Discover Education

Research

Students' acceptance of e-learning: extending the technology acceptance model with self-regulated learning and affinity for technology

Nathalie Barz[1] · Manuela Benick[2] · Laura Dörrenbächer-Ulrich[1] · Franziska Perels[1]

Received: 5 February 2024 / Accepted: 4 July 2024
Published online: 30 July 2024

Abstract
The present study examines university students' acceptance of e-learning according to the Technology Acceptance Model (TAM). We also investigate the influence of external factors, including self-efficacy with digital media, self-regulated learning, prior experience, and affinity for technology, to extend the model with valid individual factors. Structural equation modeling with maximum-likelihood estimation served to evaluate the proposed research model, which included online questionnaire data from $N = 225$ undergraduates studying various subjects in 53 universities. The results indicate that the TAM is replicable regarding e-learning for German-speaking university students. Additionally, we found self-regulated learning and affinity for technology to be significantly positively related to the two main components of the TAM, perceived ease of use and perceived usefulness, implying their importance in technology acceptance. However, self-efficacy with digital media and prior experience showed no significant impact on university students' technology acceptance. We also found a significant positive relationship between attitudes toward e-learning and behavioral intention, showing that university students with positive attitudes are more willing to use it in the future. Therefore, higher education should consider students' individual prerequisites for e-learning and support students during the use of e-learning environments, to promote the development of positive experiences and attitudes toward e-learning.

Keywords Technology acceptance · University students · e-learning · Self-regulated learning · Affinity for technology

1 Introduction

The use of digital technologies can support learning processes and adapt to learners' needs, enabling ideal learning conditions [1]. Because e-learning is a digital technology that gained even more impact on university learning during the COVID-19 pandemic, it is the focus of the recent study and defined as "instruction that is delivered on a digital device that is intended to promote learning" [2]. E-learning includes digital media, a "wide variety of instructional material (via

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s44217-024-00195-7.

✉ Nathalie Barz, nathalie.barz@uni-saarland.de; Manuela Benick, manuela.benick@uni-saarland.de; Laura Dörrenbächer-Ulrich, laura.doerrenbaecher@uni-saarland.de; Franziska Perels, f.perels@mx.uni-saarland.de | [1]Department of Educational Science, Saarland University, Campus A4.2, 66123 Saarbrücken, Germany. [2]Department for Teaching and Studies, Saarland University, Campus A4.4, 66123 Saarbrücken, Germany.

audio, video, and text mediums) conveyed through e-mail, live chat sessions, online discussions, forums, quizzes and assignments" [3] which are used, for example, in learning management systems.

The Technology Acceptance Model (TAM) [4], a popular and valid model in the field of e-learning and technology acceptance [5], provides the basis of the current study. Although the examination of TAM [4] is well established, research gaps remain. Therefore, the objective of the current study is to merge important factors for successful e-learning with the TAM and to include two new factors in the TAM, namely self-regulated learning (SRL) and affinity for technology. In addition, the study investigates two inconsistent factors (self-efficacy, prior experience) in the model. The presented factors for learning contribute to successful learning with e-learning environments, but the best preconditions are useless when the learners are not willing to use e-learning environments. According to Pan [6], university students with low-level technology acceptance use fewer digital technologies than university students with a high level of technology acceptance. Introducing digital technology and supporting its use by university students as early as possible should reduce fears and misconceptions about it [7].

Over time, the TAM was extended with external factors to increase the explanatory power of the model. An important factor for learning successfully via e-learning is SRL. SRL is "a process whereby learners activate and sustain cognitions, affects, and behaviors that are systematically oriented towards the attainment of personal goals" [8]. Because learners have a lot of autonomy in e-learning environments, they must plan when and how to engage with the presented learning material, stay motivated, and reflect on their own learning progress [9]. Prior studies had only used SRL as an outcome of technology acceptance in the TAM [10], which leaves its influence as an external factor unclear. The current study scrutinizes SRL as an external factor in the TAM because it is an important requisite for online learning [11], so concluding that SRL is an external factor in the TAM seems reasonable. Assessing its component structure in TAM had not yet been pursued thus contributing to further evidence of how SRL affects technology acceptance.

Furthermore, individuals' affinity for technology also plays an important role when learning via e-learning. Karrer and colleagues [12] define affinity for technology as a personality trait characterized by a positive attitude toward technology, enthusiasm about it, and accompanying trust in technological devices. This could lead to a high intrinsic motivation to use e-learning and promote successful e-learning. Because those with a positive attitude toward technology may be more likely to accept it, we exploratively included affinity for technology as external factor in TAM.

Together with self-efficacy, prior experience is one of the most examined external factors in TAM but there are inconsistent findings for both constructs regarding students. In their systematic review, Abdullah and Ward [13], analyzed the most frequently used factors in TAM for different target groups. They found satisfying results for the influence of self-efficacy and prior experience on technology acceptance overall, but placing a focus on the student population reveals that 33% of the studies regarding self-efficacy and 78% regarding prior experience could not find a significant influence on technology acceptance. The systematic review by Rosli et al. [14] examined studies between 2020 and 2022 regarding TAM in higher education focusing on the COVID-19 pandemic, indicating that the TAM is still a valid model after the pandemic. According to their findings based on $N=104$ studies, self-efficacy, and prior experience were the most frequent external factors in TAM during the pandemic. The authors highlight that the two factors should be included in future studies because "they have major theoretical roots in TAM" (p. 14). This calls for further analysis of the two factors in student populations. Therefore, the current study contributes to further examination of the prominent, but inconsistent factors self-efficacy and prior experience for the student population.

Another contribution of the current study concerns the validity of TAM in Western countries. In their systematic review, Granić and Marangunić [15] examined studies in the educational context using TAM regarding digital learning technology. Their sample included $N=71$ studies from 2003 to 2018 which comprise different educational target groups. When only students are considered regarding e-learning environments, their findings indicate a majority of studies coming from Asia ($n=28$) compared to Europe ($n=8$). The same results were reported for in-service teachers by Scherer and Teo [16]. In their meta-analysis, they examined $N=45$ studies regarding technology acceptance of in-service teachers and revealed that most studies took place in Asian countries. These results are strengthened by the systematic review by Rosli et al. [14], revealing that most of the studies during the COVID-19 pandemic were also conducted in Asia, calling for more studies from Western countries.

Although there are studies from Europe regarding the TAM in e-learning, the number is still not sufficient to draw generalized conclusions for Western countries. This exposes a lack of studies on technology acceptance for university students in Western countries and especially Europe, which restricts the validity of the TAM for that population. In their meta-analysis with $N=51$ studies, Schepers and Wetzels [17] revealed that one main factor in the TAM, perceived usefulness, was very influential in Western countries. The other main factor of TAM, perceived ease of use, was crucial in nonwestern cultures. This shows that technology acceptance differs between cultures. Hence, it is important to increase the studies in Western countries to increase TAM's validity, enabling cross-cultural comparisons.

Based on the research gaps that the current study depicts, its objective is to analyze the influence of factors for successful e-learning as external factors in the TAM, namely, SRL, affinity for technology, self-efficacy with digital media, and prior experience with e-learning, on the one hand. On the other hand, this study examines the technology acceptance of German-speaking university students by assessing their acceptance of e-learning environments, contributing to the extension of TAM's validity for Western countries.

2 Theoretical background

2.1 The TAM

The TAM [4] (see Fig. 1) predicts users' acceptance of technology and focuses on two main components that influence attitude, namely, perceived ease of use (PEU) and perceived usefulness (PU). The model assumes that if users perceive a specific technology as convenient and beneficial for their own performance, they are also more likely to develop a positive attitude toward it [18, 19]. Furthermore, such a positive attitude toward the technology increases users' behavioral intention to use it [20, 21] and, hence, its actual use [15]. Thus, attitudes as well as observable behavior determine technology acceptance.

We decided to use the TAM because the competing and often used model, the Unified Theory of Acceptance and Use of Technology (UTAUT) [22], could not be confirmed in its entirety [23]. Rondan-Cataluña et al. [24] compared variations of the TAM and UTAUT and revealed that the UTAUT2 [25] had the best model fit, but the TAM was comparable in explained variance for behavioral intention ($R^2 = 0.64$).

A specific model for technology acceptance in the e-learning context is the General Extended Technology Acceptance Model for E-Learning (GETAMEL; [13]), which systematically included the five most examined variables in TAM. However, the results of studies on this model lack consistency [26]. This is because the influence of self-efficacy and prior experience is often not significant for students in the model. In the literature review by Abdullah and Ward [13], out of 31 studies on the impact of self-efficacy on PEU, 7 were not significant. Similarly, out of 18 studies regarding self-efficacy and PU, 9 did not yield significant results. For prior experience, 4 out of 5 studies on PEU and 3 out of 4 regarding PU were not significant. That strengthened the decision to use the TAM for the current study.

Over time, researchers applied the TAM to the acceptance of different technologies, such as the Internet [27] and e-learning [28–30]. This supports claims of the TAM being well investigated and considered valid for different technologies [14, 31]. The next chapter describes TAM's components in more detail and presents evidence for their relationships.

