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Modeling Factors Associated with Continuance Intention to Use E-Learning During and After COVID-19

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Research Article

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Abstract

Background/purpose. Widespread adoption of e-learning was triggered worldwide during the COVID-19 pandemic and modern higher education institutions dedicated significant resources to the use of diverse e-learning systems. However, to maximize the benefits of these investments, it is crucial that the degree to which end-users accept and continue using these systems is evaluated. Employing an integrative theoretical framework based on the extended Technology Acceptance Model (TAM) and Expectation Confirmation Model (ECM), this study aimed to scrutinize factors affecting students' continuance intention to use an e-learning platforms following the pandemic.

Materials/methods. The research employed a cross-sectional design, and 343 university students were surveyed. Partial least squares structural equation modeling (PLS-SEM) was employed in the data analysis.

Results. The findings indicate perceived usefulness and satisfaction to be direct predictors of e-learning system usage, whilst confirmation of expectation, perceived usefulness, perceived ease of use, and system interactivity were shown as indirect predictors.

Conclusion. Discussed along with the literature, the study's results revealed satisfaction to be the most vital indicator of continuance intention. Some suggestions are put forward, aimed towards helping both instructors and system designers.

1. Introduction

The introduction to this study sets the stage for an exploration into the transformative potential of combining neuropedagogy, neuroimaging, artificial intelligence (AI), and deep learning within educational systems. At the heart of this research is a commitment to understanding and enhancing the personalization of learning processes, and the use of advanced technologies to cater educational strategies to the neurocognitive profiles of individual students.

The coronavirus (SARS-CoV-2), which first came to light in December 2019, caused the world to find itself in the grip of a severe pandemic. During the early stages, there were no effective measures beyond isolation and social distancing to prevent the spread of the infection. Accordingly, widespread adoption of e-learning was triggered worldwide, leading many colleges and universities to shift their classes to an online format, and the demand for e-learning seems to have continued beyond the crisis (Rajeh et al., 2021; Taghizadeh et al., 2022). Witze (2020, p. 163) stated that, "over the long term, universities might shift many classes online." The pandemic exacerbated a blurring of the lines between distance and traditional classrooms, with the trend moving away from a traditional single mode of educational delivery to multimodal instruction (Lockee, 2021).

The e-learning community has derived certain operational and pedagogical benefits from the various sophisticated technological solutions currently available (Choudhury & Pattnaik, 2020). However, mere technological sophistication does not always ensure that a system is adopted by its intended end users. When students fail to use a system, the advantages it offers will see limited realization (Abdullah & Ward, 2016; Dağhan & Akkoyunlu, 2016; Tarhini et al., 2017). In other words, success in e-learning is reliant upon human-related factors such as learners and instructors, as well as other non-human factors such as learning management systems (Al-Fraihat et al., 2020). In recognition of the widespread use of online education throughout the pandemic and the potential for a certain level of adoption since, it is crucial to examine students' perceptions concerning e-learning adoption and continuance usage. Given this rationale, the current study's aim was to assess a model of continuance intention of using an e-learning system during and after COVID-19 from the lens of users according to an integrated model based on the extended TAM and the ECM.

Significance of the Study and Problem Statement

This research was administered and contextualized in Turkey, where e-learning is not considered a particularly new phenomenon. Prior to the pandemic, common obligatory undergraduate courses such as "Principles of Atatürk" and "History of the Turkish Revolution and Turkish Language" had been delivered online by many universities in accordance with a directive from Turkey's Council of Higher Education (Kocatürk Kapucu & Uşun, 2020; Kondakci et al., 2019). Research was conducted on students' perceptions related to the teaching of these courses via online mediums. In light of the literature's findings, one of the most significant problems reported was a low level of student participation in these courses (Akbaba et al., 2016; Eroğlu & Kalayci, 2020); thus, it may be argued that successful online learning implementation is contingent upon students' intention to use a system in addition to its quality. More essentially, the determinants of continuance should be identified and tested regarding e-learning usage intention both during the recent pandemic and since in terms of its general adoption.

A broad range of models have been put forward to account for individuals' adoption or dismissal of information systems (Venkatesh et al., 2003). However, recent comprehensive reviews have revealed the TAM and the ECM as the two most frequently prevailing theories on this topic (Franque et al., 2020; Yan et al., 2021). The TAM was predominantly built upon the associations between perceived usefulness, perceived ease of use, attitude toward using the system, and behavioral intention (Davis et al., 1989; Vankatesh et al., 2003). However, it has since been criticized for being too parsimonious (Venkatesh & Bala, 2008), and was therefore later extended to include external factors that expanded its predictive validity (Abdullah & Ward, 2016). Another criticism of the TAM was that it did not consider satisfaction, which plays a pivotal role in explaining pre-acceptance and discontinuance anomaly (Bhattacherjee, 2001). This limitation may be compensated for by including the ECM, since it predicts continuance intention based on experiential usage (i.e., confirmation of expectations) and emotional response (i.e., satisfaction) in addition to expectations of benefits (i.e., perceived usefulness) (Ambalov, 2018). Hence, combining the extended TAM with the ECM is suggested as pertinent to the current research (Bhattacherjee, 2001).

Recent works have been undertaken to delve into the factors that affect e-learning adoption, and which have utilized or combined different theoretical models in terms of the COVID-19 context (Aguilera-Hermida et al., 2021; Chauhan et al., 2021; Mailizar et al., 2021; Rajeh et al., 2021; Taghizadeh et al., 2022; Vladova et al., 2021). However, further research in this area is still needed.

The current study utilized both the extended TAM and the ECM. The extended TAM allows for the incorporation of the most influential external determinants that fit the study context. Furthermore, in considering the intensive and experiential e-learning exposure during the COVID-19 era, the ECM makes it possible to test perceived usefulness and confirmation of expectations' impact on user satisfaction, which is considered the crucial driving motivator behind the continuous ongoing use of a system. Based on experiential satisfaction, students' current and post-COVID e-learning usage intentions could be investigated rather than their mere initial acceptance (Bhattacherjee, 2001).

This integrated approach may serve to increase its predictive power when compared to that of a single model. Results are anticipated to help establish more effective e-learning systems going forwards. Furthermore, with two different models applied together (i.e., extended TAM and ECM), the current study's aim was to better explain students' continuance intention through the determination of various factors that may affect the outcome. The research question that guided the current study was therefore as follows:

- How well does an integrative model based on the extended TAM and the ECM account for students' continuance intention of using an e-learning system during and after COVID-19?

