information, and adapt problem-solving strategies in self-directed e-learning settings (Elsayary, 2023). Finally, LM integrates both behavioral and cognitive engagement because effective self-regulation, time management, and digital literacy are essential for navigating asynchronous coursework, meeting deadlines, and utilizing learning platforms efficiently.

Theoretically, this study contributes to the literature on engagement by confirming that essential aspects of sustainable student engagement are generalizable across contexts while still requiring cultural adaptation. Practically, the adapted scale provides Turkish higher education institutions with a diagnostic tool that captures how students participate in e-learning and how they sustain engagement over time. This instrument can support instructional design, program evaluation, and institutional strategies intended to improve online learning retention and quality. Overall, all the constructs validated in the adapted SSE-eL-S provide a comprehensive framework for understanding how students engage with e-learning in higher education and enlighten the issues for online learning environments, which are expected to support motivation, collaboration, problem-solving, and self-regulated learning.

LIMITATIONS AND FUTURE CONSIDERATIONS

Several limitations should be acknowledged in this study. Despite rigorous translation and adaptation procedures, cultural and linguistic differences may still influence how Turkish students interpret certain scale items, which may potentially affect measurement equivalence. Besides, although the purposeful selection of participants with B2 English proficiency in Group 1 was necessary to assess the linguistic and conceptual equivalence of the scale versions, this choice inherently limits the generalizability of pre-test results to students with advanced English skills. For Groups 2 and 3, the participants were recruited through convenience sampling, a non-probability sampling method, from multiple universities, which increased the diversity of the sample compared to a single-institution design. However, the absence of probability-based selection may limit the full representation of the university student population in Turkiye. Additionally, the sample representativeness is limited to the respondents having participated in different groups; however, since the study sample may primarily reflect the engagement of a specific group studying at different Turkish universities, it may be difficult to generalize the findings in other contexts. The cross-sectional design further restricts the ability to examine how engagement evolves over time in e-learning settings. Another limitation results from measurement invariance because latent constructs may still differ in meaning between the original and adapted versions despite statistical validation. Finally, potential response bias due to self-reporting could impact data accuracy because students might overestimate or underestimate their actual engagement levels in e-learning environments.

To address these limitations, future research should focus on longitudinal studies to track changes in engagement over time, which may help understand students' evolving interactions with digital learning platforms. Expanding studies to include diverse samples from various universities, disciplines, and educational levels would enhance the scale's generalizability. Additionally, cross-cultural comparisons with international student populations could provide deeper insights into how engagement varies across diverse cultural contexts. A mixed-methods approach, integrating qualitative data from student interviews or focus groups, would help validate the scale's relevance and improve item clarity. Finally, intervention-based studies could explore how specific e-learning strategies, such as gamification or interactive learning modules, influence student engagement and offer valuable insights for improving digital education in higher education.

CONCLUSION

The SSE-eL-S developed by Lee et al. (2019) was validated and adapted to the Turkish language and culture to be utilized as a reliable research instrument measuring sustainable student engagement in e-learning in higher education. It was ensured that the adapted scale is linguistically and culturally appropriate for university students taking online courses. Its reliability and validity were confirmed; therefore, it can be used to measure PM, PC, CPS, and LM within e-learning contexts. Administrators and practitioners in higher education are recommended to ensure sustainable student engagement in e-learning environments. Notably, the adapted scale can contribute to a more comprehensive understanding of sustainable student engagement in e-learning, which may ultimately improve online learning practices and increase the effectiveness of e-learning in higher education.

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REFERENCES

Ahmadi, G., Mohammadi, A., Asadzandi, S., Shah, M., & Mojtahedzadeh, R. (2023). What are the indicators of student engagement in learning management systems? A systematized review of the literature. *International Review of Research in Open and Distributed Learning*, *24*(1), 117–136. https://doi.org/10.19173/irrodl.v24i1.6453

Ali Krishan, E. A., Almsaiden, A. H. I., al Njadat, E. N., & Abohelalah, A. A. (2023). The impact of e-learning on the learning motivation of Jordanian university students. *Journal of Educational and Social Research*, *13*(5), 313–327. https://doi.org/10.36941/jesr-2023-0139