2.1.1 Perceived ease of use

One of the key components of the TAM is a technology's perceived ease of use. PEU represents the user's expectation regarding the degree to which a technology is "free of effort" [4]. Despite empirical evidence for a positive relation to PU [21, 29, 32, 33], some studies could not reveal this relationship [34–37]. Most findings indicate that if a system is difficult to use, no matter how useful it seems, users will not accept it [38]. Studies involving technology acceptance among

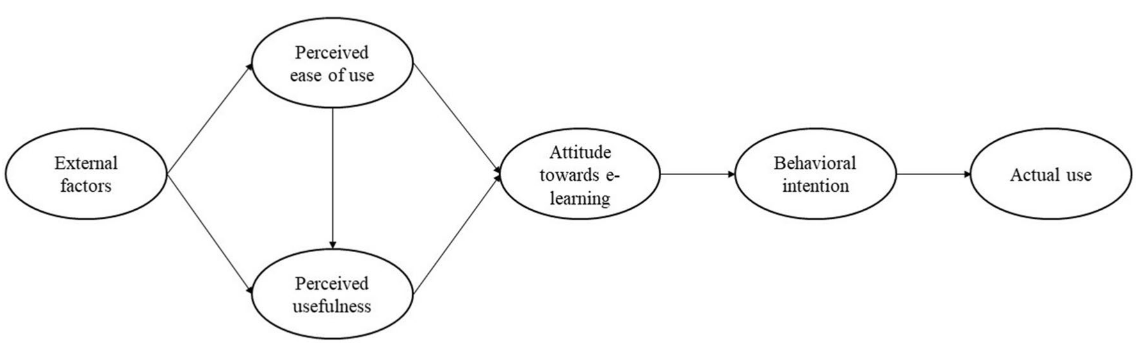

Fig. 1 The technology acceptance model [4]

university students in Oman found high-level e-learning acceptance and confirmed the positive relationship between PEU and PU [29]. The same was true for samples of university students from Parkistan [32] and China [39, 40], findings that also supported the positive relation between PEU and PU. In other words, if an e-learning system is easy to use, then users are more likely to perceive the system as useful.

Furthermore, PEU has a positive effect on attitude. If users perceive a technology as easy to use, they will likely have a positive attitude toward it as well [41]. Several studies with university students (e.g., [42, 43]) support this assumption. In their meta-analysis, Šumak et al. [44] examined $N=42$ studies and revealed a positive relation between PEU and positive attitude, with a medium effect size.

2.1.2 Perceived usefulness

The second key component of the TAM is users' perceived usefulness of a technology. Davis [4] originally defined PU as the belief that "using a specific application system will increase their job performance within an organizational context" (p. 320). In the context of e-learning, PU refers to the belief that e-learning would facilitate users' learning process. This belief directly relates to the attitude toward the technology [21]. Perceiving e-learning as useful leads to greater probability of developing a positive attitude toward it. According to Vladova et al. [37], PU positively relates to university students' attitude toward e-learning [45]. Chibisa and colleagues [42] strengthened that assumption by examining a sample of 163 pre-service teachers' acceptance of e-learning.

2.1.3 Attitude toward e-learning

As mentioned above, PEU and PU beliefs directly affect the attitude toward a technology. Attitude is "an individual's positive or negative feeling about performing the target behavior (e.g., using a system)" [46]. The attitude toward a technology in the TAM consists of not only affective components but also cognitive aspects—for example, the belief about the technology's actual use [20]. In its original form, the TAM included the attitude toward a technology. Currently, a controversial discussion continues about the role of attitudes in the model. Some researchers exclude attitudes from the model and assume a direct effect of PEU and PU on behavioral intention (e.g., [29, 47]). Others use the TAM in its original form, where attitude influences the behavioral intention directly, and PEU and PU only influence behavioral intention indirectly via their impact on attitude [16].

Recent empirical findings show that a positive attitude toward a technology strengthens the behavioral intention to use the technology [32, 41, 48], an important factor in the TAM that investigators should not neglect [49]. Furthermore, findings of the direct effect of PEU and PU on the behavioral intention to use the technology are inconsistent. Some studies also imply a negative correlation between the two factors [20]. By examining students' technology acceptance in three different U.S. universities, Ranellucci and colleagues [50] promoted the positive impact of attitude on the behavioral intention to use e-learning.

2.2 External variables for technology acceptance

In its original form, the TAM could not explain all facets of technology acceptance [21, 51]. Venkatesh and Davis [52] included external variables to extend the model's informational value, as did prior research that examined the relation of numerous external variables to the TAM's key components, e.g., self-efficacy and social norms [13, 53]. The current study examines SRL, self-efficacy with digital media, prior e-learning experience, and affinity with technology.

2.2.1 Self-regulated learning

According to Zimmerman [8], SRL describes a process in which learners try to reach their goals by invoking and retaining cognitions, affects, and behaviors. Zimmerman [54] divides the learning process into three phases. The forethought phase serves as preparation for learning, initially, learners set goals and choose adequate learning strategies that seem beneficial in reaching the desired goals. The performance phase refers to the actual learning activity; cognitive strategies (e.g., elaboration) particularly function to consolidate newly acquired knowledge, and volitional and motivational strategies (e.g., incentives) provide a basis for maintaining the learning activity. In the last phase—the self-reflection phase—learners undertake a performance evaluation by contrasting the goals set in the forethought phase with the achieved results. SRL can comprise both different phases and different components, namely, cognition, metacognition, and motivation [55].

In TAM, SRL often serves as an outcome. Zheng and Wang [56] revealed PEU and PU as predictors of SRL, despite PEU showing a negative relation and PU showing a positive relation with SRL. In a study with adult learners in a public welfare course, Wang and Zhang [57] examined the influence of the SRL phases on the technology acceptance of web-based learning spaces. They found a positive predictive relationship between the forethought phase's strategies and both PEU and PU. People with higher-level SRL skills perceived e-learning as useful and easy to use. There are mixed findings regarding behavioral intention. On the one hand, evidence shows behavioral intention positively relating to SRL as an outcome. Zhou and colleagues [58] examined the influence of behavioral intention on SRL, represented by goal setting and task and self-evaluation strategies, with 580 undergraduate students in China. They found significant positive paths for all three strategies in their model, indicating a positive relationship between behavioral intention and SRL. But the examined strategies do not illustrate the whole process of SRL because they focus on the metacognitive component. On the other hand, Al-Adwan [59] found a negative relationship between SRL as an input variable and behavioral intention, regarding the use of massive open online courses in Jordan. Due to the unknown impact of SRL on behavioral intention, the current study focuses on the investigation of the relation between SRL, PEU, and PU. The current study considers SRL an input variable (external factor) for technology acceptance. E-learning environments offer a high degree of autonomy, favoring learners with high levels of SRL because they are more skillful in planning, regulating, and adapting their learning process to reach their goals [60, 61]. This leads to the assumption that learners with high-level SRL perceive e-learning environments as easy to use and useful.

2.2.2 Self-efficacy

Self-efficacy represents "people's beliefs about their capabilities to exercise control over events that affect their lives" (p.1175) [62]. Self-efficacy is an important motivational part of SRL which is why it was included in several theoretical models regarding SRL [63]. For example, it influences whether a learning activity will be initiated [54]. Learners convinced that they could solve an exercise will more likely work for a solution, learners with low-level self-efficacy will become discouraged and may procrastinate about starting to learn. Therefore, the two constructs are positively related [64]. Bandura [65] assumes that self-efficacy is context-specific and, once established, stable for a specific context. Regarding the specific context of e-learning, self-efficacy with digital media plays an important role. Hence, it represents the belief in how confident people feel about using digital media (e.g., e-learning environments) and whether they believe they can overcome technical obstacles. In prior studies, computer self-efficacy (e.g., [35]) often arose in TAM, but not self-efficacy with digital media. The present study's focus is self-efficacy with digital media, concerning this desideratum and its relation to SRL.

In their meta-analysis, Abdullah and Ward [13] revealed 45 studies that confirmed self-efficacy as the antecedent of PU and PEU, making it the most frequent external factor figuring in the TAM. Obstacles will not hinder people with high levels of self-efficacy with digital media, who will continue with their learning activities, perceiving e-learning environments as effortless and easy to use [66]. Conversely, e-learning environments could easily frustrate people with low levels of self-efficacy with digital media and interrupt their use of e-learning environments more often. Previous studies showed a positive relationship between self-efficacy and PEU (e.g., [21, 35, 47, 67]) and PU (e.g., [21, 48]). But other studies could not find a predictive function of self-efficacy for PU (e.g., [47]) or even a negative relation [31]. Despite the mixed results regarding self-efficacy and PU, most findings suggest a positive relationship between the two constructs. Self-efficacy is therefore a widely considered factor for technology acceptance [68]

Research suggests that self-efficacy has a positive impact on behavioral intention [38, 69]. Self-efficacy beliefs contribute to the initiation and maintenance of the learning process, and the final evaluation in the self-reflection phase can influence them. Empirical evidence can strengthen the positive relationship between self-efficacy and SRL [64, 70]. Thus, we consider the relation of the two constructs in our empirical model.

2.2.3 Prior experience with e-learning

In the current study, prior experience with e-learning represents whether a user has used e-learning before. Studies of the TAM excessively study prior experience with technology. Evidence shows prior experience affecting the PEU, PU, and behavioral intention to use a technology [71]). In educational settings, learners without prior experience with e-learning require orientation before they can use the tool to support their learning process [72]. Consequently, according to Liu and Pu [21], learners with more experience with e-learning can better endorse and use e-learning platforms. Regarding e-learning with high school students from Taiwan, Liu and colleagues [73] found positive effects of prior experience on PEU and PU. Experienced learners may find a system easy to use, experiencing it as useful for their own learning because they can incorporate their prior knowledge [74]. Research findings indicate not only a positive relation between PEU and PU with prior experience but also a positive impact on behavioral intention to use e-learning when users have prior experience [21, 71]. The findings by Liu and Pu [21] and Suki and Suki [71] supported this theoretical assumption, revealing experienced participants' stronger intention to use an online learning community. The evidence shows that prior experience can positively influence PEU, PU, and behavioral intention to use e-learning.

2.2.4 Affinity for technology

TAM research has not yet examined affinity for technology often. Regarding PU, Drueke and colleagues [20] revealed a negative relation with affinity for technology. However, their results also showed a ceiling effect regarding affinity for technology in their sample of medical students, making the findings hard to interpret. For PEU, they found no significant effect. The unclear impact of affinity for technology in the TAM requires further investigation. Findings also show that people more oriented toward technology can better estimate whether a new technology is useful and find it easier to familiarize themselves with it, with less effort [12, 75].