In summary, this study aimed to investigate critical determinants of continued use of an e-learning system in Turkey, a country where e-learning was already utilized prior to the pandemic. This research study's aim was to address a gap in the literature of long-term e-learning usage beyond initial acceptance by users.

2. Background and Hypotheses

Technology Acceptance Model (TAM)

The TAM is a well-known framework used to test technology adoption (Granić & Marangunić, 2019). According to the TAM, perceived ease of use, perceived usefulness, and attitude affect intention to accept a specific technology (Davis et al., 1989). However, it was later discovered that attitude has only a limited effect (Davis et al., 1989), and many researchers opted not to include it when applying the model (Abdullah et al., 2016; Chang et al., 2017; Tarhini et al., 2017). Therefore, the current study also dropped the attitude dimension.

Perceived Usefulness and Perceived Ease of Use

Perceived usefulness (PU) is the extent to which a person perceives that utilizing a certain system could enhance their job performance (Davis, 1989). In the current study, benefits of the e-learning system, as seen from the students' perspective, are expected to predict continuance intention. When students recognize that the online educational/learning system could advantageously affect their academic achievement, they are more likely to persist in using it. Studies have demonstrated that PU significantly increases students' likelihood of utilizing e-learning tools (Ashrafi et al., 2022; Chauhan et al., 2021; Eraslan Yalcin & Kutlu, 2019; Goh & Yang, 2021; Lee, 2010; Vladova et al., 2021; Wang et al., 2021), while some (e.g., Mailizar et al., 2021) revealed a non-significant PU impact.

Perceived ease of use (PEOU) reflects a person's assessment of the ease of operating a particular system (Davis, 1989). In the current study, PEOU denotes a student's competency in utilizing the e-learning system without experiencing difficulties. It has been put forth in the literature that PEOU significantly and positively predicts behavioral intention (Abbad et al., 2009; Al-Emran & Teo, 2020), whilst some studies found no such effect (Han & Sa, 2021; Ros et al., 2014).

According to the TAM, the PEOU of a system also impacts its PU. While some studies confirmed this link (Cheng, 2019; Han & Sa, 2021; Lee, 2010; Mailizar et al., 2021), some revealed no significant association (Ashrafi et al., 2022; Chang et al., 2017; Vladova et al., 2021). Accordingly, we argue that:

- H1: PU is directly and positively related to the continuance intention (CI) of using an e-learning system during and after the pandemic.
- H2: PEOU is directly and positively related to the continuance intention (CI) of using an e-learning system during and after the pandemic.
- H3: PEOU is directly and positively related to PU of an e-learning system during and after the pandemic.

External Variables of TAM

Although the TAM is arguably a powerful framework and easy to implement, it presents "very general information on users' opinions about a system" (Mathieson, 1991, p. 173). Considering its limitations, the original TAM was extended to augment its predictive power (Huang et al., 2022; Venkatesh & Bala, 2008). Abdullah and Ward (2016) investigated frequently employed external antecedents of the TAM, and concluded that self-efficacy, enjoyment, experience, computer anxiety, and subjective norms were the most frequently adopted external components. Similarly, in a meta-analysis study by Baki et al. (2018), it was concluded that enjoyment, self-efficacy, interaction, subjective norm, anxiety, and compatibility were the external antecedents of PU and PEUO.

Although various external variables may be incorporated into the model, deciding upon which variables is contingent upon the technology employed, the users, and the area of implementation (Iqbal & Bhatti, 2015). The current study incorporated external variables according to the context of the research. We also took note of various meta-analyses published on the topic of our research (Abdullah & Ward, 2016; Baki et al., 2018; Franque et al., 2020; Yan et al., 2021). The external variables utilized in the current study are explained in the following.

Subjective Norm

Subjective norm (SN) is the influence of significant others on a student's decision to execute a particular behavior (Ajzen, 1991). Both TAM2 and TAM3 argue that subjective norm is a direct antecedent of PU (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Research has shown that SN influences PU in diverse contexts, including use of the Moodle learning management system (Teo et al., 2019) and in mobile learning (Park, Nam, & Cha, 2012), whilst some studies found SN to have little or no influence (Abbad et al., 2009; Abdullah et al., 2016). In the current study, it is supposed that a learner's significant others' (e.g., friends, peers, instructors) opinions about e-learning might relate to their own feelings regarding the system's usefulness (PU). Hence, we postulate that:

- H4: SN is directly and positively related to PU of an e-learning system during and after the pandemic.

System Interactivity

Interaction is critical in distance education. The quality of interaction between learner-instructor, learner-learner, and learner-system affects the efficiency of the system (Moore & Kearsley, 2011).

System Interactivity (SI) was found to be the third most frequently used external antecedent of the TAM (Baki et al., 2018). In the current study, SI denotes the system's interactive communication capabilities. In addition, system affordances such as e-mail, forum, and chat are also expected to impact perceived SI, which might have an influence on the system's perceived usefulness (PU) (Abbad et al., 2009; Pituch & Lee, 2006). The literature shows that a significant positive influence exists between SI and PU (e.g., Cheng, 2013; Liaw & Huang, 2013; Pituch & Lee, 2006), although some studies did not observe such an effect (e.g., Abbad et al., 2009; Li et al., 2012). Considering its importance, we postulate that:

- H5: SI is directly and positively related to PU of an e-learning system during and after the pandemic.

Self-Efficacy

Computer self-efficacy (SE) is a user's confidence belief in their own ability to operate a certain system (Venkatesh & Bala, 2008). Research findings have shown that SE significantly influences PEOU (Huang et al., 2022; Moreno et al., 2017), although some research obtained a null SE effect on PEOU (Agudo-Peregrina et al., 2014). Meta-analysis studies have demonstrated SE to be the most potent determinant of PEOU (Abdullah & Ward, 2016; Baki et al., 2018). Considering the literature, SE was included in the current research model since students' SE beliefs regarding use of the e-system may be associated with their PEOU. In other words, the more students feel confidence in using the system, the more they may find it easy to use. Accordingly, we postulate that:

- H6: SE is directly and positively related to PEOU of an e-learning system during and after the pandemic.