Amane, M., Aissaoui, K., & Berrada, M. (2023). Shaping students' learning for a specific learning environment. In S. Motahhir, & B. Bossoufi, B. (Eds.), *Digital technologies and applications. ICDTA 2023, Lecture notes in networks and systems* (Vol. 668). Springer, Cham. https://doi.org/10.1007/978-3-031-29857-8_38

Axelson, R. D., & Flick, A. (2010). Defining student engagement. *Change: The Magazine of Higher Learning*, *43*(1), 38–43. https://doi.org/10.1080/00091383.2011.533096

Balasooriya, I., Rodriguez, M. E., & Mor, E. (2018). Assessment of engagement: Using microlevel student engagement as a form of continuous assessment. In E. Ras & A. Guerrero Roldan (Eds.), *Technology enhanced assessment. TEA 2017, Communications in computer and information science* (Vol. 829). Springer, Cham. https://doi.org/10.1007/978-3-319-97807-9_12

Barendse, M. T., Oort, F. J., & Timmerman, M. E. (2015). Using exploratory factor analysis to determine the dimensionality of discrete responses. *Structural Equation Modeling*, *22*(1), 87–101. https://doi.org/10.1080/10705511.2014.934850

Benabbes, K., Housni, K., Hmedna, B., Zellou, A., & Mezouary, A. E. (2023). A new hybrid approach to detect and track learner's engagement in e-learning. *IEEE Access*, *11*, 70912–70929. https://doi.org/10.1109/ACCESS.2023.3293827

Browne, M. W., & Cudeck, R. (1993). Alternate ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 136-162). Sage.

Cholisoh, N., Anugrah, R. W., Fazri, M. F., Wahid, S. M., & Pramudya, R. D. (2024). Optimizing engagement dynamics in e-learning environments with insights and strategic approaches. *2024 3rd International Conference on Creative Communication and Innovative Technology, ICCIT 2024*. https://doi.org/10.1109/ICCIT62134.2024.10701120

Cruchinho, P., Lopez-Franco, M. D., Capelas, M. L., Almeida, S., Bennett, P. M., Miranda da Silva, M., Teixeira, G., Nunes, E., Lucas, P., & Gaspar, F. (2024). Translation, cross-cultural adaptation, and validation of measurement instruments: A practical guideline for novice researchers. *Journal of Multidisciplinary Healthcare, 17*, 2701–2728. https://doi.org/10.2147/JMDH.S419714

Daher, W., Sabbah, K., & Abuzant, M. (2021). Affective engagement of higher education students in an online course. *Emerging Science Journal*, *5*(4), 545–558. https://doi.org/10.28991/esj-2021-01296

Da Silva Gomes De Oliveira, E., & Nunes, J. M. G. (2011). Cognitivism and e-learning: A view from the learning theories of Ausubel and Bruner. *Proceedings of the IADIS International Conference E-Learning 2011, Part of the IADIS Multi Conference on Computer Science and Information Systems (MCCSIS)*, *2*, 327–331.

D'Errico, F., Paciello, M., & Cerniglia, L. (2016). When emotions enhance students' engagement in e-learning processes. *Journal of E-Learning and Knowledge Society*, *12*(4), 9–23.

Dewi, L. T. (2010). User satisfaction analysis of an e-learning site. *Proceedings - APCHI-ERGOFUTURE 2010* (pp. 614–619). Udayana University Press.

Dixson, M. D. (2015). Measuring student engagement in the online course: The online student engagement scale (OSE). *Online Learning Journal*, *19*(4). https://doi.org/10.24059/olj.v19i4.561

Dong Chiong, N. L., & Fu, N. (2020). Exploring the drivers and barriers for e-learning system impact in the higher education sector. In S. Allen, K. Gower, & D. K. Allen (Eds.), *Handbook of teaching with technology in management, leadership, and business* (pp. 364–376). https://doi.org/10.4337/9781789901658.00045

Estes, J. S. (2016). The pivotal role of faculty in online student engagement and retention. In Information Management Association (Ed.), *Educational leadership and administration: concepts, methodologies, tools, and applications* (pp. 1501–1525). https://doi.org/10.4018/978-1-5225-1624-8.ch069

Elsayary, A. (2023). Students' active engagement in online learning. In A. ElSayary & A. Olowoselu (Eds.), *Overcoming challenges in online learning: Perspectives from Asia and Africa* (1st ed.). Routledge. https://doi.org/10.4324/9781003342335-12

Franklin-Guy, S., & Schnorr, D. (2016). Student engagement in schools: Examination of a construct for effective instructional and educational practices. *International Journal of Pedagogy and Curriculum*, *23*(4), 17–23. https://doi.org/10.18848/2327-7963/cgp/v23i04/17-23

Gaskin, J., & Lim, J. (2016). *Master validity tool: AMOS plugin*. Gaskination's StatWiki.