2.3 Research model and hypotheses

Based on this theoretical background, we created a hypotheses-based research model to test the relations between the relevant constructs, deducing the following hypotheses (H):

H1: PEU of e-learning positively affects the PU of e-learning.
H2: PEU of e-learning positively affects the attitude toward e-learning.
H3: PU of e-learning positively affects the attitude toward e-learning.
H4: A positive attitude toward e-learning positively affects behavioral intention.
H5: SRL positively affects the PEU of e-learning.
H6: SRL positively affects the PU of e-learning.
H7: Self-efficacy with digital media positively affects the PEU of e-learning.
H8: Self-efficacy with digital media positively affects the PU of e-learning.
H9: Self-efficacy with digital media positively affects the behavioral intention to use e-learning.
H10: Self-efficacy with digital media positively affects SRL.
H11: Prior experience with e-learning positively affects the PEU of e-learning.
H12: Prior experience with e-learning positively affects the PU of e-learning.
H13: Prior experience positively affects the behavioral intention to use e-learning.
H14: The affinity for technology positively affects the PEU of e-learning.
H15: The affinity for technology positively affects the PU of e-learning.

The resulting model, including all deduced hypotheses, appears in Fig. 2.

3 Method

3.1 Sample

The sample consisted of $N=225$ undergraduates from 53 different German-speaking universities. $N=218$ participants studied at universities in Germany, $n=4$ participants studied in Austria, and $n=1$ participant studied in Switzerland and in Luxemburg, respectively. $N=1$ participant did not provide information about his or her university. Most of the participants studied at a brick-and-mortar university ($n=214$); $n=11$ participants studied at a virtual university. In total, the participants studied 34 different subjects. Most frequently, the participants studied teaching, psychology, and economics. Participants' mean age was $M=23.18$ ($SD=4.67$) years, and on average, they were enrolled in the fourth semester

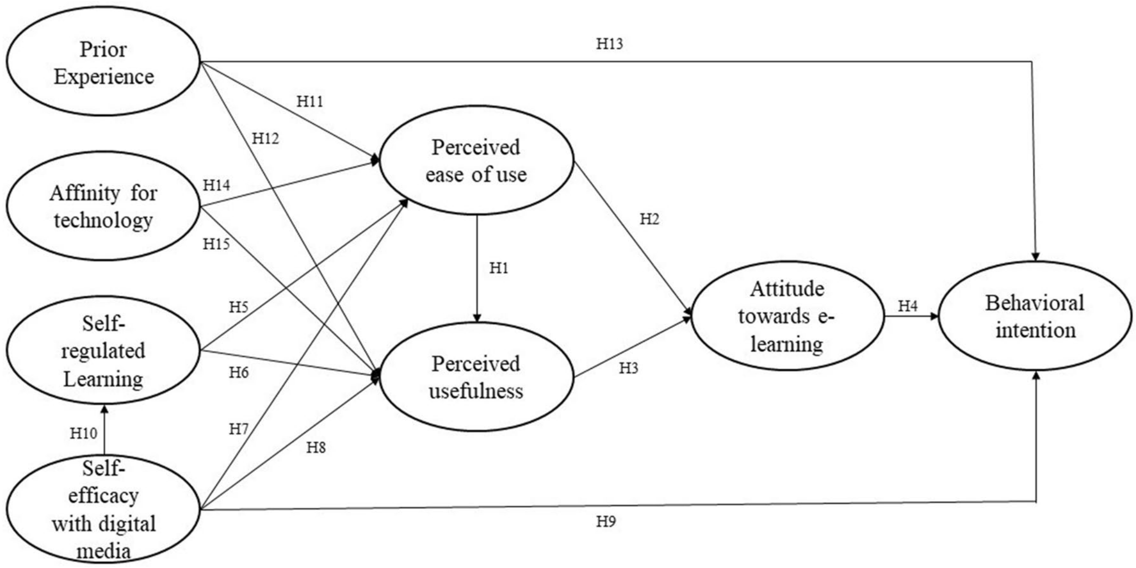

Fig. 2 Research model with paths and hypotheses

($M = 4.23$, $SD = 2.75$). Regarding gender identity, $n = 44$ participants identified as male, $n = 176$ as female, and $n = 2$ as diverse. $N = 3$ participants did not provide gender identity information.

3.2 Procedure

The data were assessed by using non-probability, voluntary response sampling. An online survey was implemented on the platform Tivian and was disseminated via links on social media and placards in various university buildings. Participation was voluntary, and all participants used a consent form to confirm their consent to participate. Data were anonymized by the application of individualized codes. The participants received no monetary compensation, but psychology and teaching university students could receive credit toward their studies. As an e-learning platform that is examined, we chose *Moodle* because this is a popular open-source e-learning platform that is often used for e-learning and is widely known by German-speaking students. *Moodle*'s high functionality has contributed to its widespread use as learning management system in higher education institutions across the globe. For example, learners can track their course progression via the course completion status and teachers can offer a variety of predefined tasks and activities (e.g., multiple choice quizzes, peer-review exercises, lessons, wiki [76]) which can be adapted to learners' needs. Figure 3 shows an example of a blended-learning environment in *Moodle*. Only participants who had previously taken courses on *Moodle* were eligible to participate in the study.

The completion of the survey took approximately 15 min, and it was possible to skip questions. The first part of the survey collected participants' demographic information (e.g., age, gender identity) and the second part presented the relevant scales regarding the research questions. The next section further describes the applied instruments.

3.3 Instruments

To comprise all relevant variables of the TAM, PU and PEU of e-learning, the attitude toward e-learning as well as the behavioral intention to use it were assessed. As external variables assumed to influence technology acceptance, we assessed self-efficacy with digital media, SRL, affinity for technology, and prior e-learning experience.

PU was measured with six items by Masrek et al. [77]. All items were adapted to e-learning, and the current sample revealed excellent reliability (see Table 1). PEU was assessed with the System Usability Scale [78] consisting of ten items adapted to e-learning. As Table 1 shows, a high level of reliability for the current sample was found. The "attitude toward e-learning" scale [79] included 12 items that showed a high reliability (see Table 1). The behavioral intention to use e-learning was examined with three items by Venkatesh and Bala [80] which were also adapted to e-learning, resulting in excellent reliability for the current sample (see Table 1). Self-efficacy with digital media was measured with seven items in total. Five items were adopted from Lin et al. [81] and two items were adopted from Hung [82]. As Table 1 shows, an

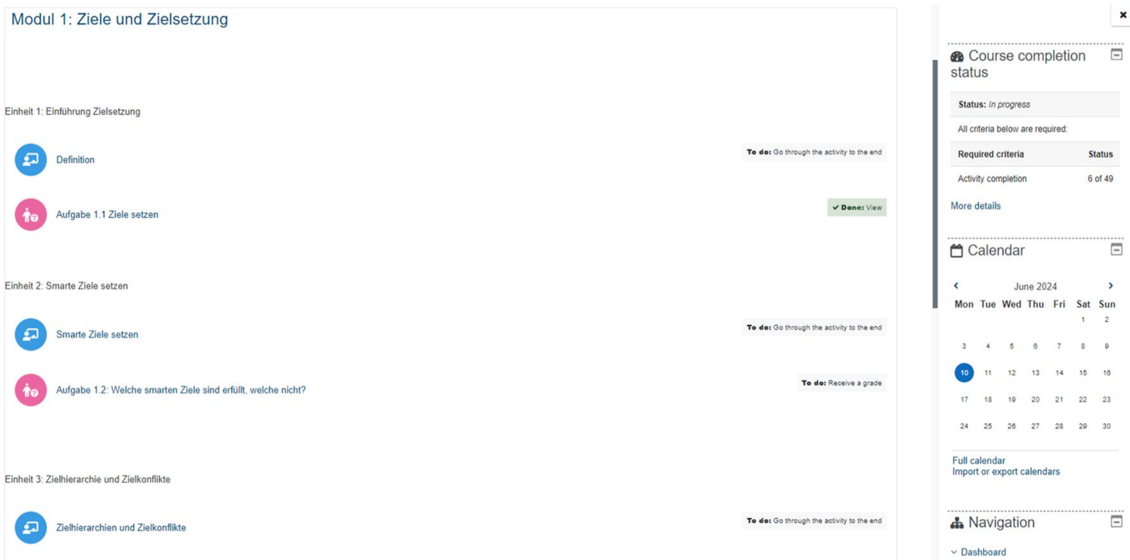

Fig. 3 Example of a Moodle course. Note. The different icons represent different types of tasks. Blue icons indicate theoretical learning content, red icons indicate exercises

acceptable reliability for the current sample was achieved. SRL was examined with a scale consisting of 55 items [83] that could be assigned to three different subscales, representing the three components of SRL (cognition, metacognition, and motivation). An acceptable to good reliability could be reached in the current sample (see Table 1). For this scale, a four-point Likert scale was used (1 = totally disagree, 4 = totally agree). Affinity for technology was measured with 19 items by Karrer et al. [12]. In the current sample, a four-point Likert scale was used, and a high reliability was achieved (see Table 1). Prior experience with e-learning was assessed with a self-designed item (see Table 1) using a four-point Likert scale. If not reported otherwise, all scales were assessed by using a five-point Likert scale (1 = totally disagree, 5 = totally agree) and all items were translated to German.