Perceived Enjoyment

Perceived enjoyment (ENJOY) is the degree to which a system's usage is regarded subjectively as pleasurable, regardless of performance consequences (Venkatesh, 2000). It appeared in TAM3 as a direct antecedent of PEOU (Venkatesh & Bala, 2008). Research has postulated that people consider more enjoyable mediums as being easier to use, since such mediums decrease cognitive load (Huang et al., 2022; Park, Son, & Kim, 2012; Salomon, 1984). Research has demonstrated that ENJOY is a significant antecedent of PEOU (Huang et al., 2022; Park, Son, & Kim, 2012; Unal & Uzun, 2021), and the second-best predictor of PEOU after SE (Abdullah & Ward, 2016). Given the preceding literature, ENJOY is included in the current study as an emotional antecedent of PEOU. We foresee that if students enjoy using an online educational system, they will likely experience a sense of ease and comfort in its use, therefore we postulate that:

- H7: ENJOY is directly and positively related to PEOU of an e-learning system during and after the pandemic.

Expectation Confirmation Model (ECM)

To explain individuals' intentional usage behaviors of a system, Bhattacherjee (2001) formulated the ECM. The model asserts that elements that determine one's desire to persist in utilizing a specific information system are perceived usefulness, confirmation, and satisfaction (Bhattacherjee, 2001). In terms of the current study's context, first, students may have an initial expectation of the system used during the COVID-19 era. Second, after having used the system, they may evaluate its performance based on their own experiences. They may ultimately then reach a decision about their ongoing usage of the platform based on how satisfied or dissatisfied they were with their experiences compared to their expectations (Bhattacherjee, 2001).

Satisfaction (SAT) refers to the level of satisfaction and contentment attained by users in connection with prior use of a system (Lee & Lehto, 2013). Different studies have addressed the impact of SAT on intention. For example, according to Dağhan and Akkoyunlu (2016), SAT may predict students' inclination to adopt online learning environments with the most significant beta coefficient. In a study of Saudi healthcare students, Rajeh et al. (2021) revealed SAT to be the strongest indicator. Similarly, in a comprehensive cross-country study with data drawn from Oman, Iran, Bangladesh, Romania, and Malaysia, it was shown that for all participating nations, SAT was substantially and positively related to continued intention (Taghizadeh et al., 2022).

In the current investigation, students had prior e-learning experience and were therefore expected to like or dislike the system. Accordingly, their satisfaction may have influenced their intention to use the system. To put that differently, students' e-learning usage intentions may be linked with their SAT; therefore, we hypothesize that:

- H8: Satisfaction (SAT) is directly and positively related to the continuance intention (CI) of using an e-learning system during and after the pandemic.

Confirmation (CONF) pertains to determining the extent to which a user's pre-use system expectation is achieved after their having used the system (Bhattacherjee, 2001; Oghuma et al., 2016). Furthermore, according to the ECM, confirmation of expectation affects students' satisfaction with and perceived usefulness of the system (Bhattacherjee, 2001), which has also been corroborated by the literature (Chauhan et al., 2021; Wang et al., 2021). Hence, we postulate that:

- H9: CONF is directly and positively related to SAT in using an e-learning system during and after the pandemic.
- H10: CONF is directly and positively related to PU of an e-learning system during and after the pandemic.

PU is a common construct addressed by both the TAM and the ECM. Various studies have stated that PU has a significant influence on satisfaction (SAT). For example, it was revealed that PU is closely related to SAT, which consecutively affects continuance intention. In a longitudinal study, Cheng and Yuen (2018) revealed that although PU is strongly associated with SAT, this association weakens as time passes. Taghizadeh et al. (2022) conducted a comprehensive cross-cultural study that included Oman, Iran, Bangladesh, Romania, and Malaysia. In their study, they revealed that the perceived relative advantage of a system was linked with greater student satisfaction in all countries except Romania, where the participants were primarily engineering students having practice-based tasks that would be challenging to implement via e-learning. Hence, we hypothesize that:

- H11: PU is directly and positively related to SAT using an e-learning system during and after the pandemic.

Although not addressed by the ECM, the influence of PEOU on satisfaction was also scrutinized. Many researchers have found PEOU to be significantly and positively related to system satisfaction (Ashrafi et al., 2022; Han & Sa, 2021). Hence, we postulate that:

- H12: PEOU is directly and positively related to SAT using an e-learning system during and after the pandemic.

3. Methodology

The current investigation adopted a cross-sectional design in which data were gathered at a single point in time. An integrative model based on the extended TAM and the ECM was employed. In selecting the model's relevant variables, we applied different studies from the relevant literature (Abdullah & Ward, 2016; Baki et al., 2018; Bhattacherjee, 2001; Franque et al., 2020; Lee, 2010; Yan et al., 2021). The study's aforementioned 12 hypotheses are illustrated in Figure 1.

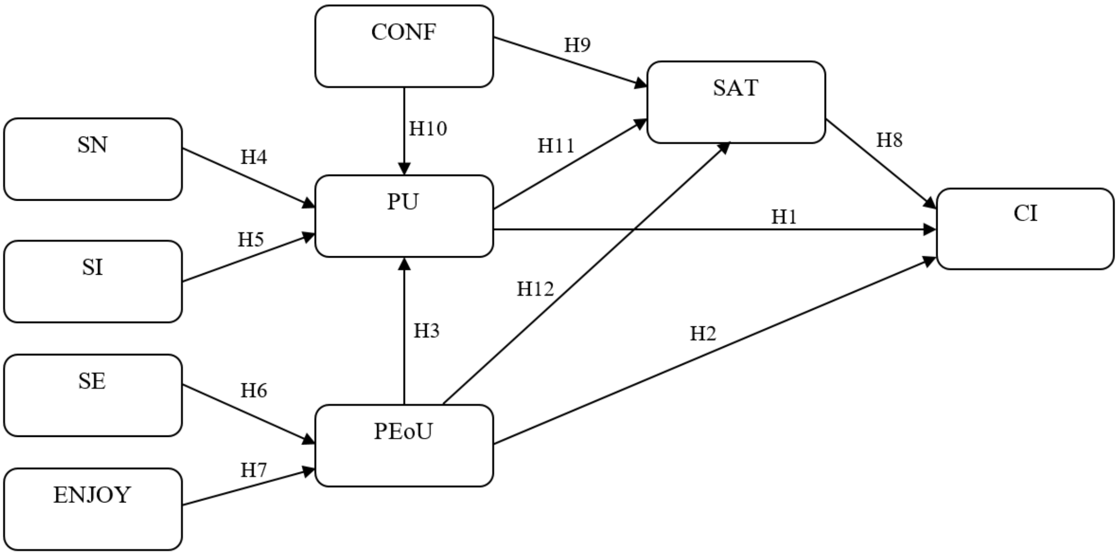

Figure 1. Research Model

SN: Subjective norm, SI: System interactivity, SE: Self-efficacy, ENJOY: Perceived enjoyment, CONF: Confirmation of expectations, PU: Perceived usefulness, PEOU: Perceived ease of use, SAT: Satisfaction, CI: Continuance intention