Griffiths, A.-J., Sharkey, J. D., & Furlong, M. J. (2009). Student engagement and positive school adaptation. In R. Gilman, E. S. Huebner, & M. Furlong (Eds.), *Handbook of positive psychology in schools* (1st ed.). Routledge. https://doi.org/10.4324/9780203884089-26

Heilporn, G., Raynault, A., & Frenette, E. (2024). Student engagement in a higher education course: A multidimensional scale for different course modalities. *Social Sciences & Humanities Open*, *9*, 100794. https://doi.org/10.1016/J.SSAHO.2023.100794

Holmes, N. (2018). Engaging with assessment: Increasing student engagement through continuous assessment. *Active Learning in Higher Education*, *19*(1), 23–34. https://doi.org/10.1177/1469787417723230

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huda, S., Alyahya, S., Pan, L., & Al-Dossari, H. (2022). Combining innovative technology and context based approaches in teaching software engineering. *International Journal of Advanced Computer Science and Applications*, *13*(10), 305–314. https://doi.org/10.14569/IJACSA.2022.0131037

Hussain, M., Zhu, W., Zhang, W., & Abidi, S. M. R. (2018). Student engagement predictions in an e-learning system and their impact on student course assessment scores. *Computational Intelligence and Neuroscience*, 6347186, 1–21. https://doi.org/10.1155/2018/6347186

Hussin, W. N. T. W., Harun, J., & Shukor, N. A. (2019). Online interaction in social learning environment towards critical thinking skill: A framework. *Journal of Technology and Science Education*, *9*(1), 4–12. https://doi.org/10.3926/jotse.544

Inder, S. (2022). Factors influencing student engagement for online courses: A confirmatory factor analysis. *Contemporary Educational Technology*, *14*(1). https://doi.org/10.30935/cedtech/11373

Jabeen, S. S., Banerjee, A., & Bhatia, P. D. (2015). Strategizing for the future: Introducing e-learning in educational and corporate houses. *2014 International Conference on Web and Open Access to Learning, ICWOAL 2014*. https://doi.org/10.1109/ICWOAL.2014.7009196

Karatas, S., Gules, H., & Aypay, A. (2014). University students' motivation levels towards learning and learning strategies they use. *Journal of Educational Policy Analysis, 3*(2), 31–48. https://izlik.org/JA75DS79XD

Kim, H. J., Kong, Y., Hernandez, C., & Soban, M. (2023). Student emotions and engagement: Enacting humanizing pedagogy in higher education. *IAFOR Journal of Education*, *11*(3), 185–206. https://doi.org/10.22492/ije.11.3.09

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Kocak, O., & Goksu, I. (2023). Engagement of higher education students in live online classes: Scale development and validation. *TechTrends, 67*(3), 534–549. https://doi.org/10.1007/s11528-023-00849-7

Kumaravel, J. P. S., & Manoharan, A. (2010). E-learning for distance learners - A qualitative design. *ICDLE 2010 - 2010 4th International Conference on Distance Learning and Education, Proceedings*, 167–169. https://doi.org/10.1109/ICDLE.2010.5606014

Lam, E. T. C. (2024). Scale validation. In P. M. Pedersen (Ed.), *Encyclopedia of Sport Management* (pp. 831–832). Edward Elgar Publishing. https://doi.org/10.4337/9781035317189.ch485

Lee, J., Song, H.-D., & Hong, A. J. (2019). Exploring factors, and indicators for measuring students' sustainable engagement in e-learning. *Sustainability, 11*(4). https://doi.org/10.3390/su11040985

Maroco, J., Maroco, A. L., Campos, J. A. D. B., & Fredricks, J. A. (2016). University student's engagement: Development of the university student engagement inventory (USEI). *Psicologia: Refexão e Critica*, 29(1), 21. https://doi.org/10.1186/s41155-016-0042-8

Meyer, K. A. (2014), Student engagement in online learning: What works and why. *ASHE Higher Education Report, 40*, 1–129. https://doi.org/10.1002/aehe.20018