3.4 Data analysis

SPSS (Version 28.01) was used to conduct descriptive and correlational analyses. To examine our hypotheses, we performed structural equation modeling (SEM) with the lavaan package in R (version 2021.09.02). First, missing values were examined. In total, there were 25,774 values of which were 0.39% missing. 80.9% of all participants had complete data. The missing values were analyzed using the Little test. The test showed a nonsignificant result, indicating that all missing values are missing completely at random [$\chi^2(4274) = 4361{,}54$, $p = 0.172$]. Furthermore, the requirements to calculate SEM were considered. Different suggestions arose regarding the required sample size. According to Kline [84], a sample for SEM should include at least 200 participants, Matsunaga [85] refers to 150 participants as sufficient. Given that the previously mentioned sample sizes disregard the complexity of the estimated model, as a rule of thumb, the sample size should be five times greater than the number of items in the model [86]. With 113 items in our model, the sample size of $N = 225$ was not sufficient for the analyses. In the next step, multicollinearity was checked for all constructs. According to Field [87], correlations higher than 0.80 indicate multicollinearity between the variables, and Hair et al. [88] suggest that the variance inflation factor (VIF) should be lower than 10. All correlations and VIF scores were below the thresholds, indicating that no multicollinearity occurred. Moreover, the analyses revealed the violation of the assumption of normality because some variables (e.g., self-efficacy with digital media and PU) showed a non-normal distribution. Therefore, item parceling was applied to reduce measurement error. Parceling combines individual items into joint parcels, which has the advantage of reducing model complexity, resulting in a smaller required sample size [85, 89]. Furthermore, parceling compensates for non-normal distributed data, increases the power to identify model misspecifications, and stabilizes parameters [90]. Using the single-factor method to build parcels with equal factor loadings, three parcels per factor were established [91] for all constructs, except for SRL because of its multidimensionality. In this case, three facet-representative parcels representing the three components of SRL (cognition, metacognition, and motivation) were built. Due to the use of parcels, the sample size is five times higher than the items in the estimated model, indicating a sufficient sample

Table 1 Measurement instruments and their reliability

Scale	Author(s)	Number of items	Reliability (Cronbach's α)	McDonald's Omega	Example item
Perceived usefulness	[77]	6	0.91	0.91	"Using e-learning enables me to accomplish my study task more quickly."
Perceived ease of use	[78]	10	0.86	0.86	"I thought the e-learning platform was easy to use."
Attitude toward e-learning	[79]	12	0.86	0.86	"E-learning increases the flexibility of teaching and learning."
Behavioral intention	[80]	3	0.96	0.96	"I plan to use e-learning in the future."
Self-efficacy with digital media	[81, 82]	7	0.75	0.73	"I feel confident in performing the basic functions in digital media."
Self-regulated learning (cognition)	[83]	6	0.66	0.63	"I use the content of a course as a starting point to develop my own ideas on the topic"
Self-regulated learning (metacognition)	[83]	22	0.92	0.92	"While learning for a course I consider how to proceed."
Self-regulated learning (motivation)	[83]	27	0.86	0.82	"I complete whatever I set out to do in a course."
Affinity for technology	[12]	19	0.83	0.93	"I have fun testing electronic devices."
Prior experience	Self-designed	1	/		"I already made experiences with e-learning."

size [86]. Supplemental material 1 shows the assignment of the items to the parcels. Following the recommendation of Hair and colleagues [92], a two-step approach was adopted. First, a measurement model was tested to confirm the reliability and validity of the included constructs. Second, the proposed structural model was tested, examining the causal relationships between the constructs. For all statistical tests, a significance level of $\alpha = 0.05$ was postulated.

4 Results

4.1 Descriptive results

Table 2 shows the descriptive statistics and correlations of the assessed manifest constructs. Compared to the theoretical mean of each scale, the means indicate that PEU, PU, attitude toward e-learning, self-efficacy with digital media, SRL, and behavioral intention were positive in the current sample; the experience and affinity for technology were moderate. Supplemental material 2 presents the descriptive statistics and correlations for the parcels. To confirm a multivariate normal distribution, Kline [84] recommended a skewness value lower than 3 and a kurtosis value lower than 10 for each construct. For skewness, the values are between – 0.79 and 0.22, resulting in an acceptable skewness for the distribution. The kurtosis values range from – 0.36 to 0.98, indicating no violation of the multivariate normal distribution assumption.

4.2 Measurement model evaluation

First, we examined the proposed measurement model by using SEM with maximum-likelihood estimation. We handled missing data with listwise deletion. To determine whether our research model was adequate, we examined the model fit and the measures' reliability as well as the convergent and discriminant validity.

4.2.1 Model fit

The model fit was investigated by using the χ^2-test. Furthermore, the comparative fit index (CFI), the standardized root mean square residual (SRMR), and the root mean square error of approximation (RMSEA) were chosen as indices to interpret the fit of the measurement model. According to Hu and Bentler [93], the assumption of a good model fit depends on whether the CFI is higher than 0.95, the SRMR is lower than 0.08, and the RMSEA is lower than 0.06. All indices surpass the cut-off criteria, indicating that the proposed research model is robust (CFI = 0.96, SRMR = 0.04, RMSEA = 0.05). The χ^2-test leads to a significant result ($\chi^2(218) = 338.40$, $p < 0.001$), implying that the data deviate from the proposed research model.

Table 2 Correlations and descriptive statistics of the research constructs

Construct	PEU	PU	ATE	BI	SWM	TA	EXP	SRL
PEU	–							
PU	0.18**	–						
ATE	0.22**	0.74**	–					
BI	0.25**	0.26**	0.25**	–				
SWM	0.08	0.24**	0.31**	– 0.01	–			
TA	0.16*	0.26**	0.36**	0.07	0.45**	–		
EXP	0.06	0.10	0.16*	– 0.02	0.23**	0.14*	–	
SRL	0.15*	0.22**	0.33**	0.26**	0.06	0.03	0.05	–
Mean	40.00	30.56	30.54	30.71	30.98	20.90	30.45	20.79
Standard deviation	0.97	0.87	0.62	10.21	0.66	0.51	0.65	0.43
Skewness	0.22	– 0.26	– 0.19	– 0.79	– 0.55	– 0.04	– 0.97	– 0.18
Kurtosis	0.02	– 0.25	0.20	– 0.36	– 0.14	0.10	0.16	0.98

* p<.05, ** p<.001

PEU Perceived ease of use, *PU* Perceived usefulness, *ATE* Attitudes toward e-learning, *BI* Behavioral intention, *SWM* Self-efficacy with digital media, *TA* Affinity for technology, *EXP* Prior experience, *SRL* Self-regulated learning

Given that the χ^2-statistic is very sensitive to the sample size and the requirement of multivariate normal distribution, other fit indices (as the indices mentioned above) also deserve consideration [94].

4.2.2 Reliability and validity

To evaluate the proposed measurement model, we relied on three criteria by Fornell and Larcker [95]. They proposed that all indicator factor loadings should significantly exceed 0.50, and the reliability (Cronbach's α) should exceed 0.70. Moreover, each construct should demonstrate an average variance extracted (AVE) greater than 0.50.

The analysis revealed items with factor loadings lower than 0.50. To ensure a good model fit, the model excluded all items with factor loadings below 0.50. This led to a large dropout of items that represented the motivational component of SRL. The factor loadings of the chosen indicators ranged between 0.50 and 0.97 for their corresponding factors, supporting a reliable measure. Supplemental material 3 provides an overview of all chosen items and their factor loadings.

As Table 3 shows, the reliability scores (Cronbach's α) indicate a high internal consistency, demonstrating good reliability. Furthermore, the AVE scores for the factors support the high-level convergent validity of the measurement model.

According to Kline [84], assuming discriminant validity can occur when the correlations between latent variables are smaller than 0.80 and the AVE scores should exceed the square of correlations. All correlations between the latent variables are smaller than 0.80 (see Table 2) and the squared correlations (0.03–0.55) are smaller than the AVE scores (0.57–0.90), strengthening the discriminant validity of the model.

4.3 Structure model evaluation

After evaluating the measurement model, the structural model was examined by using SEM with maximum-likelihood estimation. The results reveal that the structural model, except for the χ^2-test ($\chi^2(213) = 365.06$, $p < 0.001$), shows a good fit because all other fit indices exceed the minimum criteria (CFI = 0.95, RMSEA = 0.06, SRMR = 0.07). After confirming the fit of the structural model, the structural paths, t-values, and the variance explained (R^2), were investigated. Table 4 presents the estimated values and their significance. Of the 15 hypothesized relationships, seven were supported. All significant paths between the latent constructs were in the proposed direction. H1 was rejected because the results did not show a significant relationship between PEU and PU. However, in compliance with our hypothesis, we found a positive influence of PEU and PU on attitude toward e-learning, supporting H2 and H3. As proposed, the results indicate a positive relationship between attitude toward e-learning and behavioral intention, endorsing H4. The findings also show a positive relationship between SRL and both PEU and PU, confirming H5 and H6. However, the results showed a significant positive influence of self-efficacy with media on neither PEU, PU nor behavioral intention or SRL, leading to the rejection of H7–H10. Furthermore, in contrast to our hypotheses, prior experience showed no significant influence on PEU, PU, or behavioral intention, rejecting H11–H13. Affinity for technology proved a significant positive predictor of PEU and PU, supporting H14 and H15.

Figure 4 visualizes the resulting model. The affinity for technology and SRL, which explain 7% of PEU's variance ($R^2 = 0.07$), predict PEU. Both predictors also explain 21% of PU's variance. PEU and PU explain 73%, whereas attitude explains 10% of behavioral intention.