The research was conducted at a public higher education institution located in the Black Sea region of Turkey. During the COVID-19 pandemic era, all programs were switched to e-learning, except for health sciences and those of the medical faculty where blended learning was adopted due to the highly practical nature of some hospital-based courses. The research itself was undertaken within the institution's education faculty, where all programs and courses were delivered completely within an online environment. Moodle, a free-to-use open-source learning and course management system, was used to deliver course content, assignments, and exams. Virtual classes were held using the BigBlueButton and Google Meet videoconferencing technology for synchronous lessons, where both students and instructors met together on a predetermined day and at a certain time each week. Additionally, virtual classes were digitally video-recorded and made available for students to watch at their convenience for continued self-study and practice purposes throughout the semester. During the synchronous lessons, instructors would teach the course contents, ask questions of the students, or hold class discussions in order to engage learners. As for the asynchronous classes, the course contents were made accessible to the students over the Internet on a weekly basis. The course materials included documents, readings, videos, and slides, with online exams, assignments, and research papers used to measure student performance. The exams were held synchronously using the Moodle learning management system.

The study utilized a convenience sampling method, which is a non-probabilistic quantitative sampling technique. Following this procedure, the study participants were determined based on their willingness and availability (Creswell, 2012). As a requirement of ethical human-based research principles, the participants' consent was sought in written form, after having been duly informed about the nature and extent of the research. Moreover, their anonymity and confidentiality of the data collected were assured. The sample included 343 undergraduate students from numerous fields of study within the faculty of education. Although a total of 350 students were initially accessed, seven cases were eliminated from the dataset due to incomplete responses having been submitted. Of the 343 students in the final sample, 79% (n = 271) were female and 21% (n = 72) were male. Additionally, their ages ranged from 18 to 36 years old (M = 20.83). Most of the students were sophomores (n = 132, 39%), followed by seniors (n = 87, 25%), freshmen (n = 83, 24%), and juniors (n = 41, 12%). Finally, the frequency level of their having used the e-learning system was found to be substantially high, with several times a week (n = 160, 47%), followed by almost every day (n = 123, 36%), once a week (n = 30, 9%), and more than once in a day (n = 29, 8%); while only one student failed to respond to the question.

The data collection instrument sought demographic information about the students, plus 27 questions presented as a 7-point, Likert-type scale with 1 point for *strongly disagree* through to 7 points for *strongly agree*. The items were derived from similar well-known studies from the literature that referred to various sources (see Table 1), and which were then modified slightly in order to best fit the current study's context.

Table 1. Constructs of data collection instrument used in the study

Construct	Item	Source
Continuance Intention (CI)	CI1	Adapted from Bhattacherjee (2001), Chauhan et al. (2021), and Lee (2010)
	CI2	
	CI3	
Confirmation (CONF)	CONF1	Adapted from Bhattacherjee (2001) and Lee (2010)
	CONF2	
	CONF3	
Perceived Enjoyment (ENJOY)	ENJOY1	Adapted from Lee (2010)
	ENJOY2	
	ENJOY3	
Perceived Ease of Use (PEOU)	PEOU1	Adapted from Davis (1989) and Lee (2010)
	PEOU2	
	PEOU3	
Perceived Usefulness (PU)	PU1	Adapted from Davis (1989) and Lee (2010)
	PU2	
	PU3	
Satisfaction (SAT)	SAT1	Adapted from Bhattacherjee (2001) and Lee (2010)
	SAT2	
	SAT3	
Self-Efficacy (SE)	SE1	Adapted from Liaw (2008)
	SE2	
	SE3	
System Interactivity (SI)	SI1	Adapted from Abbad et al. (2009) and Pituch and Lee (2006)
	SI2	
	SI3	

Construct	Item	Source
Subjective Norm (SN)	SN1	Teo et al. (2019)
	SN2	
	SN3	

The current study administered a version of the scale that had been adapted to the Turkish context. The researchers first translated the original scale's questions into the Turkish language, as both are native Turkish speakers and fluent in English. Then, two Turkish-speaking English language experts compared the original items to the translated versions following completion of the translation process. The researchers then compared the scales and applied any necessary final corrections. Finally, a Turkish language expert checked the translated scale regarding its readability, clarity, and the grammar used. Google Forms and printed materials were used to collect the study's data during the spring semester of the 2021-2022 academic year.

Structural equation modeling using the partial least square method (PLS-SEM) was employed to analyze the collected data. PLS is a regression-based method for predicting target dependent variables from multiple independent variables, affording advantages over covariance-based – structural equation modeling (CB-SEM). It is more advantageous for theory prediction than confirmation. In PLS-SEM, complex models with various constructs can be tested, even those with one or two items (Hair et al., 2011). The collected data was subjected to a two-stage analysis technique. First, the measurement model was tested in order to ensure that the data-gathering tool was valid and reliable. Second, the structural model was assessed to test the hypothetical relationships. The obtained data were analyzed using SmartPLS 3.2.7 software.

4. Results

Measurement Model

This subsection reports values regarding the measurement model, with values regarding the reliability and validity of the data collection tool presented in Table 2.