Nawi, S. M., Yusof, S. M., Kamaludin, P. N. H., & Sain, N. (2021). Exploring Malaysian tertiary students' behavioural, cognitive, emotional and social engagement and disengagement in ODL. *International Journal of Academic Research in Business and Social Sciences, 11*(4), 1296–1311. http://dx.doi.org/10.6007/IJARBSS/v11-i4/9826

Pandita, A., & Kiran, R. (2023). The technology interface and student engagement are significant stimuli in sustainable student satisfaction. *Sustainability (Switzerland)*, *15*(10). https://doi.org/10.3390/su15107923

Park, C., Wang, M., & Hwang, W.-Y. (2020). A study on robustness of the paired sample tests. *Industrial Engineering and Management Systems*, *19*(2), 386–397. https://doi.org/10.7232/IEMS.2020.19.2.386

Phakiti, A. (2018). Exploratory factor analysis. In A. Phakiti, P. De Costa, L. Plonsky, & S. Starfield, (Eds.), *The Palgrave handbook of applied linguistics research methodology* (pp. 423–457). Palgrave Macmillan, London. https://doi.org/10.1057/978-1-137-59900-1_20

Poondej, C., & Lerdpornkulrat, T. (2019). Gamification in e-learning: A Moodle implementation and its effect on student engagement and performance. *Interactive Technology and Smart Education*, *17*(1), 56–66. https://doi.org/10.1108/ITSE-06-2019-0030

Richardson, J. C., & Newby, T. (2006). The role of students' cognitive engagement in online learning. *American Journal of Distance Education*, *20*(1), 23–37. https://doi.org/10.1207/s15389286ajde2001_3

Rodrigues, I. B., Adachi, J. D., Beattie, K. A., & MacDermid, J. C. (2017). Development and validation of a new tool to measure the facilitators, barriers and preferences to exercise in people with osteoporosis. *BMC Musculoskeletal Disorders*, *18*(1), 540. https://doi.org/10.1186/s12891-017-1914-5

Salamanca-Sanabria, A., Richards, D., & Timulak, L. (2019). Adapting an internet-delivered intervention for depression for a Colombian college student population: An illustration of an integrative empirical approach. *Internet Interventions, 15*, 76–86. https://doi.org/10.1016/j.invent.2018.11.005

Santoni, M. M., Basaruddin, T., & Junus, K. (2023). Convolutional neural network model based students' engagement detection in imbalanced DAiSEE dataset. *International Journal of Advanced Computer Science and Applications*, *14*(3), 617–626. https://doi.org/10.14569/IJACSA.2023.0140371

Schaufeli, W. B., Salanova, M., Gonzalez-Roma, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies, 3*(1), 71–92. https://doi.org/10.1023/A:1015630930326

Shah, R. K., & Barkas, L. A. (2018). Analysing the impact of e-learning technology on students' engagement, attendance and performance. *Research in Learning Technology, 26*. https://doi.org/10.25304/rlt.v26.2070

Sharif Nia, H., Azad Moghddam, H., Maroco, J., Rahmatpour, P., Allen, K.-A., Kaur, H., Kaveh, O., Gorgulu, O., & Pahlevan Sharif, S. (2023). A psychometric lens for e-learning: Examining the validity and reliability of the Persian version of university students' engagement inventory (P-USEI). *Asia-Pacific Education Researcher*, *32*(4), 573–582. https://doi.org/10.1007/s40299-022-00677-y

She, L., Khoshnavay Fomani, F., Maroco, J., Allen, K.-A., Sharif Nia, H., & Rahmatpour, P. (2023). Psychometric properties of the university student engagement inventory among Chinese students. *Asian Association of Open Universities Journal*, *18*(1), 46–60. https://doi.org/10.1108/AAOUJ-08-2022-0111

Singh, A. (2024). Impact of e-learning on students' motivation in higher education institutions: An Indian perspective. *Revista de Educacion y Derecho*, *29*. https://doi.org/10.1344/REYD2024.29.43214

Susanti, L., Karim, N. A., & Ramdhani, Y. (2024). E-learning and sustainable user: The model of academic performance in e-learning. *E3S Web of Conferences*, *485*. https://doi.org/10.1051/e3sconf/202448501006

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Pearson.