Table 3 Reliability of measurements and average variance extracted

Scale	Number of items	Cronbach's α	AVE
PEU	9	0.86	0.83
PU	6	0.91	0.78
ATE	10	0.85	0.69
BI	3	0.96	0.90
SWM	4	0.80	0.57
TA	9	0.82	0.67
SRL	35	0.94	0.69

PEU Perceived ease of use, *PU* Perceived usefulness, *ATE* Attitudes toward e-learning, *BI* Behavioral intention, *SWM* Self-efficacy with digital media, *TA* Affinity for technology, *SRL* Self-regulated learning, *AVE* Average variance extracted

Table 4 Overview of model estimates and paths

Hypothesis	Path	β	Standard error	z	p	Interpretation
H1	PEU → PU	0.10	0.07	1.38	0.167	Rejected
H2	PEU → ATE	0.10	0.03	1.94	0.052	Supported
H3	PU → ATE	0.83	0.04	13.37	0.000	Supported
H4	ATE → BI	0.32	0.15	4.36	0.000	Supported
H5	SRL → PEU	0.17	0.23	2.28	0.023	Supported
H6	SRL → PU	0.24	0.22	3.15	0.002	Supported
H7	SWM → PEU	− 0.04	0.14	− 0.43	0.670	Rejected
H8	SWM → PU	0.18	0.13	1.87	0.062	Rejected
H9	SWM → BI	− 0.12	0.15	− 1.47	0.141	Rejected
H10	SWM → SRL	0.07	0.04	0.83	0.409	Rejected
H11	EXP → PEU	0.02	0.10	0.26	0.796	Rejected
H12	EXP → PU	0.01	0.09	0.09	0.929	Rejected
H13	EXP → BI	− 0.05	0.14	− 0.75	0.453	Rejected
H14	TA → PEU	0.20	0.19	2.07	0.039	Supported
H15	TA → PU	0.20	0.17	2.14	0.033	Supported

PEU Perceived ease of use, *PU* Perceived usefulness, *ATE* Attitudes toward e-learning, *BI* Behavioral intention, *SWM* Self-efficacy with digital media, *TA* Affinity for technology, *SRL* Self-regulated learning, *β* estimate, *z* z-value, *p* p-value

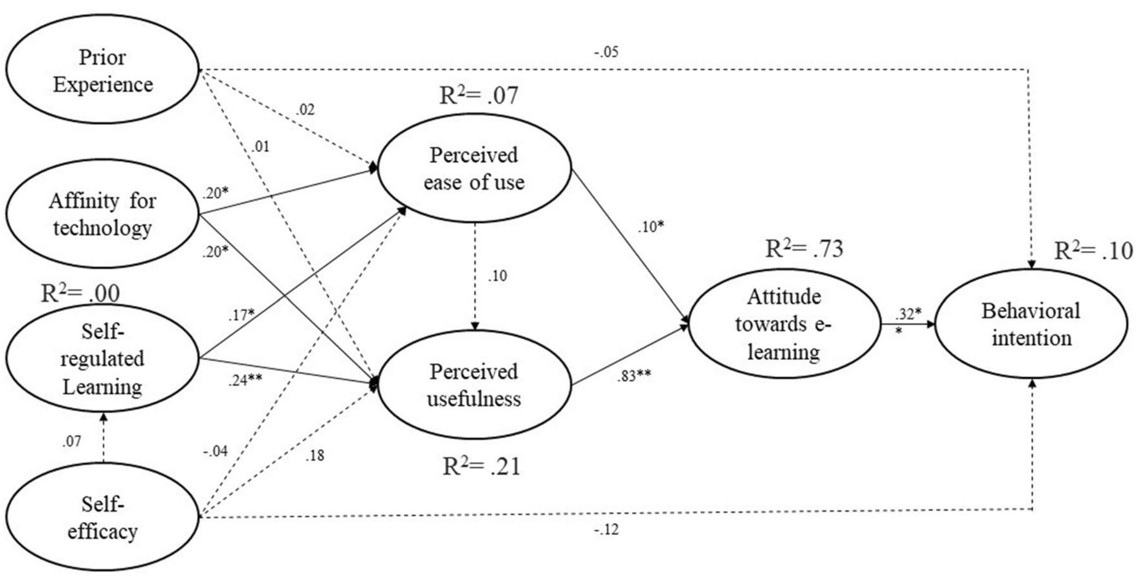

Fig. 4 Resulting model with model estimates. Solid lines illustrate significant paths

5 Discussion

5.1 Summary and interpretation of results

The present study aimed to examine German-speaking students' technology acceptance regarding e-learning environments, based on the Technology Acceptance Model [4]. Moreover, we investigated the influence of further external factors in the TAM—namely, self-efficacy with digital media, SRL, prior experience with e-learning, and affinity for technology—to extend the traditional TAM. The first research question was whether the TAM is replicable for e-learning environments of German-speaking students. The findings revealed a significant relation of PEU (β = 0.10) and PU (β = 0.83) with university students' attitudes toward e-learning. The effect sizes reveal that in our study, PU was more influential on attitude toward e-learning than PEU. This is consistent with the cultural differences that Schepers and Wetzels [17] found. They reported that PU plays a more important role in Western countries than PEU. University students who found e-learning environments useful and easy to use developed a more positive attitude toward them than university students who believed e-learning environments were complicated and not user-friendly. Thus, we could take up and replicate previous findings regarding e-learning (e.g., [21, 42, 43]). Interestingly, however, research findings show that PEU is a stronger indicator than PU when considering its direct influence on behavioral intention. In their study, Hong et al. [39] examined $N = 1568$ preschool teachers from China concerning their intention to use educational technology. The resulting structural equation model showed a stronger influence of PEU ($\beta = 0.75$) on behavioral intention than PU ($\beta = 0.09$). This raises the question of whether both constructs' direct effect should be considered or their effect of attitude as a mediating variable on behavioral intention. The controversy surrounding the use of attitude in TAM arises from studies that do not find a mediating effect of attitude in the model, suggesting a limited role of this variable (e.g., [96]) whereas there are studies that find the contrary (e.g., [97]).

In the current study, we decided to include attitude as a variable and found a significant positive relation between attitude toward e-learning and behavioral intention ($\beta = 0.32$), showing that university students with positive attitudes toward e-learning are more willing to use it in the future. This result strengthens the assumption of the positive relationship between attitude toward e-learning and behavioral intention to use it, which studies by Al-Mamary et al. [41], Ranellucci et al. [50] and Farooq et al. [32] also revealed. However, more detailed research is needed on the role of attitude in TAM.

Contrary to our hypothesis, we found no significant relation between PEU and PU. This is in line with studies that also found no direct relation between PEU and PU (e.g., [36, 37]). But studies by Lazim et al. [43] and Hong et al. [39] presented evidence for an existing relationship between the two constructs. It is possible that the lack of a significant relationship between PEU and PU in our sample could be attributed to the fact that our sample had a very high experience with e-learning ($M = 3.45$). Due to the COVID-19 pandemic, the use of e-learning environments has become a common occurrence for students. As a result, they may be familiar with different types of e-learning environments and may use them without difficulty but have higher expectations to perceive a system as useful for themselves which decreases the influence of PEU on PU.

In sum, the first research question could be approved for the impact of PEU and PU on attitudes toward e-learning and its impact on behavioral intention, but not for a direct path of PEU and PU.

The second research question dealt with the influence of further external factors in the TAM, namely self-efficacy with digital media, SRL, prior experiences with e-learning, and affinity for technology. We examined whether and how these factors influence university students' acceptance of e-learning. Surprisingly, the findings did not support self-efficacy with digital media as an external factor for the TAM, although computer self-efficacy proved several times to have a positive impact in the TAM context (e.g., [14, 67, 98]). Due to its context specificity, self-efficacy with digital media could be too general for the specific topic of e-learning, resulting in no positive relation with PEU and PU in our study. Our sample showed a high self-efficacy with digital media ($M = 3.98$), resulting in a ceiling effect and restriction of variance, and it seems that it no longer makes a difference whether e-learning is perceived as useful or user-friendly because people are convinced that they can handle the system no matter how much effort they need to use it. Although self-efficacy is high in the sample, this does not seem to influence the behavioral intention to use e-learning, which is contrary to our hypothesis. Our result is not in line with previous findings. Doan [99] examined the direct effect of technology self-efficacy on online learning intention and found a positive effect. Our result could be caused because the desire for face-to-face events was great during and after the COVID-19 pandemic [100] and e-learning is now rather avoided because personal social contacts are preferred.

Moreover, no predictive relation appeared between self-efficacy and SRL, which the current literature assumes (e.g., [64, 101]). This result subsumes findings from Wang and colleagues [102], who also found no direct relation between the SRL strategies and technology self-efficacy. In the case of this study, the fit between the self-efficacy and SRL items can raise questions. The SRL questionnaire refers to learning in general, the items to assess self-efficacy specifically address digital media. This deviation could have caused the absence of a potential effect. Self-efficacy also showed no impact on behavioral intention, inconsistent with previous literature. Self-efficacy was often identified as a positive predictor for behavioral intention regarding e-learning [51]. If not specific enough, the self-efficacy items' wording could explain this.

According to the hypotheses, SRL proved a significant influence on PEU ($\beta = 0.17$) and PU ($\beta = 0.24$). The higher the level of university students' self-regulation skills, the higher their levels of PEU and PU of e-learning environments will be. SRL includes skills that learning in digital environments requires—for example, goal setting and monitoring [103]. Therefore, the frequent perception by people who use SRL of e-learning as easier to use and more useful is plausible. They have already developed and maintained strategies to cope with e-learning environments, leading to better learning outcomes.

Conversely, prior experience did not prove to be a positive predictor for either PEU and PU or behavioral intention. This does not conform with our hypothesis. The fact that only one item figured in assessing prior experience could have confounded the measurement. Therefore, future studies should aspire to more items in examining prior experience. Our research suggests that having experience with e-learning does not necessarily correlate to finding it useful or user-friendly and subsequently using it in the future. The sample group of students has considerable experience with e-learning. Due to digital teaching during the pandemic, e-learning environments have become a regular part of their studies. However, these experiences were not necessarily voluntary and hence cannot be considered as an indicator of PU, PEU, and behavioral intention. This raises the question of whether experience is still a meaningful predictor for technology acceptance for students nowadays because most of them have forced experience with e-learning due to the pandemic. However, there are also findings from post-pandemic studies that identify experience as a significant predictor of PEU and PU [104, 105]. The impact of experience in TAM after the pandemic calls for further investigation. Instead, the intrinsic motivation to use e-learning could play a more important role, which is reflected in the significant correlations with affinity for technology. Based on these findings, we conclude that prior use of e-learning does not guarantee an increase of PEU or PU, but the prior right choice of learning strategies does. A newly introduced external factor in the model was affinity for technology. The results promote assuming that university students open to using and interested in new technologies do perceive e-learning environments as useful and can use them without effort. Conversely, university students who do not like technology will avoid e-learning use, resulting in a negative perception.