Table 2. Results of the Measurement Model

Construct	Item	Factor Loading	Mean	Median	*SD*	Cronbach's alpha	Rho_A	CR	AVE
						.943	.944	.964	.898
Continuance Intention (CI)	CI1	.946	3.399	3.000	2.167				
	CI2	.943	3.286	3.000	2.039				
	CI3	.954	3.397	3.000	2.160				
						.921	.923	.950	.863
Confirmation of Expectations (CONF)	CONF1	.910	3.892	4.000	2.004				
	CONF2	.937	3.703	4.000	1.886				
	CONF3	.940	3.458	3.000	1.878				
						.961	.978	.975	.928

Construct	Item	Factor Loading	Mean	Median	*SD*	Cronbach's alpha	Rho_A	CR	AVE
Perceived Enjoyment (ENJOY)	ENJOY1	.969	3.510	3.000	2.071				
	ENJOY2	.967	3.265	3.000	2.050				
	ENJOY3	.954	3.099	3.000	2.027				
						.941	.947	.962	.894
Perceived Ease of Use (PEOU)	PEOU1	.935	4.796	5.000	1.881				
	PEOU2	.961	4.665	5.000	1.934				
	PEOU3	.941	4.825	5.000	1.893				
						.950	.951	.968	.909
Perceived Usefulness (PU)	PU1	.964	2.942	2.000	1.863				
	PU2	.969	2.924	2.000	1.839				
	PU3	.926	3.367	3.000	2.131				
						.900	.908	.938	.834
Satisfaction (SAT)	SAT1	.933	3.554	4.000	1.899				
	SAT2	.952	3.685	4.000	1.915				
	SAT3	.853	4.093	4.000	2.132				
						.919	.920	.949	.861
Self-Efficacy (SE)	SE1	.894	4.190	4.000	2.016				
	SE2	.949	4.420	5.000	1.869				
	SE3	.940	4.571	5.000	1.825				
						.852	.873	.911	.773
System Interactivity (SI)	SI1	.919	3.601	4.000	1.929				
	SI2	.922	3.219	3.000	1.905				
	SI3	.790	4.475	5.000	1.960				
						.915	.917	.946	.855
Subjective Norm (SN)	SN1	.911	3.431	3.000	2.035				
	SN2	.946	3.557	4.000	2.068				
	SN3	.917	3.845	4.000	2.092				

AVE: Average variance extracted, CR: Composite reliability, rho_A: Dijkstra-Henseler's rho

First, we assessed the item loadings of the factors. All factor loadings were found to be satisfactorily higher than the proposed threshold of .70 (Hair et al., 2017) (see Table 2). Assessment of internal consistency reliability was conducted through inspection of Cronbach's alpha values and composite reliability (CR). Additionally, Dijkstra-Henseler's rho was reported for this purpose. All three values were found to surpass the recommended acceptable threshold (> .70), thereby meeting the required standard for internal consistency reliability (Hair et al., 2017).

The AVE was considered in order to assess whether or not convergent validity had met the advised criterion (> .50) (Fornell & Larcker, 1981). As can be seen from Table 2, all factors were found to have sufficient AVE values, suggesting that convergent validity was confirmed. Finally, discriminant validity assessment included two methods: Fornell-Larcker criterion and the heterotrait-monotrait ratio of correlations (HTMT). Fornell and Larcker (1981) proposed that the square root of the AVE for a specific factor is recommended to be superior to its correlation with other factors. As can be seen from Table 3, this criterion was also fulfilled. As for the HTMT, depending on the research context and conservativeness of the researcher, different threshold values (.85, .90, and 1) can be used (Franke & Sarstedt, 2019; Henseler et al., 2015). According to Table 3, the HTMT value for the satisfaction–confirmation link was shown to be greater than .90. However, given the conceptual similarities of these constructs, a more liberal value of 1 was referred to in the current study. A complete bootstrapping routine was conducted in order to assess the null hypotheses (H0: HTMT ≥ 1) against its alternative (H1: HTMT < 1). Confidence interval values of 1 denote an absence of discriminant validity (Henseler et al., 2015). Based on the confidence intervals, all HTMT values were found to significantly differ from 1 in the current study, suggesting that discriminant validity was ensured. In summary, evidence was established to support reliability and validity; hence, the structural model was then subjected to analysis.

Table 3. Discriminant Validity Results

	CI	CONF	ENJOY	PEOU	PU	SAT	SE	SI	SN
CI	**.948**	.794	.853	.497	.818	.870	.672	.754	.739
CONF	.742	**.929**	.792	.624	.809	.969	.690	.695	.693
ENJOY	.813	.747	**.963**	.499	.846	.853	.621	.756	.650
PEOU	.470	.582	.481	**.946**	.556	.648	.729	.548	.452
PU	.776	.758	.810	.529	**.953**	.843	.626	.697	.610
SAT	.803	.886	.796	.596	.783	**.913**	.746	.766	.694
SE	.626	.635	.587	.680	.586	.676	**.928**	.726	.561
SI	.681	.616	.688	.489	.632	.668	.638	**.879**	.609
SN	.690	.637	.612	.421	.571	.629	.514	.546	**.925**

Note: Boldfaced diagonal entries indicate the square root of the AVE values. The above diagonal values are HTMT values. CI: Continuance intention, CONF: Confirmation of expectations, ENJOY: Perceived enjoyment, PEOU: Perceived ease of use, PU: Perceived usefulness, SAT: Satisfaction, SE: Self-efficacy, SI: System interactivity, SN: Subjective norm

Structural model

First, the structural model was evaluated for collinearity issues, as suggested by Hair et al. (2017). Values of the variance inflation factor (VIF) that exceed the established critical threshold of 5 imply an occurrence of collinearity issues. All VIF values were found to be lower than the threshold value, suggesting the absence of collinearity issues (see Table 4). Next, a bootstrapping resampling routine with 5,000 subsamples was employed to test the hypothetical paths (Hair et al., 2017) (see Table 4).

Table 4. Results of the Structural Model

Hypothesis	Path Relationships	Collinearity Statistics (VIF)	Path Coefficients (β)	*t* values	*p* values	Supported?
H1	PU → CI	2.627	.389	8.364	.000	Yes
H2	PEOU → CI	1.576	-.050	1.490	.136	No
H3	PEOU → PU	1.579	.082	1.832	.067	No
H4	SN → PU	1.800	.082	1.622	.105	No
H5	SI → PU	1.786	.228	4.650	.000	Yes
H6	SE → PEOU	1.526	.606	12.116	.000	Yes
H7	ENJOY → PEOU	1.526	.125	2.526	.012	Yes
H8	SAT → CI	2.933	.528	10.740	.000	Yes
H9	CONF → SAT	2.636	.650	14.584	.000	Yes
H10	CONF → PU	2.339	.518	8.471	.000	Yes
H11	PU → SAT	2.420	.243	5.407	.000	Yes
H12	PEOU → SAT	1.555	.089	2.980	.003	Yes