Trowler, V. (2013). Leadership practices for student engagement in challenging conditions. *Perspectives: Policy and Practice in Higher Education*, *17*(3), 91–95. https://doi.org/10.1080/13603108.2013.789455

Verdeflor, R. N., Tenedero, E. Q., Bordios, A. G., Panit, N. M., & Espinosa, C. G. (2024). Instructional management strategies for addressing low student engagement in mathematics. *Environment and Social Psychology*, *9*(12). https://doi.org/10.59429/esp.v9i12.3229

Vermeulen, E. J., & Volman, M. L. L. (2024). Promoting student engagement in online education: Online learning experiences of Dutch University students. *Technology, Knowledge and Learning*, *29*, 941–961. https://doi.org/10.1007/s10758-023-09704-3

Watson, J. C. (2017). Establishing evidence for internal structure using exploratory factor analysis. *Measurement and Evaluation in Counseling and Development*, *50*(4), 232–238. https://doi.org/10.1080/07481756.2017.1336931

Xu, M., Fralick, D., Zheng, J. Z., Wang, B., Tu, X. M., & Feng, C. (2017). The differences and similarities between two-sample t-test and paired t-test. *Shanghai Archives of Psychiatry*, *29*(3), 184–188. https://doi.org/10.11919/j.issn.1002-0829.217070

Zhoc, K. C. H., Webster, B. J., King, R. B., Li, J. C. H., & Chung, T. S. H. (2019). Higher education student engagement scale (HESES): Development and psychometric evidence. *Research in Higher Education*, *60*(2), 219–244. https://doi.org/10.1007/s11162-018-9510-6

APPENDIX

E-Ogrenmede Surdurulebilir Ogrenci Bagliligi Olcegi (eO-SOB-O)*

Kod	Sira	Maddeler
PM	***PM***	***Psikolojik Motivasyon (PM)***
PM1	1	Cevrimici dersler ogrenmeye olan ilgimi artirir.
PM2	2	Cevrimici bir ders aldigimda calismaya motive olurum.
PM3	3	Cevrimici derslerin benim icin cok faydali oldugunu dusunuyorum.
PM5	4	Cevrimici bir ders aldiktan sonra, bir sonraki dersi sabirsizlikla bekliyorum.
PM6	5	Almakta oldugum cevrimici dersten memnunum.
PC	***AIB***	***Akran Is Birligi (AIB)***
PC1	6	Ders icerigini diger ogrencilerle birlikte calisirim.
PC2	7	Karsilastigim zor sorulari cevrimici sinifimdaki diger ogrencilerle beraber cozmeye calisirim.
PC3	8	Cevrimici projelerde veya odevlerde diger ogrencilerle birlikte calisirim.
PC4	9	Cevrimici sinifimda ogretilen bir kavrami anlayamadigim zaman diger ogrencilerden yardim isterim.
PC5	10	Diger ogrencilerin sordugu sorulari yanitlamaya calisirim.
CS3	11	Cevrimici derslerimde diger ogrencilerle sik sik etkilesime girerim.
CPS	***BPC***	***Bilissel Problem Cozme (BPC)***
CPS1	12	Cevrimici derslerimde ogrendigim bilgilerden yeni yorumlar ve fikirler uretebilirim.
CPS2	13	Cevrimici derslerimde ogrendigim bilgilerle ilgili dusunceleri, deneyimleri ve teorileri derinlemesine analiz edebilirim.
CPS3	14	Cevrimici derslerimde ogrendiklerimle ilgili bilgileri degerlendirebilirim.
CPS4	15	Cevrimici derslerde ogrendigim bilgileri, gercek sorunlara veya yeni durumlara uygulamaya calisirim.
CPS5	16	Cevrimici dersimin konusuna yeni bir bakis acisiyla yaklasmaya calisirim.
LM	***OY***	***Ogrenme Yonetimi (OY)***
LM1	17	Cevrimici dersim bittikten sonra ilgili konu iceriklerini kendim calisirim.
LM2	18	Cevrimici derslere katilirken dikkatimi dagitan tum cevresel faktorleri kaldiririm.
LM3	19	Cevrimici sistemi kullanarak kendi ogrenme surecimi yonetirim.
LM4	20	Cevrimici bir ders aldigimda, bir ogrenme programi planlarim.

*Ters madde bulunmamaktadir.