Summing up, self-efficacy with digital media and prior experiences did not prove influential for e-learning acceptance in this study. But SRL and affinity for technology appeared as external factors that positively related to PEU and PU.

5.2 Limitations

Although the present study could replicate the TAM regarding e-learning for German-speaking university students and reveal further external factors for the model, there are also limitations to report. One limitation of the current study is its small sample size, which is just enough for examining structural equation models. Additionally, the sample was acquired with voluntary participants. This could have led to a self-selection bias including participants which were highly motivated to participate in the study and already interested in the examined topic. This might limit the generalizability and external validity of the findings. Furthermore, the distribution of data for some constructs was not normal, prompting the decision to use item parceling to compensate for this circumstance. It must be mentioned that item parceling is discussed controversially, because it leads to a loss of information, due to the aggregation of single items. Carefully weighing the advantages and disadvantages of item parceling before using it is advisable.

Another limitation is the large dropout of items representing the motivational component of SRL, due to low factor loadings, which may have caused missing important motivational aspects in this subscale.

Moreover, the high reliabilities for the scales SRL (metacognition) and behavioral intention indicate high correlations between the items of each scale and are as often considered excellent reliability [106, 107], but could also be an indicator for measurement problems, such as redundant items [108]. The high Cronbach's α and McDonald's Omega values in the current sample for the SRL scale could be caused by the high number of items for this construct resulting in high Cronbach's α values. Therefore, the reliability of this scale might be overestimated due to the number of items. In future studies, the instrument could be revised for the potential of reduction. For the behavioral intention scale, the high values might be caused by the small number of items in general and the high correlations between the items ($r = 0.87–0.93$). In our case, the high correlations are desirable because the items assess the same aspects of behavioral intention. On the contrary, the scale SRL (cognition) shows a rather low reliability which can be regarded as just acceptable and might be caused by the small number of items.

Self-report as the complete basis of the assessed data raises a methodological issue, in that data could be biased or intentionally faked to conform to social desirability. A mixed-methods approach—e.g., using and comparing a self-report questionnaire and interviewing people close to the participant regarding participant attitudes toward e-learning—would have improved the findings' robustness.

Furthermore, SRL was not assessed specifically in the context of e-learning, but for learning in general. This could have influenced the fit with the other examined scales specifically formulated for e-learning.

Another limitation is the unspecific term of e-learning that Clark and Mayer [2] proposed, the basis for the recent study. E-learning includes a wide range of instructional methods (e.g., explanatory videos, microlearning units, simulations); thus, it is a heterogeneous construct. The participants' perception and interpretation of different e-learning components could have partially confounded the presented results.

Finally, the current study allows no conclusion about the actual use of e-learning environments; it just assumes that the behavioral intention will lead to its actual use, which the current study did not assess.

5.3 Implications

The current study offers both theoretical and practical implications. First, by investigating the relationship between acceptance-related factors and the intention to use e-learning, the study validates the use of TAM in explaining technology acceptance. Second, the proposed model expands TAM to incorporate important factors influencing German-speaking university students' e-learning usage, such as SRL and affinity for technology.

As a practical implication, the findings have the potential to help overcome obstacles that prevent students from using e-learning environments. They can also be utilized to enhance the likelihood of students embracing e-learning as a component of their educational journey. In light of the challenges of distance education due to the COVID-19 pandemic, educators must reassess their ability to cater to the requirements of their students and to understand the factors that may support or impede students' acceptance of and engagement with distance learning environments The current findings indicate that SRL and affinity for technology play a significant role in how students perceive e-learning in terms of ease of use and usefulness. Therefore, it is important to foster these two constructs as early as possible by creating learning environments that promote autonomous, self-regulated learning and providing students with opportunities to use technological devices during their studies to reduce fear of technology and encourage its use as a study aid. By providing opportunities for mastery experiences, students' confidence in using e-learning can be enhanced.

5.4 Conclusion

The current study contributes to a better understanding of university students' technology acceptance regarding e-learning environments. The results showed that the TAM regarding e-learning is also valid for German-speaking university students, closing this research gap and providing further evidence for TAM's validity in Western countries. The results indicate that university students with high-level SRL skills and affinity for technology will accept e-learning environments. Therefore, increasing SRL skills by incorporating explicit strategy use in university courses as early as possible is important. The confrontation with digital media and stepwise learning to use e-learning can reduce fears regarding technology, through mastery experiences that promote a positive attitude toward e-learning and technology. Moreover, for the first time, this study used SRL as input for the TAM instead of an output, using its component structure as parcels. The findings give initial insight into considering SRL as a factor for technology acceptance in the future.

The current study included self-efficacy with digital media as a new external factor for the TAM. Despite the current study finding no relation to PEU or PU, calling for more studies to confirm or refute the absence of an effect.

Additionally, future research should assess the actual use of e-learning to support the assumption that the behavioral intention to use it leads to the actual use of e-learning.

Furthermore, deploying a self-efficacy measurement specifically developed for e-learning environments would be interesting.

Author contributions NB developed the conceptualization and methodology. Furthermore, she conducted the data collection as well as the data analysis and wrote the original draft. MB supervised the research project, and reviewed and edited the written draft. LDU supervised the research project, contributed to the data analysis, and reviewed and edited the written draft. FP acquired the funding, supervised the research project, and reviewed and edited the written draft. All authors read and approved the final manuscript.

Funding This work was supported by the Project SaLUt [01JA1906A] which is part of the "Qualitätsoffensive Lehrerbildung," a joint initiative of the Federal Government and the Länder, which aims to improve the quality of teacher training. The program is funded by the Federal Ministry of Education and Research.

Data availability The datasets and code used and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Competing interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Ng W. New digital technology in education. 1st ed. Berlin: Springer; 2015.
2. Clark RC, Mayer RE. E-learning: promise and pitfalls. In: Clark RC, Mayer RE, editors. E-learning and the science of instruction. 4th ed. Hoboken: Wiley; 2016. p. 7–26. https://doi.org/10.1002/9781119239086.ch1.
3. Lee Y, Hsieh Y, Ma C. A model of organizational employees' e-learning systems acceptance. Knowl-Based Syst. 2011;24(3):355–66. https://doi.org/10.1016/j.knosys.2010.09.005.
4. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 1989;13(3):319. https://doi.org/10.2307/249008.
5. Teo T, Zhou M, Fan ACW, Huang F. Factors that influence university students' intention to use Moodle: a study in Macau. Educ Tech Res Dev. 2019;67(3):749–66. https://doi.org/10.1007/s11423-019-09650-x.
6. Pan X. Technology acceptance, technological self-efficacy, and attitude toward technology-based self-directed learning: learning motivation as a mediator. Front Psychol. 2020;11:564294. https://doi.org/10.3389/fpsyg.2020.564294.
7. Mason OJ, Stevenson C, Freedman F. Ever-presenting threats from information technology: the Cyber-Paranoia and Fear Scale. Front Psychol. 2014;5:1298. https://doi.org/10.3389/fpsyg.2014.01298.
8. Zimmerman BJ. Motivational sources and outcomes of self-regulated learning and performance. In: Zimmerman BJ, Schunk DH, editors. Handbook of self-regulation of learning and performance. Milton Park: Routledge; 2011. p. 39–64.
9. Broadbent J, Poon WL. Self-regulated learning strategies and academic achievement in online higher education learning environments: a systematic review. Internet High Educ. 2015;27:1–13. https://doi.org/10.1016/j.iheduc.2015.04.007.
10. Schlag M, Imhof M. Does perceived ease of use mitigate computer anxiety and stimulate self-regulated learning for pre-service teacher students? Int J High Educ. 2017;6(3):154–68. https://doi.org/10.5430/ijhe.v6n3p154.
11. Kizilcec RF, Pérez-Sanagustín M, Maldonado JJ. Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses. Comput Educ. 2017;104:18–33. https://doi.org/10.1016/j.compedu.2016.10.001.
12. Karrer K, Glaser C, Clemens C, Bruder C. Technikaffinität erfassen—der Fragebogen TA-EG. ZWM Spektrum. 2009.
13. Abdullah F, Ward R. Developing a general extended technology acceptance model for e-learning (GETAMEL) by analysing commonly used external factors. Comput Hum Behav. 2016;56:238–56. https://doi.org/10.1016/j.chb.2015.11.036.
14. Rosli MS, Saleh NS, Md. Ali A, Abu Bakar S, Mohd Tahir L. A systematic review of the technology acceptance model for the sustainability of higher education during the COVID-19 pandemic and identified research gaps. Sustainability. 2022;14(18):11389. https://doi.org/10.3390/su141811389.
15. Granić A, Marangunić N. Technology acceptance model in educational context: a systematic literature review. Br J Edu Technol. 2019;50(5):2572–93. https://doi.org/10.1111/bjet.12864.
16. Scherer R, Teo T. Unpacking teachers' intentions to integrate technology: a meta-analysis. Educ Res Rev. 2019;27:90–109. https://doi.org/10.1016/j.edurev.2019.03.001.
17. Schepers J, Wetzels M. A meta-analysis of the technology acceptance model: investigating subjective norm and moderation effects. Inf Manag. 2007;44(1):90–103. https://doi.org/10.1016/j.im.2006.10.007.
18. Chen H-R, Lin Y-S. An examination of digital game-based situated learning applied to Chinese language poetry education. Technol Pedagog Educ. 2015;25(2):171–86. https://doi.org/10.1080/1475939X.2015.1007077.
19. Zheng J, Li S. What drives students' intention to use tablet computers: an extended technology acceptance model. Int J Educ Res. 2020;102:101612. https://doi.org/10.1016/j.ijer.2020.101612.
20. Drueke B, Mainz V, Lemos M, Wirtz MA, Boecker M. An evaluation of forced distance learning and teaching under pandemic conditions using the technology acceptance model. Front Psychol. 2021. https://doi.org/10.3389/fpsyg.2021.701347.
21. Liu N, Pu Q. Factors influencing learners' continuance intention toward one-to-one online learning. Interact Learn Environ. 2020;31(3):1742–63. https://doi.org/10.1080/10494820.2020.1857785.
22. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. MIS Q. 2003;27(3):425–78. https://doi.org/10.2307/30036540.
23. Williams MD, Rana NP, Dwivedi YK. The unified theory of acceptance and use of technology (UTAUT): a literature review. J Enterp Inf Manag. 2015;28(3):443–88. https://doi.org/10.1108/JEIM-09-2014-0088.
24. Rondan-Cataluña FJ, Arenas-Gaitán J, Ramírez-Correa PE. A comparison of the different versions of popular technology acceptance models: a non-linear perspective. Kybernetes. 2015;44(5):788–805. https://doi.org/10.1108/K-09-2014-0184.
25. Venkatesh V, Thong JYL, Xu X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Q. 2012;36(1):157–78. https://doi.org/10.2307/41410412.