SN: Subjective norm, SI: System interactivity, SE: Self-efficacy, ENJOY: Perceived enjoyment, CONF: Confirmation of expectations, PU: Perceived usefulness, PEOU: Perceived ease of use, SAT: Satisfaction, CI: Continuance intention

First, hypotheses concerning the extended TAM were analyzed. The results revealed that PU significantly predicted CI to use the e-learning system (H1) (β = .389, t = 8.364, p < .001), whilst PEOU did not (H2) (β = -.050, t = 1.490, p > .05). The findings also indicated that PEOU was not significantly related to PU (H3) (β = .082, t = 1.832, p > .05). When the effect of the external TAM constructs was analyzed, it was observed that PU was not significantly influenced by SN (H4) (β = .082, t = 1.622, p > .05), but it was significantly influenced by SI (H5) (β = .228, t = 4.650, p < .001). Regarding the antecedents of PEOU, both SE (H6) (β = .606, t = 12.116, p < .001) and ENJOY (H7) (β = .125, t = 2.526, p < .05) significantly contributed to the prediction of PEOU.

Secondly, hypotheses concerning the ECM were analyzed, and the results indicated that all hypotheses formulated for the ECM were confirmed. Specifically, SAT exhibited the strongest significant effect on CI in using the e-learning system (H8) (β = .528, t = 10.740, p < .001). Moreover, SAT was significantly predicted by both CONF (H9) (β = .65, t = 14.584, p < .001) and PU (H11) (β = .243, t = 5.407, p < .001). CONF exerted a significant influence on PU (H10) (β = .518, t = 8.471, p < .001). Finally, PEOU significantly and positively influenced SAT (H12) (β = .09, t = 2.980, p < .01).

When the indirect effects were examined, it was found that CONF was indirectly and positively associated with CI in using the e-learning system through PU (β = .202, t = 6.509, p < .001) and SAT (β = .363, t = 8.655, p < .001). PU indirectly and significantly influenced CI through SAT (β = .138, t = 4.803, p < .001). SI was indirectly and positively linked with continuance intention via PU (β = .089, t = 3.850, p < .001). Finally, PEOU indirectly and significantly affected continuance intention mediated by SAT. Figure 2 depicts the results of the structural model.

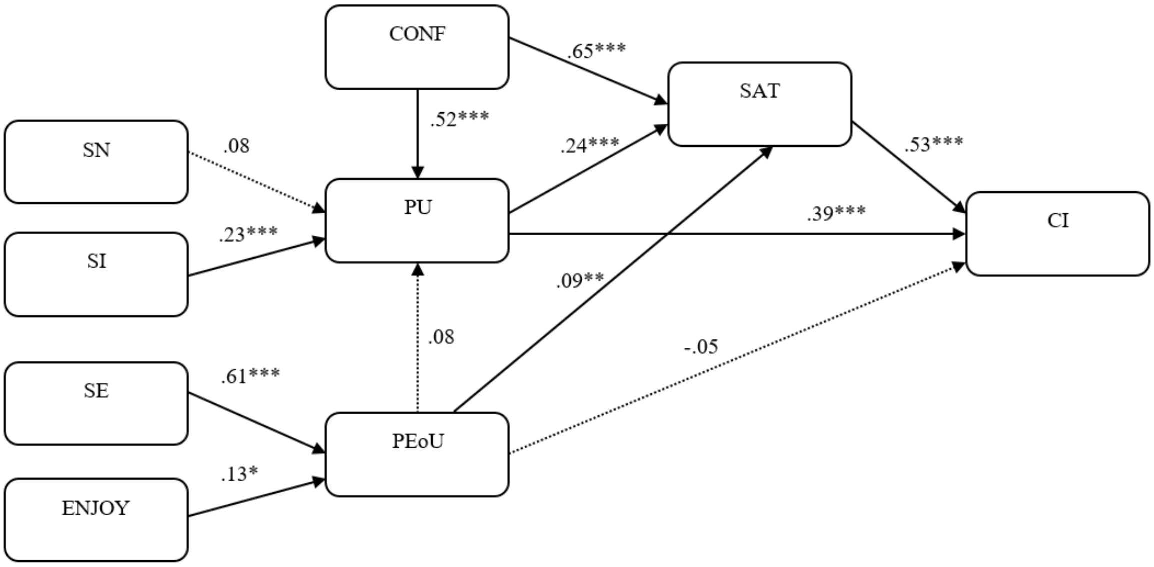

Figure 2. Results of the Structural Model

*Dashed line: Insignificant relationship, Solid line: Significant relationship. *p < .05; **p < .01; ***p < .001. SN: Subjective norm, SI System interactivity, SE: Self-efficacy, ENJOY: Perceived enjoyment, CONF: Confirmation of expectations, PU: Perceived usefulness, PEOU: Perceived ease of use, SAT: Satisfaction, CI: Continuance intention*

As a next step, coefficient determination (R^2) was analyzed, and it was found that the whole model explained 70% of the total variance in continuance intention. According to Chin (1998), R^2 values of .67, .33, and .19 imply substantial, moderate, and weak explanatory power, respectively. Accordingly, the examined model was found to have substantial power in explaining intention to continue using the e-learning system (see Table 5). Other R^2 values are reported in Table 5.

Table 5. Predictive relevance and explained variance

Construct	Q^2	R^2
CI	.62	.70
SAT	.68	.82
PU	.56	.63
PEOU	.42	.47

The predictive relevance and effect size, reflected by the Q^2 and f^2 values, respectively, were provided in the next step of the analysis. Q^2 values should exceed 0 in order to attain predictive significance (Hair et al., 2017). In the current investigation, all Q^2 values, computed using the eight omission distances, exceeded the established minimum value. Consequently, it may be said that the model provides sufficient predictive relevance (see Table 5). For interpretation of the effect sizes, f^2 values were used, where .02, .15, and .35 correspond to small, moderate, and significant effects, respectively (Hair et al., 2017). The current study found that SAT (f^2 = .32) had a marginally large effect on CI, whilst PU (f^2 = .19) had a moderate effect on CI, and PEOU (f^2 = .01) had no effect. Concerning the antecedents of SAT, CONF (f^2 = .89) had a large effect, PU (f^2 = .14) had a marginally moderate effect, and PEOU (f^2 = .03) had a small effect. PEOU and SN did not affect PU, whereas SI had a small to moderate effect (f^2 = .08), and CONF had a moderate to strong effect (f^2 = .31) on PU. Regarding the antecedents of PEOU, the f^2 value of ENJOY (.020) was considered a small effect size, while the f^2 value of SE (.46) was considered a large effect.

5. Discussion

This research evaluated how an integrated framework combining the extended TAM and the ECM explained continuous intentional usage of an e-learning system during and after the COVID-19 era. The extended TAM facilitated the integration of the external determinants relevant to the study's context. The ECM enabled the assessment of the influence of perceived usefulness and expectation confirmation on user satisfaction, which is considered a critical driver for continuous system utilization, particularly in the context of intensive e-learning exposure during the COVID-19 period. A total of 343 undergraduates enrolled in teacher education programs provided the study's data. The model put forward adequately explained 70% of the overall variance. According to the findings, two variables significantly and directly affected intention: satisfaction (SAT) and perceived usefulness (PU). However, perceived ease of use (PEOU) failed to have an apparent impact. Amongst the external variables of PU, system interactivity but not subjective norms possessed a significant impact. Considering the external variables of PEOU, both antecedents (self-efficacy and perceived enjoyment) significantly predicted PEOU. The results also revealed that confirmation and system interactivity indirectly affected intention when mediated by PU. Lastly, confirmation, perceived usefulness, and ease of use indirectly affected continuance intention, mediated by satisfaction. The following discusses these results in more detail.

First, the components of the extended TAM were evaluated. It was revealed that PU, a common construct of both the extended TAM and the ECM, possessed a moderately significant influence on continuance intention (CI). This finding matches mainstream literature revealing a significant positive influence of PU (Ashrafi et al., 2022; Chauhan et al., 2021; Eraslan Yalcin & Kutlu, 2019; Goh & Yang, 2021; Han & Sa, 2021; Lee, 2010). However, some studies also demonstrated a null effect (Mailizar et al., 2021). What may be deduced from this result is that PU can positively contribute to students' continued use of a system. If students feel that they can improve upon their academic performance, they may continue to make use of it (Davis, 1989). Considering the current study's context, the participant students had gained experience having used the e-learning system since the emergence of the pandemic. They may therefore have understood the system's potential benefits in terms of their academic performance, contributing positively to their continuance intention. Despite predictions, perceived ease of use (PEOU) was not found to predict continuance intention (CI). Nevertheless, this result conforms with some of the published literature (Han & Sa, 2021; Ros et al., 2014), whilst contradicting others (Abbad et al., 2009; Al-Emran & Teo, 2020). In the current investigation, it was revealed that students tended to hold the perception that the e-learning system was not complex to operate, as reflected by relatively high median values obtained for PEOU (see Table 2). This finding may be explained by the increased adoption of the e-learning system throughout the pandemic. As students used the system over a considerable period, they may have become somewhat automated in their use of it, which negated the need for a decision to adopt it in subsequent periods. To put that differently, as Han and Sa (2021) postulated, the students' decisions may have been primarily influenced by their PU of the system rather than its PEOU. As for the influence of PEOU on PU, it was found that PEOU did not affect PU, as similarly reported in earlier research (Ashrafi et al., 2022; Chang et al., 2017; Vladova et al., 2021), whilst opposing the findings of some other studies (Cheng, 2019; Han & Sa, 2021; Lee, 2010; Mailizar et al., 2021). Again, this result may be owing to the students' familiarity with the e-learning platform due to its prolonged usage. As for the external antecedents of PU, it was found that system interactivity was a significant predictor, while the subjective norm was not. As found in the current study, research has corroborated the positive relation of system interactivity to perceived usefulness (Girish et al., 2021). This finding shows that interactive communication tools provided by the e-learning system were deemed to have satisfied the participant students. When COVID-19 prevented face-to-face instruction, such system affordances were highly critical for students. Hence, interaction among students, teachers, and the system used is critical for continued system usage during and after a pandemic.

Regarding the subjective norm, the lack of impact upon perceived usefulness demonstrated by the findings of the current study coincides with outcomes documented in prior research (Abbad et al., 2009; Abdullah et al., 2016; Humida et al., 2022); although the results also differed from some studies (Park, Nam, & Cha, 2012; Teo et al., 2019). Accordingly, it may be assumed that students' social circuits, which may include their instructors, peers, and significant others, may not have been decisive in impacting their decision to continue using the e-learning system. This assumption may be considered reasonable since the students will have already used the system for a significant period from the outset of the pandemic, if not previously too. The effect of social influence diminishes as users gain experience since they discover the various advantages and disadvantages of a system by themselves. In such situations, social impact then plays less of a role (Venkatesh & Davis, 2000).

Regarding the antecedents of perceived ease of use (PEOU), both perceived enjoyment (ENJOY) and self-efficacy (SE) were found to have contributed to its prediction. Similar findings were obtained in the literature regarding the influence of SE (Eraslan Yalcin & Kutlu, 2019; Roca et al., 2006) on PEOU. When students' e-learning SE is high, they may recognize the system as being easy to use. This also concurs well with Bandura's (1997) research, in which it was posited that confidence in performing a behavior is associated with better task performance. The positive influence of ENJOY on PEOU also aligns with the literature, suggesting that enjoyable mediums decrease cognitive burden and are thereby perceived as being easy to use (Huang et al., 2022; Park, Son, & Kim, 2012; Salomon, 1984).

Regarding the ECM components, it was found that satisfaction (SAT) was significantly associated with continuance intention. This substantiates earlier research by Chauhan et al. (2021), Han and Sa (2021), Lee (2010), Rajeh et al. (2021), Roca et al. (2006), Taghizadeh et al. (2022), and Wang et al. (2021). Additionally, SAT was revealed as the largest indicator of future conduct, which also corroborated other findings in the literature (Chauhan et al., 2021; Dağhan & Akkoyunlu, 2016; Lee, 2010; Rajeh et al., 2021). Considering that satisfaction with a system or product is a critical aspect of its continued usage in the future (Liao et al., 2011), it is reasonable that such a result was obtained. As for the antecedents of SAT, it was evidenced that both confirmation (CONF) and perceived usefulness (PU) had significant influence, and which explained 82% of the total variance in satisfaction. The influence of PU and CONF on SAT supports earlier research by Ashrafi et al. (2022), Han and Sa (2021), Lee (2010), and Roca et al. (2006). According to this result, it may be postulated that by using the e-learning platform, the students' expectations of the system were confirmed over time and that the students formed the belief that e-learning would contribute to their acquisition of knowledge and skills, and, as a result, may have positively affected their satisfaction level. Besides, it appeared that confirmation significantly impacted the perception of usefulness. This output also concurs well with the literature (e.g., Ashrafi et al., 2022; Chauhan et al., 2021; Lee, 2010; Roca et al., 2006; Wang et al., 2021). Meeting the students' system's expectations might lead to their belief that its usage is beneficial to them. Even though the ECM did not explicitly take into account the implications of perceived ease of use on SAT, the current study also addressed this connection, and its reported significant impact coincides with that of research published by Ashrafi et al. (2022) and also Han and Sa (2021). Finally, it is essential to note that satisfaction also functions as a mediator variable, showing that CONF, PU, and PEOU affected continuance intention through SAT.