26. Doleck T, Bazelais P, Lemay DJ. Is a general extended technology acceptance model for e-learning generalizable? Knowl Manag E-Learn. 2018;10(2):133–47.
27. Lee W, Xiong L, Hu C. The effect of Facebook users' arousal and valence on intention to go to the festival: applying an extension of the technology acceptance model. Int J Hosp Manag. 2012;31(3):819–27. https://doi.org/10.1016/j.ijhm.2011.09.018.
28. Al-Azawei A, Lundqvist K. Learner differences in perceived satisfaction of an online learning: an extension to the technology acceptance model in an Arabic sample. Electron J e-Learn. 2015;13(5):408–26.
29. Al-Nuaimi MN, Al Sawafi OS, Malik SI, Al-Emran M, Selim YF. Evaluating the actual use of learning management systems during the covid-19 pandemic: an integrated theoretical model. Interact Learn Environ. 2023;31(10):6905–30. https://doi.org/10.1080/10494820.2022.2055577.
30. Tarhini DA, Hassouna DM, Abbasi DMS, Orozco DJ. Towards the acceptance of RSS to support learning: an empirical study to validate the technology acceptance model in lebanon. Electr J e-Learn. 2015;13(1):30–41.
31. Abdullah F, Ward R, Ahmed E. Investigating the influence of the most commonly used external variables of TAM on students' Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of e-portfolios. Comput Hum Behav. 2016;63:75–90. https://doi.org/10.1016/j.chb.2016.05.014.
32. Farooq S, Ahmad Z, Hassan N, Khan MS. A technology acceptance model for e-learning during COVID-19: empirical insight from Pakistan. Elem Educ Online. 2021;20(4):975–84. https://doi.org/10.17051/ilkonline.2021.04.105.
33. Sternad Zabukovšek S, Picek R, Bobek S, Šišovska Klančnik I, Tominc P. Technology acceptance model based study of students' attitudes toward use of enterprise resource planning solutions. J Inf Organ Sci. 2019;43(1):49–71. https://doi.org/10.31341/jios.43.1.4.
34. Hanif A, Jamal FQ, Imran M. Extending the technology acceptance model for use of e-learning systems by digital learners. IEEE Access. 2018;6:73395–404. https://doi.org/10.1109/ACCESS.2018.2881384.
35. Ibrahim R, Leng NS, Yusoff RCM, Samy GN, Masrom S, Rizman ZI. E-learning acceptance based on technology acceptance model (TAM). J Fundam Appl Sci. 2017;9(4S):871. https://doi.org/10.4314/jfas.v9i4S.50.
36. Koutromanos G, Styliaras G, Christodoulou S. Student and in-service teachers' acceptance of spatial hypermedia in their teaching: the case of HyperSea. Educ Inf Technol. 2015;20(3):559–78. https://doi.org/10.1007/s10639-013-9302-8.
37. Vladova G, Ullrich A, Bender B, Gronau N. Students' acceptance of technology-mediated teaching—how it was influenced during the COVID-19 pandemic in 2020: a study from Germany. Front Psychol. 2021;12:636086. https://doi.org/10.3389/fpsyg.2021.636086.
38. Abbas TM. Human factors affecting university hospitality and tourism students' intention to use e-learning: a comparative study between Egypt and the UK. J Hum Resour Hosp Tour. 2017;16(4):349–66. https://doi.org/10.1080/15332845.2017.1266866.
39. Hong X, Zhang M, Liu Q. Preschool teachers' technology acceptance during the COVID-19: an adapted technology acceptance model. Front Psychol. 2021;12:691492. https://doi.org/10.3389/fpsyg.2021.691492.
40. Wong GKW. Understanding technology acceptance in pre-service teachers of primary mathematics in Hong Kong. Australas J Educ Technol. 2015;31(6):713–35. https://doi.org/10.14742/ajet.1890.
41. Al-Mamary YHS, Siddiqui MA, Abdelraheem SG, Jazim F, Abdulrab M, Rashed RQ, Alquhaif AS, Alhaji AA. Factors Impacting Saudi students' intention to adopt learning management systems using the TPB and UTAUT integrated model. J Sci Technol Policy Manag. 2023. https://doi.org/10.1108/JSTPM-04-2022-0068.
42. Chibisa A, Sibaya DC, Mutambara D. Factors affecting pre-service teachers' acceptance of online learning to promote social distancing. Progressio. 2022. https://doi.org/10.25159/2663-5895/12229.
43. Lazim CSL, Ismail NDB. Application of technology acceptance model (TAM) towards online learning during covid-19 pandemic: accounting students perspective. Int J Bus Econ Law. 2021;24(1):13–20.
44. Šumak B, Heričko M, Pušnik M. A meta-analysis of e-learning technology acceptance: the role of user types and e-learning technology types. Comput Hum Behav. 2011;27(6):2067–77.
45. Akman I, Turhan C. User acceptance of social learning systems in higher education: an application of the extended technology acceptance model. Innov Educ Teach Int. 2017;54(3):229–37. https://doi.org/10.1080/14703297.2015.1093426.
46. Fishbein M, Ajzen I. Belief, attitude, intention and behavior: an introduction to theory and research reading. Boston: Addison-Wesley; 1975.
47. Ching-Ter C, Hajiyev J, Su C-R. Examining the students' behavioral intention to use e-learning in Azerbaijan? The general extended technology acceptance model for e-learning approach. Comput Educ. 2017;111:128–43. https://doi.org/10.1016/j.compedu.2017.04.010.
48. Fathema N, Shannon D, Ross M. Expanding the technology acceptance model (TAM) to examine faculty use of learning management systems (LMSs) in higher education institutions. MERLOT J Online Learn Teach. 2015;11(2):210–32.
49. Kemp A, Palmer E, Strelan P. A taxonomy of factors affecting attitudes towards educational technologies for use with technology acceptance models. Br J Edu Technol. 2019;50(5):2394–413. https://doi.org/10.1111/bjet.12833.
50. Ranellucci J, Rosenberg JM, Poitras EG. Exploring pre-service teachers' use of technology: the technology acceptance model and expectancy-value theory. J Comput Assist Learn. 2020;36(6):810–24. https://doi.org/10.1111/jcal.12459.
51. Joo YJ, Park S, Lim E. Factors influencing preservice teachers' intention to use technology. J Educ Technol. 2018;21(3):48–59.
52. Venkatesh V, Davis FD. A theoretical extension of the technology acceptance model: four longitudinal field studies. Manag Sci. 2000;46(2):186–204. https://doi.org/10.1287/mnsc.46.2.186.11926.
53. Scherer R, Siddiq F, Tondeur J. The technology acceptance model (TAM): a meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. Comput Educ. 2019;128:13–35. https://doi.org/10.1016/j.compedu.2018.09.009.
54. Zimmerman BJ. Attaining self-regulation: a social cognitive perspective. In: Boekaerts M, Pintrich PR, Zeidner M, editors. Handbook of self-regulation. Cambridge: Academic Press; 2000. p. 13–39.
55. Boekaerts M. Self-regulated learning: where we are today. Int J Educ Res. 1999;31(6):445–57. https://doi.org/10.1016/S0883-0355(99)00014-2.
56. Zheng CP, Wang LL. The relationship between English language learners' self-regulation and technology acceptance. Foreign Lang Educ. 2020;41(2):64–70.