Contributions to Theory and Practice

Theoretically, the adapted model was partially confirmed for the context of Turkish higher education. The current study may also contribute to the literature with a higher acceptable explanation rate than was achievable based on each model having been applied in isolation. In practical terms, perceived usefulness, satisfaction, expectation confirmation, ease of use, and system interactivity were shown as the most vital determinants of continuous intention.

In order to promote the usefulness of an e-learning system, instructors can inform their students about both the actual and potential benefits of its usage, and also to teach them in practical terms how to maximize their benefit through use of the system. Instructors can also question students about their expectations regarding their use of the e-learning system and focus on how best to help them achieve satisfaction by working to meet their expectations. Different learning materials and activities, such as interactive Web 2.0 tools, can also help students become more satisfied with the system in use. Considering that system interactivity is a critical determinant of continuance intention, instructors should afford students sufficient assistance and prompt feedback whenever necessary. On the other hand, system designers should embed interactive communicational tools such as chat, forums, and e-mail functionality into e-learning platforms, and teachers should subsequently encourage their students to make good use of these tools (Cheng, 2013; Pituch & Lee, 2006). Finally, learning management systems that integrate social networking architecture can also be utilized (Unal & Uzun, 2021).

In light of PEOU indirectly impacting intention to continue using the system, as mediated by satisfaction, instructors may also work to improve their students' system usage skills with a greater focus on online teaching. When students' self-efficacy beliefs regarding their capability to use an e-learning system are high, they will be more likely to consider it as being easy to use. This would also occur if they enjoy and feel comfortable using and surfing within the e-learning environment. Thus, the current study recommends that system developers consider the comfort and ease of logging in for users looking to surf and navigate within an e-learning system. To help increase students' ability to use a system, they should be offered how-to-do seminars, supporting documentation, videos, and other appropriate guidance. Additionally, educational institutions could offer supporting documentation and guidance services to their students on how to best use and benefit from use of the system, as well as its features and facilities. Institutions could also invest more in human resources, organization, management, support, and innovative tools and technology (Prodanova et al., 2021).

In a general sense, the dynamics and structure of educational systems worldwide are expected to undergo significant change in the short to medium term. Under the current or "normal" conditions, a new critique is likely to be revealed: Blended learning may be increasingly adopted as the new educational norm. Investing more in on-the-job training could also seem reasonable since the world will inevitably face other crises in the future. Not only online teaching pedagogy, but also social and emotional issues related to students and the learning environment they use should also be on the agenda going forwards (Bozkurt & Sharma, 2020). In order to minimize the effect of the digital divide and inequity while maximizing new generations' needs and expectations, educational institutions, policymakers, and governments should become better prepared in advance. Additionally, saving educational resources whilst enhancing educational practices and ameliorating known shortages are actions that should attract the attention of all stakeholders.

Limitations and future directions

The current study presents certain limitations that may spark further research. First, the study adopted a cross-sectional survey approach, collecting data within a certain time interval. Future research could apply a longitudinal design, as technology acceptance behaviors are known to form over a more considerable period (Venkatesh & Davis, 2000). Measuring students' continuance intention following the COVID-19 pandemic for programs or courses where online learning has been adopted may be worthwhile.

Second, the research was conducted only with students from teacher education programs at one specific university. As a result, the findings may not be generalizable to different student cohorts or those studying other subjects. Future research could focus on students from other educational programs, as well as from different-sized and/or different types of universities (i.e., technical, private, public, or leading established universities, or from those more recently formed) as the services, sources, and facilities offered to students are likely to vary considerably.

Third, future research could aim to study students from other educational levels, such as primary or secondary education. As all levels of educational institutions have moved substantially towards the utilization of distance education following the pandemic, researching student groups from other educational levels is highly recommended (Chauhan et al., 2021). However, not only students, but also other important agents such as instructors/teachers could also be examined in terms of varying aspects pertinent to the pandemic. Moreover, nationwide research could realize more comprehensive results or new directions of study, which would help to generalize findings to further enhance e-learning systems going forwards.

6. Conclusion

Low participation remains a critical issue for e-learning environments, prompting researchers to reveal the underlying factors behind sustained e-learning usage. In the current study, beyond initial adoption, determinants of students' adoption of e-learning technologies during the pandemic and since were examined in terms of continuance intention. The extended Technology Acceptance Model (TAM) and Expectation Confirmation Model (ECM) were adopted as theoretical frameworks.

To summarize, perceived usefulness and satisfaction emerged as direct determinants. Confirmation of expectation, perceived usefulness, perceived ease of use, and system interactivity served as indirect determinants of continuance intention of using the e-learning system. In other words, improved usefulness and ease of use of a system may align better with user expectations, resulting in more satisfied users. System interactivity indirectly aids continuance intention, highlighting the importance of considering how e-learning systems facilitate high-quality interactions between learner-instructor, learner-learner, and learner-system. Considering that satisfaction is the most vital determinant, the current study concludes that system and instructional designers prioritize creating systems that are easy to use and sufficiently interactive in order to satisfy learners' needs in accordance with established learning and design theories.

Declarations

Author Contributions. Conceptualization, A.M.U., E.Ü., S.K.; methodology, A.M.U., E.Ü.; investigation, S.K.; formal analysis, A.M.U., E.Ü.; writing—original draft preparation, A.M.U., E.Ü., S.K.; writing—review and editing, A.M.U., E.Ü., S.K. All authors have read and agreed to the published version of the manuscript.

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Ethical Approval. Data for this quantitative study were collected through anonymous surveys, and the personal information of the participants was not collected. Additionally, students' consents were granted before the data collection process.

Data Availability Statement. Data for this study is available upon request.

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