57. Wang Y, Zhang H. An influencing factors model of self-regulated learning of adult in web-based learning space. In: 2019 International Joint Conference on Information, Media and Engineering (IJCIME), 2019. p. 32–7. https://doi.org/10.1109/IJCIME49369.2019.00016.
58. Zhou S, Zhou Y, Zhu H. Predicting Chinese university students' E-learning acceptance and self-regulation in online English courses: evidence from emergency remote teaching (ERT) during COVID-19. SAGE Open. 2021. https://doi.org/10.1177/21582440211061379.
59. Al-Adwan AS. Investigating the drivers and barriers to MOOCs adoption: the perspective of TAM. Educ Inf Technol. 2020;25(6):5771–95. https://doi.org/10.1007/s10639-020-10250-z.
60. Ishaq E, Bashir S, Zakariya R, Sarwar A. Technology acceptance behavior and feedback loop: exploring reverse causality of TAM in post-COVID-19 scenario. Front Psychol. 2021. https://doi.org/10.3389/fpsyg.2021.682507.
61. Tabak F, Nguyen NT. Technology acceptance and performance in online learning environments: impact of self-regulation. MERLOT J Online Learn Teach. 2013;9(1):1–11.
62. Bandura A. Human agency in social cognitive theory. Am Psychol. 1989;44(9):1175–84. https://doi.org/10.1037/0003-066X.44.9.1175.
63. Panadero E. A review of self-regulated learning: six models and four directions for research. Front Psychol. 2017. https://doi.org/10.3389/fpsyg.2017.00422.
64. Zhu Y, Zhang JH, Au W, Yates G. University students' online learning attitudes and continuous intention to undertake online courses: a self-regulated learning perspective. Educ Tech Res Dev. 2020;68(3):1485–519. https://doi.org/10.1007/s11423-020-09753-w.
65. Bandura A. Guide for constructing self-efficacy scales. In: Urdan T, Pajares F, editors. Self-efficacy beliefs of adolescents. Charlotte: Information Age Publishing; 2006. p. 307–33.
66. Shao Z. Examining the impact mechanism of social psychological motivations on individuals' continuance intention of MOOCs: the moderating effect of gender. Internet Res. 2018;28(1):232–50. https://doi.org/10.1108/IntR-11-2016-0335.
67. Cigdem H, Topcu A. Predictors of instructors' behavioral intention to use learning management system: a Turkish vocational college example. Comput Hum Behav. 2015;52:22–8. https://doi.org/10.1016/j.chb.2015.05.049.
68. Salloum SA, Alhamad AQM, Al-Emran M, Monem AA, Shaalan K. Exploring students' acceptance of E-learning through the development of a comprehensive technology acceptance model. IEEE Access. 2019;7:128445–62. https://doi.org/10.1109/ACCESS.2019.2939467.
69. Dele-Ajayi O, Strachan R, Anderson EV, Victor AM. Technology-enhanced teaching: a technology acceptance model to study teachers' intentions to use digital games in the classroom. In: 2019 IEEE Frontiers in Education Conference (FIE), 2019. p. 1–8. https://doi.org/10.1109/FIE43999.2019.9028527.
70. Lee D, Allen M, Cheng L, Watson S, Watson W. Exploring the relationships between self-efficacy and self-regulated learning strategies of English language learners in a college setting. J Int Stud. 2021;11(3):567–85. https://doi.org/10.32674/jis.v11i3.2145.
71. Suki NM, Suki NM. Determining students' behavioural intention to use animation and storytelling applying the UTAUT model: the moderating roles of gender and experience level. Int J Manag Educ. 2017;15(3):528–38. https://doi.org/10.1016/j.ijme.2017.10.002.
72. Leong LW, Ibrahim O, Dalvi-Esfahani M, Shahbazi H, Nilashi M. The moderating effect of experience on the intention to adopt mobile social network sites for pedagogical purposes: an extension of the technology acceptance model. Educ Inf Technol. 2018;23(6):2477–98. https://doi.org/10.1007/s10639-018-9726-2.
73. Liu I-F, Chen MC, Sun YS, Wible D, Kuo C-H. Extending the TAM model to explore the factors that affect intention to use an online learning community. Comput Educ. 2010;54(2):600–10. https://doi.org/10.1016/j.compedu.2009.09.009.
74. Tarhini A, Elyas T, Akour MA, Al-Salti Z. Technology, demographic characteristics and E-learning acceptance: a conceptual model based on extended technology acceptance model. High Educ Stud. 2016;6(3):72–89. https://doi.org/10.5539/hes.v6n3p72.
75. Hesse LS, Walter G, Tietze S. Influence of personality, affinity for technology and risk awareness on technology acceptance using the example of voice control. In: Proceedings of the Conference on Mensch und Computer, 2020. p. 211–21. https://doi.org/10.1145/3404983.3405592.
76. Egorov EE, Prokhorova MP, Lebedeva TE, Mineeva OA, Tsvetkova SY. Moodle LMS: positive and negative aspects of using distance education in higher education institutions. Propós Represent. 2021;9(2): e1104. https://doi.org/10.20511/pyr2021.v9nSPE2.1104.
77. Masrek M, Jamaludin A, Awang Mukhtar S. Evaluating academic library portal effectiveness: a Malaysian case study. Libr Rev. 2010;59(3):198–212. https://doi.org/10.1108/00242531011031188.
78. Brooke J. SUS—a quick and dirty usability scale. In: Jordan PW, Thomas B, McClelland IL, Weerdmeester B, editors. Usability evaluation in industry. 1st ed. Boca Raton: CRC Press; 1996. p. 4–7.
79. Mishra S, Panda S. Development and factor analysis of an instrument to measure faculty attitude towards e-learning. Asian J Distance Educ. 2007;5(1):27–33.
80. Venkatesh V, Bala H. Technology acceptance model 3 and a research agenda on interventions. Decis Sci. 2008;39(2):273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x.
81. Lin H-H, Lin S, Yeh C-H, Wang Y-S. Measuring mobile learning readiness: scale development and validation. Internet Res. 2016;26(1):265–87. https://doi.org/10.1108/IntR-10-2014-0241.
82. Hung M-L. Teacher readiness for online learning: scale development and teacher perceptions. Comput Educ. 2016;94:120–33. https://doi.org/10.1016/j.compedu.2015.11.012.
83. Dörrenbächer L, Perels F. Self-regulated learning profiles in college students: their relationship to achievement, personality, and the effectiveness of an intervention to foster self-regulated learning. Learn Individ Differ. 2016;51:229–41. https://doi.org/10.1016/j.lindif.2016.09.015.
84. Kline RB. Principles and practice of structural equation modeling. 4th ed. New York: Guilford Press; 2016.
85. Matsunaga M. Item parceling in structural equation modeling: a primer. Commun Methods Meas. 2008;2(4):260–93. https://doi.org/10.1080/19312450802458935.
86. Hatcher L. A step-by-step approach to using the SAS® system for factor analysis and structural equation modeling. Cary: SAS Institute; 1994.
87. Field A. Discovering statistics using IBM SPSS statistics. Newcastle upon Tyne: Sage; 2018.
88. Hair J, Anderson R, Tatham R, Black W. Multivartiate data analysis. 5th ed. Hoboken: Prentice Hall; 1998.
89. Little TD, Cunningham WA, Shahar G, Widaman KF. To parcel or not to parcel: exploring the question, weighing the merits. Struct Equ Model. 2002;9(2):151–73. https://doi.org/10.1207/S15328007SEM0902_1.

90. Rhemtulla M. Population performance of SEM parceling strategies under measurement and structural model misspecification. Psychol Methods. 2016;21(3):348–68. https://doi.org/10.1037/met0000072.
91. Kenny DA. Correlation and causality. Hoboken: Wiley; 1979.
92. Hair JF, Sarstedt M, Hopkins L, Kuppelwieser VG. Partial least squares structural equation modeling (PLS-SEM): an emerging tool in business research. Eur Bus Rev. 2014;26(2):106–21. https://doi.org/10.1108/EBR-10-2013-0128.
93. Hu L, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct Equ Model. 1999;6(1):1–55. https://doi.org/10.1080/10705519909540118.
94. Kelloway EK. Using LISREL for structural equation modeling: a researcher's guide. Newcastle upon Tyne: Sage; 1998.
95. Fornell C, Larcker DF. Structural equation models with unobservable variables and measurement error: algebra and statistics. J Mark Res. 1981;18(3):382–8. https://doi.org/10.1177/002224378101800313.
96. Jiang MY, Jong MS, Lau WW, Meng Y, Chai C, Chen M. Validating the general extended technology acceptance model for e-learning: evidence from an online English as a Foreign language course amid COVID-19. Front Psychol. 2021;12:671615.
97. Astari AAE, Yasa NNK, Sukaatmadja IPG, Giantari IGAK. Integration of technology acceptance model (TAM) and theory of planned behavior (TPB): an e-wallet behavior with fear of covid-19 as a moderator variable. Int J Data Netw Sci. 2022;6(4):1427–36. https://doi.org/10.5267/j.ijdns.2022.5.008.
98. Li Y, Duan Y, Fu Z, Alford P. An empirical study on behavioural intention to reuse e-learning systems in rural China: a study on intention to reuse e-learning in rural China. Br J Edu Technol. 2012;43(6):933–48. https://doi.org/10.1111/j.1467-8535.2011.01261.x.
99. Doan TTT. The effect of perceived risk and technology self-efficacy on online learning intention: an empirical study in Vietnam. J Asian Finance Econ Bus. 2021;8(10):385–93. https://doi.org/10.13106/JAFEB.2021.VOL8.NO10.0385.
100. Mali D, Lim H. How do students perceive face-to-face/blended learning as a result of the Covid-19 pandemic? Int J Manag Educ. 2021;19(3):100552. https://doi.org/10.1016/j.ijme.2021.100552.
101. Sadi O, Uyar M. The relationship between self-efficacy, self-regulated learning strategies and achievement: a path model. J Baltic Sci Educ. 2013;12(1):21–33. https://doi.org/10.33225/jbse/13.12.21.
102. Wang C-H, Shannon DM, Ross ME. Students' characteristics, self-regulated learning, technology self-efficacy, and course outcomes in online learning. Distance Educ. 2013;34(3):302–23. https://doi.org/10.1080/01587919.2013.835779.
103. Azevedo R, Moos DC, Johnson AM, Chauncey AD. Measuring cognitive and metacognitive regulatory processes during hypermedia learning: issues and challenges. Educ Psychol. 2010;45(4):210–23. https://doi.org/10.1080/00461520.2010.515934.
104. Alismaiel OA. Using structural equation modeling to assess online learning systems' educational sustainability for university students. Sustainability. 2021;13(24):13565. https://doi.org/10.3390/su132413565.
105. Rizun M, Strzelecki A. Students' acceptance of the COVID-19 impact on shifting higher education to distance learning in Poland. Int J Environ Res Public Health. 2020;17(18):6468. https://doi.org/10.3390/ijerph17186468.
106. George D, Mallery P. SPSS for Windows step by step: a simple guide and reference. 4th ed. Boston: Allyn & Bacon; 2003.
107. Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate data analysis. Pearson College Division. 2010.
108. Taber KS. The use of Cronbach's alpha when developing and reporting research instruments in science education. Res Sci Educ. 2018;48(6):1273–96. https://doi.org/10.1007/s11165-016-9602-2.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.